MEDICAL DECISION SUPPORT

an approach in the domain
of brachial plexus injuries
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PROEFSCHRIFT

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Chapter 1

Introduction

1.1 GENERAL INTRODUCTION TO MEDICAL DECISION SUPPORT

Today, computers are part of all areas of health care. Hospital information systems, medical instrumentation and assistive devices can no longer be thought of, without the availability of large-scale or micro computer systems. The potential of computer assistance in medical decision making has been explored extensively for the past three decades. The introduction of these systems, however, has not always been undisputed. The appreciation of these systems’ ability to improve health care often conflicted with their conceivable effect on medical practice and concerned such issues as the depersonalization of medical care and the loss of jobs. However, due to the rapid growth of medical knowledge and the increasing specialization of medicine that goes with it, together with the seemingly uncheckable introduction of computers in all areas of daily life, the medical community seems to have become more amenable to computerized decision support. Increasingly, information processing has become an important task for primary care physicians as well as for experts in a specialized field of medicine. Accordingly, the potential of computer assistance has been increasingly recognized. This does not automatically guarantee success for each decision support system that can possibly be developed in research laboratories. Many questions remain to be solved in order to guarantee the application of a decision support system. Such a system should alleviate a well-demonstrated need in a cost effective way, i.e. physicians should benefit from the use of the system. In this thesis, the aspects that determine the cost effectiveness of a medical decision support system are dealt with for different approaches to medical decision support. A medical decision support system is very broadly defined to be "An interactive computer system that assists physicians, or other health care professionals, in medical decision making". These aspects are elucidated in the domain of brachial plexus injuries, which was the area in which the research in question was conducted.

1.2 HISTORY

The research presented in this thesis is part of a research program concerning
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rehabilitation technology conducted at the Man-Machine Systems Group of the Delft University of Technology. The research program started in 1968 at the Laboratory for Measurement and Control with the development and evaluation of externally powered prostheses and orthoses for the upper extremity. The focus of the projects was on the man-machine interaction in general, i.e. the interaction between patient and prosthesis, e.g. the use of tactile information in arm prostheses (Stassen et al, 1970) as well as that between the patient with a prosthesis and his environment. This immense research area gave rise to a number of derived projects in the field of communication aids (Soede et al, 1973; Janssen, 1984) as well as in the field of upper extremity prostheses, such as a study of the mental load in arm prosthesis control (Soede, 1980), the role of proprioceptive and visual feedback in goal-directed movements (Eland, 1981; Ruitenbeek, 1985). But also laboratory and field evaluations of prostheses (Van Lunteren et al, 1983) and development of decision support systems in the treatment of quadriplegics (Stassen et al, 1980) became areas of interest. The research in question originally started in 1981 from a cross-fertilization of these two projects, i.e. the evaluation of arm orthoses and decision support systems in the treatment of brachial plexus injuries (Jaspers et al, 1982; De Louw and Van Huygevoort, 1982; Stassen, 1989). For this purpose the cooperation with the rehabilitation center 'De Hoogstraat', Utrecht, in particular the Orthotics and Prosthetics Treatment Team proved to be very useful. In 1985 this cooperation was extended to include also the departments of Neurosurgery of both the Leiden University Hospital and the De Wever Hospital in Heerlen. The results of this cooperation are reported in this thesis.

1.3 HEALTH CARE

Health care aims at diagnosing patients' diseases and curing them through therapy, or diminishing the disabling effects of the disease as in the rehabilitation and treatment of chronically ill patients. In the sequel this will be called the process of medical consultation. Medical consultation is an iterative process (Elstein et al, 1978; Kassirer and Gorry, 1978) in which the physician interacts with the patient. It incorporates diagnosing a patient's disease, selecting an appropriate therapy and determining a prognosis. In contrast to a definition that is sometimes found in medicine,
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In this thesis prognosis is not defined to be the natural course a disease is likely to take, but the course a disease is likely to take if a specified therapy is to be applied. The decisions in medical consultation are based on the interpretation of findings from patient examination. The consultation cycle can be summarized as follows (Fig. 1.1):

1. elicitation of findings
   - medical history
   - physical examination
   - subsequent tests
2. interpretation of findings
3. establishing a (tentative) diagnosis
4. (re)assessment of therapy
5. determining a (tentative) prognosis

At first, patient findings from the medical history or provisional physical examination will suggest certain diagnostic hypotheses. These findings and the associated tentative diagnosis will indicate the need for acute treatment or for subsequent diagnostic testing. For instance, in the case of traumatic injuries, initial findings of arterial lesions will lead to acute vascular reconstruction, whereas signs of bone fractures will probably lead to radiological examination. If the necessary acute treatments have been applied and the patient's condition is more or less stable, the physician is confronted with the question as to whether his initial decisions regarding diagnosis, therapy and prognosis are sufficient, or whether additional information is needed to improve these decisions.

diagnosis and treatment

As is clear from Fig. 1.1, at each decision node in the medical consultation cycle it is determined whether sufficient information about the patient has been acquired to allow a decision. Therapeutic and prognostic decisions largely rely on the established diagnosis. Therapy is started when additional testing will not influence the choice of therapy, or when the complaints are so serious that therapy can no longer be postponed, as in the acute stage. Selecting a therapy that is not optimal for the patient may have serious consequences. The diagnostic process therefore concerns the evaluation of the risk of misdiagnosis with the associated risk of applying the wrong treatment,
and the cost of further testing with the associated benefit of improving the diagnosis or optimizing the therapy. By applying diagnostic tests, the uncertainty associated with the tentative diagnosis may be decreased, until in view of the possible decisions regarding patient management a satisfactory diagnosis has been achieved. This means the physician will cease testing either when he is certain (enough) about the diagnosis, or when the cost of further testing outweighs its benefit in reducing the risk of applying the wrong treatment. Then the diagnosis is established and a treatment plan will be selected. When a patient is suffering from serious complaints with strong indications for therapy, a detailed diagnosis will be pursued. When the patient suffers from less serious complaints, diagnosis is only global and therapy will be applied merely to fight symptoms. This general description of the medical consultation process applies to all areas of medicine. As it has been made clear in the previous section, the research presented in this thesis stems from the treatment of patients with disorders of the musculo-

![Diagram](image.png)

**Figure 1.1** The medical consultation cycle.
Introduction

skeletal system. In this domain, apart from well-known, long-established disciplines such as neurology, neurophysiology, orthopedics, neurosurgery, hand surgery and plastic surgery, another area of medicine is of great importance, i.e. rehabilitation.

1.3.1 Rehabilitation

Rehabilitation satisfies the general characteristics described in the previous section. However, due to certain features which distinguish it from curative medicine, it deserves to be considered in its own right. In order to understand the specific nature of rehabilitation medicine, the concepts of impairment, disability and handicap, as introduced by Wood and Badley (1981), will be described here:

- Impairment is the lack or deviation of the psychological, physiological or anatomical structure or function.
- Disability is the restriction in activities due to any impairment.
- Handicap is the hindrance that prevents one from functioning as a social human being dependent on the attitude of other persons, social values and institutional structure.

Rehabilitation aims at diminishing or, if possible, removing a patient's handicap and its effects, in order for the patient to function in society in the best possible way. In contrast to curative medicine, in rehabilitation medicine itself, the recovery of the biological system is not possible. Because of this, the treatment does not concentrate on the somatic field only. Rehabilitation comprises a complex of activities in the medical, paramedical, occupational, technical, social and psychological areas. Therefore a multidisciplinary approach is necessary for optimal rehabilitation treatment.

For the rehabilitation team to be able to treat the patient optimally, it has to take part in the medical treatment as soon as possible. This means that a patient may have to enter a rehabilitation program soon after the acute treatments have finished, when the diagnosis has not yet been clearly established. This is the case, for instance, in the rehabilitation of brachial plexus injuries (Jaspers, 1986). Therefore rehabilitation is not necessarily
limited to conservative treatment. Surgical treatments may have to be applied in parallel, such as neurosurgical repair or orthopedic reconstruction in the treatment of brachial plexus injuries.

As will be clear from the previous description of the process of rehabilitation, it is not merely defined as the conservative treatment of patients with motoric defects, but it is the integration of all disciplines involved in the medical consultation process. In this multidisciplinary treatment process, the rehabilitation physician plays a key role in treatment planning. Ultimately, he should decide what priorities in function restoration have to be chosen for a specific patient, since ideally he should have an overview of the patient’s handicap and the possibilities for treatment. This decision should be based upon the diagnosis, the treatment possibilities, operative as well as non-operative, the prognosis and the patient’s needs concerning Activities of Daily Living, ADL, vocational activities and hobbies. Since rehabilitation, as defined above, consists of treating the impairment as well as its effects, it is both a healing and a learning process. In the learning process, the patient learns to accept his disability, to accommodate to the lasting functional defects and to reintegrate in society, which very often means that he has to change his plans for future life. Because of this learning process and since so many disciplines are involved, the rehabilitation process may be of considerable duration. For brachial plexus injuries the average rehabilitation takes about 3 years (Jaspers et al, 1982). Therefore, in general, rehabilitation is not purely an in-patient treatment. It will either be a combination of periods of in-patient treatment at the rehabilitation center and out-patient treatment at home, or the treatment will be purely out-patient. In this way, the patient is not totally isolated from normal life and his reintegration in society is facilitated.

1.3.2 The need for support

As it will be clear from the foregoing, rehabilitation is a very complex process of long duration in which many disciplines are involved. In order to achieve the intended results of the treatment, the treatment team members and the patient have to be well informed about all aspects of the diagnosis,
therapy and prognosis. This requires an enormous amount of information exchange among the team members. Since often a specific function may be restored in a number of ways, e.g. by neurosurgical repair, orthopedic reconstruction, or the application of orthoses, the ultimate choice of therapy depends on the patient's needs and the prognosis of each treatment plan. However, often objective knowledge of the prognosis for different combinations of diagnosis and treatment is almost unavailable. Each treatment team has its own treatment strategy, dependent on its particular approach. A team in a rehabilitation center, for instance, will rather tend to non-invasive treatment, whereas a team in a surgical center will be more apt to opt for surgical treatment. The results of several treatment strategies can not be easily compared, since no standardized way of recording patient data is available. This indicates the need for an information system for standardized data acquisition, which may be used for the evaluation of treatment methods. Nevertheless, even if such a system were available, the amount of data to be dealt with is still very large and covers a broad field of expertise. Supporting treatment team members in data interpretation and decision making may remedy the situation. For instance, the treatment team and the patient could get diagnostic advice or an early prognosis of the patient's future state, as well as an advice for optimal treatment. The basis of medical decision support systems is the modeling of the treatment process. An objective model of the treatment can also be helpful in another way. It is well known that, due to the complexity of medical treatment processes, physicians tend to get biased because of similar but not identical cases they treated before. By giving physicians insight into the total treatment process, and making the criteria for decisions explicit and reproducible by means of a model, this source of bias can be avoided.

what need?

Although the above issues demonstrate the need for support in the health care area in a general sense, this will generally be insufficient to guarantee that a medical decision support system is acceptable to its users. For this purpose it will be necessary to demonstrate a clear need for support in the domain the system is to be developed for. This is an absolute necessity for the acceptance of the system, apart from many other criteria that will be discussed in Ch. 6. A need for support in the domain can be present in either
one of two areas:

1. There is an overall lack of knowledge in the domain concerning one of the stages in medical consultation, i.e. diagnosis, therapy, prognosis.
2. Knowledge about diagnosis, therapy and prognosis is available only to a few experts and there is a lack of knowledge in daily practice.

The first condition applies to domains where knowledge is still very limited, or where new diagnostic or therapeutic procedures have been introduced that can not yet be clearly appreciated. In these cases, where there is an overall lack of sufficient domain knowledge, the development of a decision support system calls for what will be called in this thesis a data based approach. The necessary knowledge to support physicians in their decision-making task has to be acquired from the analysis of data from the domain. The resulting decision support system must be suitable to support all physicians in the domain, experts as well as non-experts. This system may be used to evaluate different treatment schemes.

Due to the increasing specialization, the second need for support can be found in many domains in medicine. A physician who is confronted with a complex problem outside his area of expertise will often not be able to accurately diagnose and optimally treat the patient. Or he will do so only with the expenditure of great effort. In this case, the knowledge based approach to decision support may be a viable alternative to the data based approach, since knowledge of the domain is available, though to experts only. The decision support system to be developed is primarily meant to aid non-experts in the domain, although sometimes experts may find its consultation useful as a second opinion, to check whether they have overlooked important evidence.

1.4 MEDICAL DECISION SUPPORT

Computer applications in medicine cover all areas of medical practice, from taking a patient’s history to diagnosis and therapy, and range from automated data acquisition through data interpretation to decision making. This last issue will be the main concern of this section. What techniques are available to aid medical decision making? What are their merits? In what areas of
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medical practice may decision support be useful?
In addition to the use of computers in hospital administration, computer-aided instruction or medical instrumentation and assistive devices, computer applications have been developed for all medical consultation tasks to aid physicians. Typical applications include data acquisition, storage and retrieval (Weed, 1973; Bleich et al, 1985), data analysis (Pryor et al, 1969) and patient monitoring (Warner, 1968). However, many of these tasks are relatively straightforward and require few real decisions. Yet, determining a patient’s diagnosis and selecting a therapy often require a substantial amount of reasoning based on large amounts of information.
The amount of information that can be successfully processed by physicians is limited. Exceeding this limit may cause errors like overlooking important evidence, or failure to react properly to certain findings. This might be the cause of many medical errors (McDonald, 1976). Supporting physicians in data interpretation and decision-making may remedy this. Modeling the diagnostic and treatment process is the basis of such medical decision support systems.

1.4.1 Goals

In a general sense, the aim of decision support systems can be said to be the optimization, in some sense, of the diagnostic and treatment process, directly or indirectly affecting the health of the patient. To be able to assess the effect of such systems, these goals should be more clearly defined. They can be more or less objectively assessable criteria like reduction of patients’ length of stay, or physicians’ time savings, or those which are more difficult to assess like improved patient care, possibly resulting in functional improvement which, hopefully, facilitates reintegration in society. The rising costs in medicine and recent budget cuts necessitate the justification of decision support systems as cost effective, requiring a comparison of system benefits and costs. Is a system to be considered successful if its use results in a more accurate diagnosis without improving a patient’s health? Probably not; diagnosis should provide the basis for patient management, which is the goal of health care, rather than being considered a goal in its own right.
Effective computer applications require the determination of clinical problems and require a need for support as well as a clear cut definition of the
system's objectives. Unfortunately, some of these objectives may inherently increase the medical costs, whereas the pay-off may be outside the medical area. For instance, a decision support system in the domain of brachial plexus injuries could clearly be of support in the area of clinical problems to do with diagnosis and treatment planning (Ch. 2). Inevitably, this will lead to an increase in the number of expensive, time-consuming reconstructive surgical procedures. Whereas this will significantly increase the cost of medical treatment for these patients, it will potentially benefit their successful reintegration in society, resulting in savings in productivity or the number of people eligible for social security, both of which are more difficult to quantify. Even more important, this will result in increased patient wellbeing, a benefit which is even harder to quantify. These issues concerning the assessment of medical decision support systems surely influence the acceptance and use of this technology. They demand a thorough evaluation of system performance not only in respect to cost-effectiveness, but also in respect to issues as safety and ethical, psychological and legal implications. System evaluation will be discussed in Ch. 6.

1.4.2 Approaches to medical decision support

Except for the simplest database analysis systems, computer based decision support systems call for some form of automated decision-making. This poses the need to make the knowledge, required to make the decision, available to the computer. This may be done in the form of a mathematical model. The model is the central notion in decision support systems. It can be defined as a representation of that part of reality we are interested in, i.e. the system. In order not to become confused, in the following the term system will be used

![Figure 1.2 The medical consultation process.](image)
Introduction

only for the support device that is used as an aid in medical decision-making, i.e. the decision support system, the system that is modeled in the decision support system will be called process. The model describes the essential properties of the process. Models in medical decision support systems can be constructed for various purposes, depending on the particular decision problem, and may vary accordingly:

- diagnostic models
- prognostic models
- models for control purposes, i.e. therapy selection, treatment planning
- other goals like instruction

It is important to notice that although a model is a reflection of reality it is not a complete description of reality. Dependent on the purpose of the model, it should only describe those process properties that are significant for that purpose.

Medical consultation tasks that may benefit from decision support, e.g. diagnosis, prognosis, treatment planning, all involve the kind of interaction depicted in Fig. 1.2. The physician, either a single person or a multidisciplinary team, performs actions \( u \), upon the patient, which can be either diagnostic tests or actual treatments, resulting in a patient's reaction \( y \), which in turn is observed by the physician, who may adjust his actions accordingly. Clearly, both physician and patient interact in a closed loop. If the relationship between the actions, \( u \), and the patient’s reaction, \( y \), would be completely known, these could be implemented in a model, allowing the exact calculation of \( y \) for every \( u \). However, apart from the physician’s actions, other signals affect the patient that can not as easily be modeled, like his interaction with the social environment (family, work). The physician is subjected to similar disturbances, like measurement noise in observing the patient. Thus, disturbances, which influence physician actions and patient reactions act upon the physician, \( e_1 \), as well as upon the patient, \( e_2 \). Another complicating factor is that the goals that determine the physician's actions, may vary during treatment, dependent on the treatment results, or on unanticipated influences.

Whether these issues may cause problems in constructing a model depends upon the model’s purpose as well as the modeling approach and the intensity of the disturbances.
Models may differ in two important aspects especially. The process to be modeled may be viewed as static, i.e. the dynamics of the process may be neglected, which makes the closed loop problem less important, or the model is dynamic and takes into account the dynamic properties of the process. Also, an important distinction between models is the extent to which a priori knowledge of the process is utilized to construct a model. In this section the different approaches that have been proposed for developing medical decision support systems are described. Although in these systems the methodologies used to derive an advice differ significantly, all decision support systems satisfy a general description as is depicted in Fig. 1.3. The basis of the system is formed by the model that contains, in some specific form, the knowledge of the process under consideration required to solve a particular problem. For instance, a model of the physician's (diagnostic) reasoning, or a model describing a patient's reaction to treatments. The input to such a model typically consists of a description of the specific situation, like information concerning the patient's condition or the proposed treatment. The output is some sort of supportive advice, for instance concerning the diagnosis, prognosis or treatment of the patient. Generally, this advice is derived by the inference mechanism that operates upon the model, which uses the information concerning the specific situation.

Knowledge based versus data based

Basically, a model may be constructed in two different ways. Knowledge of the process to be modeled, e.g. the patient or the diagnostic process, can be used to derive a model. This may be either experts' judgmental knowledge or

![Figure 1.3 Global architecture of a medical decision support system.](image)
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well-established quantitative mathematical relationships in the domain. Also these knowledge sources may be combined to obtain a model. In this thesis this approach to model construction is called knowledge based. Knowledge for knowledge based models is based on the abstraction of data from earlier empirical work. In many areas of medicine this knowledge is not available. Therefore, the alternative approach that started the work in medical decision support relies on the analysis of data concerning the process, in order to be able to infer a model, with little or no reference to a priori knowledge about the process. In these data based models, the model output is fitted to the data by adjusting the model parameters. In the sequel, examples of both the data based and the knowledge based approach will be discussed briefly. However, a categorization of models in either knowledge based or data based is not at all straightforward. Between these extremes there is a continuum of systems relying on both methodologies. Therefore, the classification presented here is highly subjective. A more extensive overview of medical decision support systems can be found in Shortliffe (1976), Shortliffe et al (1979) and Reggia and Tuhrim (1985).

1.4.3 Data based systems

Data based decision support systems either provide carefully selected data to support decision making or use large amounts of data to infer new knowledge. Typically, these systems compare a new patient to previous similar patients. The simplest data based systems are database analysis systems.

database analysis systems

Database analysis systems provide methods to retrieve information on previous patients to do with diagnosis and management. In this way physicians can compare their current patient to previously treated similar patients and identify how these responded to various treatments. Statistical methods may be added to provide further assistance by revealing information that is difficult to deduce merely by looking at the data. Applications can be found in many areas of medicine like treating lung cancer (Feinstein et al, 1972), rheumatology (Fries, 1972), coronary heart disease (Starmøer et al, 1979), stroke rehabilitation (Feigenson et al, 1979) and many others.
The amount of modeling in these systems is very limited. The model merely consists of a database that has all knowledge only implicitly incorporated. The inference mechanism is used to make this knowledge more explicit by identifying patients similar to the current patient. The assumption underlying the use of these systems is that the new patient will respond similarly to therapy. The main difficulty, as in all data based methods, lies in the reliance on a large database of patient information. The acquisition of this data is one of the major impediments to the construction of data based systems. In addition, database analysis systems impose high requirements on data storage space, since the entire database must be kept available when an advice is desired for a new patient. A way to remedy this is to make the model derived from the data more explicit, which inherently means a shift in the direction of the knowledge based approach. The following two methods employ this more explicit modeling and acquire their knowledge through the data. In classification systems, static models are employed to aid decision making. Dynamic system identification yields dynamic models to support the physician.

Classification systems

For some time, the major approach to constructing medical decision support systems has been the use of statistical decision theory, including Bayes' theorem, pattern recognition techniques and decision analysis. Of these, Bayes' theorem has received the most attention by far. Its potential for computer assistance in medical decision making had already been realized in 1959 by Ledley and Lusted (1959) who analyzed the reasoning processes in medical diagnosis. After they proposed the use of probabilistic models for diagnostic support, the Bayesian model received a great deal of attention as a basis for diagnostic models (Overall and Williams, 1963; Warner et al, 1964). Although Bayesian systems have been applied mostly to diagnostic problems, they can be constructed for other applications also, like treatment planning and prognosis.

In classification systems, a classification $d_i$ is sought that represents the true state of the world. Typically it is assumed that this state $d_i$ is one of a set of mutually exclusive hypotheses $d_1,\ldots,d_k$, where $D = \{d_1,\ldots,d_k\}$ is a finite set of $k$ states of the world. Let $x$ be a vector of $n$ discrete observations, then in Bayesian systems a classification is achieved by computing the a
posteriori probability of each hypothesis from the a priori probability and the conditional probabilities relating observations \( x \) to hypotheses:

\[
P(d_i|x) = \frac{P(d_i)P(x|d_i)}{\sum_{j=1}^{k} P(d_j)P(x|d_j)} \quad i = 1, 2, \ldots, k
\]

The model consists of the set of a priori and conditional probabilities. The inference mechanism applies Bayes' rule to compute the a posteriori probabilities. This method provides a sound basis for computing the probability of a disease based on observations. However, a straightforward application of Eq. (1.1) requires a large number of conditional probabilities to be available, imposing the requirement for an immense amount of data. Usually this impediment leads to the simplifying assumption that the observations \( x_m \), constituting \( x \), are conditionally independent. However, even with this assumption it may not always be possible to establish all probabilities required. This may lead to subjective estimation of probabilities, which according to several authors may cause a substantial decrease in system performance (Leaper et al., 1972; Shapiro, 1977). Other serious impediments of this approach that apply to other classification methods as well, will be discussed at the end of this section.

Pattern recognition provides a general scheme of classification. In this approach a classification is sought by the recognition of a symptom pattern representative for a specific class that best matches the observed pattern of symptoms. To determine which class is most similar to the observed case, a discriminant function is required. This is an equation relating a feature vector \( x \) to a diagnostic class \( d_i \). In the case of linear functions \( g_i(x) \):

\[
g_i(x) = w_0 + w_1x_1 + \ldots + w_nx_n \quad i = 1, \ldots, k
\]

As in Bayesian systems, these discriminant functions are derived from a database of previous cases of which the classification is known, the learning patterns. The discriminant functions, which constitute the system's model are computed according to some criterion. The most common of these is the least-squares criterion, which minimizes the sum of squared differences between observed classifications and predicted ones and leads to the linear
regression model. But also other criteria are used, like Bayes rule.
In pattern recognition systems the inference mechanism simply evaluates the value of the discriminant function for a specific case, and classifies the case according to a pre-defined criterion. The main difficulty in this approach is the selection of the set of discriminating patient variables.

Systems based on decision analysis employ a decision tree as a model. Branches in the tree either represent potential decisions (e.g. selecting a diagnostic test) or chance outcomes (e.g. the occurrence of a complication), viz. Fig. 1.4. Chance nodes have probabilities associated with them, whereas decision nodes may have associated cost values, which represent the cost of the decision, which may be in terms of money, patient discomfort etc. The ultimate outcomes of the tree have associated values representing the cost or benefit of the outcome. Basically the classification process performed by the inference mechanism consists of selecting a path through the decision tree.

Although classification methods in decision support systems have received a great deal of attention, some disadvantages of the method have to be pointed out. The assumption that a patient’s symptoms are conditionally independent is often violated, which could possibly lead to substantial errors. Also the assumption that categories are mutually exclusive is often false, which may lead to wrong conclusions. Furthermore the enormous data requirements, necessary for reliable estimation of probabilities or determination of

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![Decision Tree Diagram](image_url)

**Figure 1.4** An example part of a decision tree.
discriminant functions, are largely prohibitive to the widespread use of these systems. However, when a large database is available, classification methods have been shown to yield good results (Warner et al., 1961; Gorry and Barnett, 1968; De Dombal et al., 1972; Schwartz et al., 1973).

Classification methods employ static models of the process for decision making. For diagnostic purposes or therapy selection this may be sufficient. Often, however, static models can not describe all the relevant aspects of the process. For prognosis or treatment planning, for instance, the process dynamics may come into play. For these purposes dynamic models are necessary. Some of the parameter estimation techniques described in this section may be extended to dynamic systems in what is called the system identification approach. Since in the medical domain, due to the uncertainties in the data about the process, deterministic models are mostly inadequate to describe a process, the identification of dynamic stochastic systems will be dealt with. Although this field has not received very much attention in connection with decision support in the medical area, a more thorough discussion is warranted because of the great potential this approach offers for dynamic modeling in data based decision support.

**Dynamic system identification**

Where static models are no longer applicable in a medical decision support system, the static classification approach should be extended to yield dynamic models. This is not typical for the medical domain only. Data based decision making under conditions of uncertainty has always received much attention outside the medical domain also, especially in the fields of engineering, biology and economics. In these areas approaches have been developed to identify and control dynamic processes the behavior of which is not completely foreseeable, non-deterministic processes. In these processes the future evolution is not completely determined by its present state and future control actions. There is a stochastic uncertainty associated with future process behavior. In this field the concepts of system identification and control were developed (Åström and Eykhoff, 1971; Eykhoff, 1974; Goodwin and Payne, 1977; Ljung, 1987). Applications of this approach in the medical domain can be found in Hoogendoorn et al (1983), Stassen et al (1980) concerning the rehabilitation of spinal cord injuries, Blom (1975) in the area of patient intensive care, Beneken et al (1974) concerning anaesthesia. Dynamic system
identification will be discussed in more detail in Ch. 3.

1.4.4 Knowledge based systems

In the light of the problems inherent in the data based approach to medical decision support, especially the requirement for large amounts of data concerning the process, it is not surprising that other methods of decision support have been explored. These approaches are situated more towards the knowledge end of the data-knowledge continuum. Two kinds of knowledge based approaches will be discussed in this context: deterministic models based on physiological knowledge, and Artificial Intelligence approaches.

**Deterministic models based on physiological knowledge**

Instead of modeling a process from observed data, it seems logical to build a model from basic knowledge. Some medical domains are so well understood that sound physi(olog)ical models are available that describe the behavior of the process at hand. Of course, these models are very suitable to be implemented, in mathematical form, in decision support systems. In such systems the performance is determined mainly by the quality of the available model. However, most medical domains lack the detailed understanding that yields precise quantitative models, which limits the applicability of this approach to very few areas in medicine. Notable examples are Bleich's program for the evaluation of acid-base status (Bleich, 1972) and a system for determining digitalis dosage (Jelliffe et al, 1972).

**Artificial intelligence systems**

Because of the limitations of data based systems and the narrow applicability of mathematical models in medical domains, researchers' attention shifted towards an approach that is related more closely to human-like behavior. It was found that in human decision making reasoning plays a crucial role. Experts' (judgmental) knowledge might provide useful ways to deal with problems concerning uncertainty without the need for large databases or well-understood quantitative models. Therefore, Artificial Intelligence, AI, techniques were proposed to cope with many of the problems described earlier.
Introduction

Modeling the experts' decision-making process became an important research area once the inflexibility and limited acceptance of other approaches were realized. The incorporation of domain knowledge may not only improve a system's performance, but it also allows a more natural conversation with the user, which facilitates the explanation and justification of advice and which promotes user acceptance.

AI systems may be viewed as elaborating the decision analysis approach and adding flexibility to the rigidity of a decision tree. In these systems the domain knowledge is implemented in the model, the knowledge base, clearly separated from the inference engine that applies this knowledge in combination with specific problem-related data to reach a conclusion. Instead of the statistical or probabilistic approach in data based decision support systems, most AI systems employ symbolic models of diseases and symptoms. The AI approach to knowledge based decision support raises questions concerning such issues as 'how can the knowledge to be modeled be acquired?' and 'how can this knowledge be represented in the system?'. Although this approach successfully gets round the problem of data acquisition, which was found to be the major impediment in the data based approach, it seems that it has been traded for a problem the consequences of which can not yet be clearly appreciated: The knowledge acquisition problem.

Among others, these issues will be discussed extensively in Ch. 4. Well-known examples of the AI approach are MYCIN (Shortliffe, 1976), INTERNIST (Miller et al, 1982) and its successor CADUCEUS (Pople, 1982), CASNET (Weiss et al, 1978) and PIP (Pauker et al, 1976).

1.5 SCOPE OF THIS THESIS

This thesis deals with modeling in medical decision support. As has been made clear in the previous sections, two approaches are distinguished:

1. Data based modeling.
2. Knowledge based modeling.

The goal of this research is to assess the merits and demerits of these approaches. In order to derive general recommendations for the design of modular, maintainable medical decision support systems the following questions
must be asked:

- How can domain characteristics guide the choice in deciding for a knowledge based or a data based approach?
- Once this choice has been made, how should the necessary knowledge or data be acquired?
- What specific knowledge based or data based techniques are the best to derive a suitable model for decision support?

This particular research has been conducted in the domain of brachial plexus injuries. Results from this research will therefore be illustrated with examples from this domain.

The thesis has been organized as follows:

In Ch. 2, a detailed discussion on brachial plexus injuries is presented. Anatomy, as well as diagnosis and treatment, is discussed in order to provide a basic understanding of the domain, which will make it easy to understand the examples in subsequent chapters. At the end of this chapter, it is made clear why medical decision support is called for in this domain.

For readers who are not familiar with either system identification or knowledge based systems, these will receive attention in Chs. 3 and 4. These chapters present a concise introduction to these fields, with respect to medical decision support. The different stages of the design process are described in detail. The potential problems and the merits of each approach are revealed. These chapters may be skipped by readers who already possess knowledge of the methods applied in these areas. In the final section of each of these chapters, however, some preliminary ideas that are of relevance for a proper understanding of the remainder of this thesis and which concern the applicability of these methods in medical decision support, are presented. Chapter 5 deals with the design and realization of a knowledge based system for diagnosis and treatment of brachial plexus injuries.

The results of this system, PLEXUS, are presented in Ch. 6. Chapter 7 reports on the data based approach for prognosis of brachial plexus injuries.

The thesis concludes with a discussion of the two approaches. In Ch. 8, a general method for designing a medical decision support system is presented.
Chapter 2
Brachial plexus injuries

2.1 ANATOMY

The brachial plexus is a nerve structure situated in the area between the neck and the upper extremity (Fig. 2.1). The morphology of this plexus has long been disputed (Walsh, 1877; Harris, 1904; Kerr, 1918) and probably even today no general agreement would be found on this subject. This is due to the large number of differences found among authors writing on the subject, but is especially due to the great anatomical variations within each study of the anatomy of the brachial plexus (Kerr, 1918; Hovelacque, 1927; Herzberg et al, 1985). Notwithstanding this difficulty, from the vast amount of literature on the anatomy of the brachial plexus, a common agreement has been reached as to its general morphology (Fig. 2.2).

2.1.1 Macroscopic anatomy

The brachial plexus is usually believed to be formed by the ventral primary rami of the spinal nerves C5 to T1, called the roots of the plexus, whereas the dorsal primary rami of these spinal nerves innervate the skin and extensor muscles of the neck. Often, a contribution from the spinal nerve C4 to the C5 root is also found (Kerr, 1918; Herzberg et al, 1985). In the supraclavicular area the roots join to form three trunks. Root C5 joins C6 to form the truncus superior, roots C8 and T1 unite to form the truncus inferior and root C7 constitutes the truncus medius.

Still supraclavicular, the truncus superior gives off the n. subclavius and the n. suprascapularis. From its ventral division arises the n. pectoralis lateralis, whereas the upper n. subscapularis usually arises from the dorsal division of the truncus superior. Then, the ventral divisions of the truncus superior and truncus medius constitute the fasciculus lateralis. This fasciculus gives off the n. musculocutaneus and finally constitutes the radix lateralis (lateral part) of the n. medianus. The fasciculus medialis is constituted from the ventral division of the truncus inferior. It gives rise to the n. cutaneus brachii medialis, the n. cutaneus antebrachii medialis, the radix medialis (medial part) of the n. medianus and terminates in the n. ulnaris. The fasciculus dorsalis is formed from the union of the dorsal
Figure 2.1 The right brachial plexus (After Sinelnikov, 1982).

Figure 2.2 The brachial plexus (Reprinted from Kerr, 1918. With permission).
divisions of the three trunks. The lower *n. subscapularis* and the *n. thoracodorsalis* arise from it before it branches into the *n. axillaris* and the *n. radialis*.

Even before the trunks are constituted some terminal branches arise from the plexus. The *n. dorsalis scapulae* arises from C4 and C5 just after their exit from the intervertebral foramen. The *n. thoracicus longus* is usually constituted from contributions from roots C5, C6 and C7. Also these contributions arise from the roots immediately after their emergence from the intervertebral foramen. C5 may also contribute to the *n. phrenicus*, which is principally innervated by C4.

### 2.1.2 Variations

In practice, individual variations from this general scheme frequently occur (Kaplan and Spinner, 1980). Variations are found in the spinal nerves contributing to the brachial plexus. These may be explained as a physical shift of the plexus along the axis of the body, with a possible increase in the total number of roots constituting the plexus. When this shift is in the cranial direction, i.e. the plexus is formed by roots C4 to C8 or T1, this is called a *prefixed* plexus. When there is a caudal shift, when the plexus is formed by roots C5 or C6 to T2, the plexus is defined as *postfixed*. Other variations involve the formation of trunks and cords. Kerr (1918) reported variations in the formation of the truncus superior in 10% of his cases. Root C7 joined the C5 and C6 roots in the truncus superior in 4 cases (2%), whereas in 14 cases (8%) the truncus superior did not exist but C5 and C6 each divided into anterior and posterior divisions. Similar variations were found in the formation of the truncus medius and truncus inferior. Also, frequent variations were reported in the formation of the cords and their terminal branches, especially the *fasciculus lateralis* and *fasciculus dorsalis* (Kerr, 1918). All variations may seriously hamper the physician attempting to localize a brachial plexus lesion. This is especially significant in the case of pre- or postfixed plexuses evaluated by cervical myelography, CT-scan or MRI, since an axial shift of the plexus is likely to lead to misinterpretation of the results of these tests.

The nerve plexus outlined above extends from the neck to the axilla. For the
Figure 2.3 The position of the brachial plexus in the deep compartment of the posterior triangle of the neck (Reprinted from De Palma, 1983).

Figure 2.4 The course of the n. radialis (Reprinted from De Palma, 1983).
pathology of brachial plexus injuries, apart from the general constitution of
the brachial plexus, its location in respect to other anatomical structures
like bones, muscles, fascia and vessels and the micro- and macroscopic anatomy
of its nerves are also relevant. These will be discussed here.

2.1.3 Position of the plexus

The ventral rami which form the brachial plexus are located in the lower part
of the posterior triangle in the neck. The clavicle crosses the base of the
neck above the first rib, and anterior to the subclavian vein, the scalene
muscles and the brachial plexus to form the lower border of this triangle. The
m. sternomastoideus lies on the anterior surface of the m. scalenus anterior.
Interposed between these two is the m. omohyoideus. In the area constituted
by these structures, the upper roots of the plexus, C5, C6, C7, are located
very deeply between the m. scalenus medius and m. scalenus anterior. The lower
roots, C8 and T1, first run along either side of the neck of the first rib
before entering the interscaleneic space. The trunks of the plexus are located
supraclavicularly in the posterior triangle of the neck, whereas the divisions
and cords occupy an infraclavicular position in the axilla (Fig. 2.3).
A number of anatomic structures in this area are of special importance since
these may be relevant in the pathology of brachial plexus injuries. In the
lower region of the supraclavicular space, the brachial plexus is in close
relation to the subclavian vessels, the plexus occupying a lateral position,
the vena subclavia a medial position and the arteria subclavia lying in
between the two. This neurovascular bundle runs through the costoclavicular
space, between the clavicle and the first rib, where the subclavian vessels
become the axillary vessels (Fig. 2.3). Changes in the configuration or the
size of this space, either traumatic or not, may cause compression or crushing
of this bundle (viz. Sect. 2.2). Other important anatomical aspects are the
course of the n. radialis (Fig. 2.4) and the n. axillaris (Fig. 2.5) with
respect to the humerus and the shoulder joint respectively, which makes these
nerves vulnerable to injury, for instance due to injury to the humeral neck
or greater tuberosity. To a lesser extent, the same argument applies to the
n. medianus and the n. ulnaris (viz. Sect. 2.2). The course of the n.
suprascapularis through the incisura scapulae (Fig. 2.6) makes this nerve
vulnerable in the event of injury to the shoulder. Nerve entrapment syndromes
Figure 2.5  The course of the n. axillaris (Reprinted from Bateman, 1955).

Figure 2.6  The course of the n. suprascapularis (Reprinted from Bateman, 1955).
Brachial plexus injuries

can result from a cervical rib and band. This syndrome, which is called Thoracic Outlet Syndrome in literature, and other forms of entrapment, like Carpal Tunnel Syndrome, have been extensively discussed elsewhere (Bateman, 1955; Urschell et al, 1971; Sunderland, 1978; Gilliat, 1979; De Palma, 1983).

2.1.4 Spinal nerves

A typical spinal nerve is composed of motoric ventral nerve rootlets from the anterior horn cells of the spinal cord and, sensory, dorsal rootlets that join these via the spinal ganglion (Fig. 2.7). As a result of this arrangement, nerve injury distal to the spinal ganglion (postganglionic injury) will produce motor and sensory loss, as well as Wallerian degeneration of all axons distal to the injury, since they have been separated from their neurons. In the case of injury central to the spinal ganglion (preganglionic injury), however, Wallerian degeneration will not occur in the sensory axons, since these will be still in contact with their neurons in the dorsal root ganglion. The dorsal roots are less susceptible to stretch than the ventral roots because they are thicker and have a thick ligament attached to the cord (Sunderland, 1978).

As the spinal nerves emerge from the intervertebral foramina, they receive grey rami communicantes from the sympathetic ganglia. Preganglionic sympathetic fibers from T1, that via the sympathetic chain innervate the head and neck, leave the ventral primary divisions of this spinal nerve soon after their emergence from the intervertebral foramen, which may provide a valuable sign when there is avulsion of this spinal nerve (viz. Sect. 2.3).

Since traction deformation is an important mechanism in the majority of brachial plexus injuries, it is interesting to note two more anatomical factors that influence the plexus’s susceptibility to injury, i.e. the means of fixation of the roots and the length of the roots. With respect to the means of fixation, the upper roots C5, C6 and C7 may be opposed to the lower roots C8 and T1. The upper roots are connected to the vertebral column by semionic posterosuperior ligaments. Especially in the case of root C5 are the fibers of this ligament very dense (Herzberg et al, 1985). This may be the reason why most of the traction injuries to root C5 are ruptures instead of avulsions of the root. In contrast, there is a complete absence of fixation between the lower roots and the vertebral column, possibly accounting for the
Figure 2.7 The formation of a spinal nerve.

1. plexal root C5.
2. plexal root C6.
3. plexal root C7.
4. plexal root C8.
5. plexal root T1.
6. posterior ligament of C5.
7. posterior ligament of C6.
8. posterior ligament of C7.
9. subclavian artery.
10. vertebral artery.
18. truncus superior.
19. truncus inferior.
23. posterior division of spinal root C5.
24. posterior division of spinal nerve C6.
25. posterior division of spinal nerve C7.
26. spinal nerve C5.
27. spinal nerve C6.
28. spinal nerve C7.

Figure 2.8 Anatomy of the roots of the brachial plexus (Reprinted from Herzberg et al, 1985).
Brachial plexus injuries

frequency of avulsion of these roots (Fig. 2.8). As was noted by Sunderland (1978) among others, the length of the nerve roots is of interest in the case of traction deformation also, since the tolerance of elongation before failure is proportionate to its length. The lower spinal nerve roots are relatively long compared to the upper spinal nerve roots (Sunderland, 1976).

2.1.5 Microscopic anatomy

The microscopic anatomy of the brachial plexus involves two aspects that are relevant to the pathology of brachial plexus injuries, i.e. the anatomy and mechanical characteristics of peripheral nerves (Sunderland, 1978, 1982a) and the intraneural topography of the brachial plexus (Nararakas, 1978).

A peripheral nerve consists of conducting elements, i.e. the nerve fibre and supportive tissues, i.e. endoneurium, perineurium and epineurium, and a vascular system (Fig. 2.9). A nerve fibre consists of the axon, the myelin sheath and Schwann cells. Nerve roots are composed of nerve fibers loosely held together by endoneurial tissue. The endoneurium is the connective tissue surrounding the individual fibers which constitute the endoneurial tube. The spinal nerve is composed of a single funiculus of nerve fibers (also called fasciculus) for a few millimeters after its formation. This funiculus then divides. The resulting funiculi participate in plexus formations that contribute to the tensile strength of the nerve. Each funiculus is surrounded by perineurium. According to Sunderland (1978, 1982a) this is the major component giving tensile strength to a nerve. Although others think it has less resistance to traction than the epineurium (Haftek, 1970). Epineurium is the connective tissue between the funiculi and it also provides the sleeve surrounding the nerve. It protects the funiculi from compression or crush. The nerve fibers themselves have no tensile strength whatsoever, but their elasticity is superior to that of the supportive tissues (Bonnel and Rabischong, 1981). Nerve roots lack the tensile strength and protection from compression of peripheral nerves, since they do not possess a funicular structure, so that epineurium, perineurium and funicular plexuses are absent. The intraneural topography of the brachial plexus (Fig. 2.10) is of great importance for successful reconstruction of brachial plexus injuries. Nararakas indicated however, that due to individual variability no universal map will become available that can be applied to all patients.
Figure 2.9 The structure of a peripheral nerve (cross-section).

Figure 2.10 Example of the intraneural topography of the brachial plexus as found by Narakas (Reprinted from Narakas, 1978).
2.1.6 Innervation

The motor and sensory innervation by the brachial plexus is of major importance to the interpretation of clinical findings encountered in injuries to this nerve structure. Outstanding work on this subject has been done by Kendall and Kendall (1983), who compiled the information on this subject of six well-known sources to derive a chart describing the spinal segment distribution to muscles innervated by the brachial plexus. This information

![Figure 2.11 Spinal segment distribution to the muscles of the upper extremity.](image1)

![Figure 2.12 Sensory innervation of the upper extremity. (After Merle D'Aubigné and Deburge, 1967).](image2)
Table 2.1 Etiology of brachial plexus injuries (From Narakas, 1985)

<table>
<thead>
<tr>
<th>Etiology</th>
<th>Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traumatic traction and/or crush lesions</td>
<td>722</td>
</tr>
<tr>
<td>Lacerations (excluding iatrogenic)</td>
<td>5</td>
</tr>
<tr>
<td>Gunshot wounds</td>
<td>14</td>
</tr>
<tr>
<td>Obstetrical lesions</td>
<td>80</td>
</tr>
<tr>
<td>Secondary compression after trauma</td>
<td>10</td>
</tr>
<tr>
<td>Iatrogenic lesions</td>
<td>21</td>
</tr>
<tr>
<td>Lesions due to irradiation</td>
<td>50</td>
</tr>
<tr>
<td>Tumours</td>
<td>15</td>
</tr>
<tr>
<td>Thoracic outlet syndrome</td>
<td>120</td>
</tr>
<tr>
<td>Parsonage-Turner syndrome</td>
<td>5</td>
</tr>
<tr>
<td>Vascular and other various and unknown causes</td>
<td>26</td>
</tr>
</tbody>
</table>

Table 2.2 Etiology of brachial plexus injuries in 3 Dutch series.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Traumatic traction/crush</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>motorcycle</td>
<td>36</td>
<td>24</td>
<td>12</td>
<td>104</td>
</tr>
<tr>
<td>car</td>
<td>23</td>
<td>19</td>
<td>4</td>
<td>22</td>
</tr>
<tr>
<td>moped</td>
<td>53</td>
<td>37</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>bicycle</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>13</td>
</tr>
<tr>
<td>other</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>56</td>
</tr>
<tr>
<td>Lacerations (no iatrogenic)</td>
<td>3</td>
<td>3</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Gunshot wounds</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Obstetric</td>
<td>2</td>
<td>2</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>Iatrogenic</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Lesions due to irradiation</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Tumours</td>
<td></td>
<td></td>
<td>7</td>
<td>26</td>
</tr>
<tr>
<td>Entrapment syndromes</td>
<td></td>
<td></td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>Other or unknown causes</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>136</td>
<td>93</td>
<td>43</td>
<td>94</td>
</tr>
</tbody>
</table>
serves as a basis for the work on brachial plexus injuries presented in this thesis. The spinal segment distribution that is assumed throughout this thesis only deviates in a small number of cases (Fig. 2.11): It is assumed that the m. suprascapularis, and consequently the m. infraspinatus and m. supraspinatus, receives its fibers solely from C5 (Thomeer, 1986). Moreover, the m. biceps is assumed to receive a relevant contribution from C7 (Brooks, 1949; Hollinshead, 1969; Thomeer, 1986). Finally, the innervation of the m. pectoralis major 'upper' is believed to originate from roots C5, C6 and C7 and that of the m. pectoralis major 'lower' of C7, C8 and T1 (Hollinshead, 1969). Also the sensory distribution is of vital importance for the evaluation of clinical findings. Figure 2.12 shows the spinal segment distribution to the skin from a chart adapted from Merle D'Aubigné and Deburge (1967).

2.2 THE INJURY

2.2.1 Etiology

Brachial plexus injuries have long been documented. Early publications concerned injury due to shoulder dislocation (Flaubert, 1827) and obstetrical injuries (Smellie, 1764; Duchenne, 1872; Erb, 1874; Klumpke, 1885; Kennedy, 1903, 1904). Obstetrical injuries, which were extensively reported on by Sever (1916), have long been a major cause of brachial plexus injuries, and have been known to affect well known people like emperor William II of Germany (Stensman, 1983). These days the incidence of obstetrical brachial plexus injuries has greatly diminished, although their number is still significant, as becomes clear from the etiology as described by Narakas (1985) derived from a series of 1068 patients with brachial plexus lesions (Tab. 2.1). In this series, from 902 traumatic injuries, in 80 cases (9%) the lesion was obstetrical. Presently, by far the commonest causes of injury are road traffic accidents (72% in this series) with motorcycle accidents forming the majority (70% of the road traffic accidents). In these cases, the brachial plexus injury is due to traction and/or crush on the brachial plexus. Not only do these injuries constitute the majority of traumatic brachial plexus injuries (80% in this series), they also cause the greatest problems in diagnosis and management (Wynn Parry, 1982). Therefore, in this chapter emphasis will be on this type of brachial plexus injury, although other traumatic injuries, as
well as injuries due to irradiation, will be dealt with also. Non-traumatic brachial plexus injuries, involving tumors (Narakas, 1985; Kline, 1987) and anatomical abnormalities, like cervical ribs and bands or abnormal first ribs (Bateman, 1955; Urschell et al, 1971; Sunderland, 1978; Gilliat, 1979; De Palma, 1983; Allieu, 1987) will not be considered. In 1986, a retrospective study was conducted to evaluate the diagnosis and management of traumatic brachial plexus injuries, including lesions due to irradiation, in the Netherlands (Jaspers, 1986). In this study, 136 brachial plexus injuries that had been treated in the rehabilitation center De Hoogstraat, 93 patients admitted before 1981 and 43 admitted between 1981 and 1985, were evaluated. The distribution of these injuries deviates somewhat from that of Narakas. This series mainly concerns traumatic injuries (96%). Only 2% of the injuries are obstetrical, whereas 88% are caused by road traffic accidents, of which 74% are caused by motorcycle or moped accidents (Tab. 2.2). Other Dutch series have been published by Slooff and Thomeer (1987) and Slooff (1989). These are presented in Tab. 2.2. On the whole, the Dutch series do not deviate substantially from Narakas’s series. It should be noted, however, that these series can hardly be compared, since rehabilitation centers and neurosurgical centers treat different series of patients.

2.2.2 Pathology

Severe traction on the brachial plexus results in widespread damage over considerable length of the nerves of the plexus. This damage may be of various degrees of severity, e.g. some nerves may be ruptured or even avulsed from the spinal cord, whereas others still are in continuity. The classification of nerve injuries as proposed by Sunderland (1951) can be applied to traumatic brachial plexus lesions. His classification is based on the pathoanatomical changes in nerves subjected to injury:

1. First-degree damage

   Either normal structural features of the affected nerve fibers, or minor changes. The axons are still in continuity. No Wallerian degeneration. This type of damage results in slowed or blocked conduction across the injured segment. Unless compression persists, complete recovery will occur spontaneously after a latent period that may in exceptional cases last up
Brachial plexus injuries

to several months.

2. Second-degree damage
   The axons are interrupted, resulting in Wallerian degeneration distal to the lesion. The endoneurial tubes are preserved. This damage, as well as that of degrees 3 to 5, manifests in a loss of conduction distal to the lesion. Spontaneous recovery will be complete, but is delayed due to axon regeneration. The onset of recovery depends on the level of the lesion.

3. Third-degree damage
   Intrafunicular lesion of axons and endoneurial tubes, with local fibrosis. Perineurial sheath and funicular continuity are preserved. Distal Wallerian degeneration occurs. Regeneration is complicated by intrafunicular scar tissue. Because of intrafunicular disruption, axons may enter foreign endoneurial tubes. Recovery is incomplete and slow.

4. Fourth-degree damage
   The funicular structure is destroyed, only the epineurium maintains the continuity of the nerve. Wallerian degeneration occurs distal to the lesion. Regeneration is severely hampered by excessive scarring. Few axonal sprouts eventually reach the end organ. Spontaneous recovery is functionally insignificant, very slow and late.

5. Fifth-degree damage
   All nerve structures have been interrupted. There is no spontaneous recovery at all.

This classification presents a nice view of how injury may affect a nerve, but clinically it is not very useful in fresh trauma cases. For that reason, often Seddon’s (1943) classification is used:

1. Neurapraxia
   A benign disturbance of conduction of comparatively short duration. Conduction loss only across the lesion, without interruption of axons and no Wallerian degeneration.

2. Axonotmesis
   Interruption of the axon with resulting Wallerian degeneration. Endoneurium, perineurium and epineurium are still intact. Conduction loss distal to the lesion. Spontaneous recovery will be complete.

3. Neurotmesis
   Complete disruption of axons and endoneurium. Possibly disruption of
perineurium and epineurium. Complete disorganization of the nerve by scar tissue. No spontaneous recovery whatsoever.

Apart from the degree of severity of the injury, a classification of brachial plexus injuries involves the level of the lesion, the extent of the lesion and its nature. Concerning the topography, usually 5 different levels are recognized (Narakas, 1982, 1985):

Supraclavicular

1. Avulsion of the root or rootlets from the spinal cord. Either (partially) affecting the ventral or dorsal rootlets alone, or involving both.
2. Lesion of the ventral ramus of the spinal nerve outside the foramen, or lesion of the truncus.

Retroclavicular

3. Lesion of the fasciculus.

Infraclavicular

4. Lesion of the distal part of the fasciculus.
5. Lesion of the peripheral nerve close to its origin at the brachial plexus.

This topography provides a simple means of classifying brachial plexus injuries from the surgical point of view. In view of the multiple lesions that may be caused by traffic accidents, this classification is more appealing than the clinical classification often found in literature (Seddon, 1975; Leffert, 1985). In this classification, generally 4 types of injury are defined:

1. C5-C6 or truncus superior lesions
2. C5-C6-C7 lesions
3. C8-T1 lesions
4. lesions affecting the whole plexus.

In traction and/or crush injuries, especially if these are due to motorcycle accidents, a patient may present with a multiple level injury, i.e. a two-
Brachial plexus injuries

level or even three-level injury, which often affects the whole plexus. Such lesions are more conveniently described according to Narakas's classification. For example, in such cases rupture of roots C5 and C6, in combination with avulsion of roots C7, C8 and T1 and rupture of the median nerve at the axilla is not at all hypothetical. Also, the combination of root avulsion due to traction and retroclavicular neuroma due to costoclavicular crush is not infrequently seen. This means that two mechanical agents can occur during the same traumatic event.

2.2.3 Mechanism of injury

Traumatic injury to the brachial plexus may be caused by traction, compression or penetration. Of these, compression is relatively uncommon, although it may occur in combination with traction or penetration. Compression injury has been reported to have been caused by the straps of a backpack (White, 1968), usually resulting in temporary loss of function (neurapraxia). More severely, compression of the brachial plexus can occur between the clavicle and the first or second rib, when an external force presses the clavicle down. Penetrating injuries can be caused by sharp objects such as knives or broken glass, bullets or can be caused iatrogenically. Stab wounds and iatrogenic (surgical) injuries usually produce localized sharp cuts in which the nerve stumps can easily be identified which favors neurosurgical coaptation. Shot wounds are known to produce injuries that initially look much more serious than they eventually prove to be, due to the shock wave distortion the bullet produces. Penetrating brachial plexus injuries are relatively uncommon because of their potentially lethal character. Penetrating trauma affecting the brachial plexus is likely to also put at risk the surrounding vessels and the lung, which may produce life-threatening hemorrhage or intrathoracic pathology.

traction injuries

Traction is the most frequent type of injury in brachial plexus lesions. It is usually due to a forceful widening of the angle between the shoulder and neck, or between the upper arm and the trunk which subjects the nerves to stretching. In the first case, when the arm is adducted, the upper roots
suffer most. In the second case, when the arm is fully abducted, the lower roots are subjected to most stress, when the arm is in lateral abduction when it is exposed to traction all roots are under stress. The diamond shape of the plexus and its length, as well as the microscopic structure of the individual nerves, allow it to resist considerable traction by dispersion of forces. Violent traction, however, will cause damage that can be either localized or extended. Stevens (1934) showed the role of the various anatomical structures of the shoulder girdle in this mechanism. The amount of kinetic energy imparted to the nerves is determined by the violence of the trauma. High kinetic energy, such as in motorcycle accidents, is likely to produce severe injuries, whereas low energy, such as in someone falling from small height, is likely to produce milder injury. Traction traumas may result in infraclavicular injury also, for instance due to hyperabduction or as a result of dislocation of the shoulder. In this case, the severity of the nerve injury

Figure 2.13 Mechanism of brachial plexus traction injuries.
is not determined by the dislocation itself, but by the severity of the trauma causing the dislocation (Narakas, 1985). A nice overview of the mechanisms of injury to the brachial plexus is presented in Coene (1985). Figure 2.13 shows several mechanisms of traction injury.

**associated injuries**

Apart from the mechanism that caused the trauma, the associated injuries caused by the trauma are important for diagnosing traumatic brachial plexus injuries. They can provide significant diagnostic clues. For instance, severe regional trauma, like fractures to the cervical spine, the scapula, the clavicle, the humerus or the upper ribs, or rupture of the subclavian or axillary vessels indicate a severe plexus injury (Bonney, 1959; Narakas, 1987a), with indication for surgical exploration. Moreover, some of these associated injuries provide clues for the nature and location of the brachial plexus injury. For instance, a fractured clavicle points to a supraclavicular injury, since it allowed increased distraction of the head and shoulder during the accident. Also, it may have injured the plexus directly as the fragments might have compressed the brachial plexus, or be driven downward in the retroclavicular space, leading to laceration or crush of the neurovascular bundle (De Palma, 1983; Millesi, 1984). Also, avulsion fracture of a cervical processus transversus is strongly indicative of an avulsion of the spinal nerve belonging to it (Leffert, 1985; Narakas, 1987a). As already indicated in Sect. 2.1, a number of peripheral nerves is at risk when there is fracture of bones in their vicinity. Fracture of the shaft of the humerus may cause an associated lesion of the n. radialis. The n. medianus and n. ulnaris may be involved in fractures to the humerus also, although these occur less frequently (Omer, 1982b; De Palma, 1983). The n. suprascapularis is at risk in the case of fracture of the scapula, which is usually caused by direct impact to the scapula (De Palma, 1983).

**2.3 Diagnosis**

In order to be able to establish an optimal plan for management and prognosis, the diagnosis of brachial plexus injuries involves detailed assessment of the site, the severity and the extent of the injury. Many authors indicate that
this procedure can be completed within 3 months after the trauma (Millesi, 1980; Narakas, 1981a, 1985; Van Dulken et al, 1982; Dolenc, 1985). During this period, patients whose injuries are suited to neurosurgical reconstruction, i.e. patients with fourth- and fifth-degree injury (neurotmesis), should be selected. This is extremely important, since, according to these authors, the later the reconstruction of the brachial plexus is carried out, the worse the results. To achieve this timely selection of patients, the history and the results of many diagnostic tests have to be evaluated. The global procedure that will lead to a correct diagnosis will be outlined in this section. As will have become clear from the previous section, brachial plexus injuries can be highly complicated and present major problems of diagnosis and management. The complex anatomy, the possible combinations of level of injury and the associated injuries, make precise localization of the nerve injury very difficult. Notwithstanding this complexity, Narakas (1982, 1985) found some regularities in his series of patients, the law of the seven seventies:

70% of traumatic brachial plexus lesions are due to traffic accidents.
70% of lesions in traffic accidents involve the use of a cycle or motorcycle.
70% of these patients have associated multiple injuries.
70% have a supraclavicular lesion.
70% of supraclavicular lesions will have one or more plexal root avulsions.
70% of root avulsions have the lower roots C7, C8, T1 or C8, T1 avulsed.
70% of patients with lower root avulsions will experience persisting pain.

These statistics provide relevant information for the diagnosis and treatment of brachial plexus injuries. The high incidence of supraclavicular injuries is noteworthy, since these are usually more severe and have a worse prognosis than infraclavicular injuries (Millesi, 1980; Narakas, 1981a). Narakas (1985) shows that the incidence of strong persisting pain is two or three times as high in patients with root avulsions as in patients without. Wynn Parry (1978) compared data from Barnes, Brooks, Stevens and Narakas. He found that in the first three series, rupture of the nerves of the brachial plexus was very rare, whereas in Narakas’s series, rupture of the roots between the intervertebral foramen and the clavicle occurred in one third of the traction injuries. These data, which seem in accordance with his own series from the same period, suggest an increase in the number of ruptures which are amenable to neurosurgical reconstruction. He attributes this phenomenon to the
Brachial plexus injuries

compulsory wearing of crash helmets which spare the lives of motorcyclists after an accident so that their brachial plexus lesions become manifest.

2.3.1 History

As has been made clear, the mechanism of injury and the presence of associated injuries may provide relevant diagnostic clues to establish the site and severity of the brachial plexus injury. However, often the history of the injury can not be obtained from the patient, since many patients who have been involved in traffic accidents suffer from an associated head injury. Therefore, details may have to be obtained from friends, relatives, police or bystanders. As was indicated above, the presence of severe pain immediately after the trauma may also provide significant information.

2.3.2 Physical examination

Physical examination aims at a further differentiation of the diagnostic hypotheses initiated during history taking. Repeated detailed neurologic examination of the affected upper extremity will provide indispensable information.

muscle function

First of all, extensive testing of muscle function is required, the result of which can be easily recorded on the chart in Fig. 2.14, which was originally developed by Merle D'Aubigné and Deburge (1967) and adapted at the De Wever Hospital. Kendall and Kendall (1983) provide a clear overview of the technique of manual muscle testing. Prior to muscle testing, the passive range of motion of all joints involved should be assessed. A number of muscles provide especially relevant information for localizing the injury. They are the muscles that are innervated by the nerves that arise from the plexal roots soon after their emergence from the intervertebral foramen:

- Mm. rhomboidei and m. levator scapulae, innervated by the n. dorsalis scapulae (C4-C5).
Figure 2.14 The recording form of the De Wever Hospital, adapted from Merle D’Aubigné and Deburge (1967).
Brachial plexus injuries

- M. serratus anterior, innervated by the n. thoracicus longus (C5-C7).
- Diaphragm, innervated by the n. phrenicus (C3-C4).
- Deep extensor muscles of the neck innervated by the dorsal primary rami of spinal nerves C4-C8.

Of these muscles, only the mm. rhomboidei, the m. levator scapulae and the m. serratus anterior can be physically examined. The deep extensor muscles can be examined by EMG. The diaphragm has to be examined by means of X-ray. Denervation of these muscles, in combination with motoric deficit of other muscles innervated by the concerning plexal roots, indicates injury to those roots close to or inside the intervertebral foramen, i.e. possibly avulsion of the spinal nerve. However, variations in the spinal segment distribution hampers the interpretability of these findings.

sensibility

Sensory examination provides similar but less detailed information. The interpretation of sensory findings is hindered by the large amount of overlap in the innervation by different dermatomes and because anaesthetic areas become reinnervated by adjacent dermatomes (Dykes, 1984; Thomeer, 1985).

tendon reflexes

Abolition of the biceps tendon reflex refers to a lesion in the C6 - n. musculocutaneous nerve path, whereas the triceps tendon reflex is informative for C7 - n. radialis.

sympathetic function

Sympathetic function may also be assessed. Postganglionic injuries in the upper plexus, C5, C6, C7, will present changes in color, sweating and temperature in the affected limb. In the case of preganglionic injury to these plexal roots, the sympathetic fibers remain in continuity with the spinal cord via the sympathetic chain. Without diagnostic aids, however, these changes are difficult to detect (Sunderland, 1982b). More valuable is examination of the width of the eyelids, the pupil and the skin of the ipsilateral face, innervated by sympathetic axons from the anterior nerve roots of T1, for the
presence of Horner's syndrome. The presence of this syndrome indicates an injury to plexal root T1 at or immediately beyond the foramen. When there is an avulsion of this root, however, Horner's syndrome is not necessarily found, since it may have diminished over time and may be difficult to detect.

Tinel's sign

A very important clinical finding that may be encountered in the physical examination of brachial plexus injuries is Tinel's sign. The presence of this sign, a distal tingling and/or pain after percussion of the brachial plexus, indicates that there is a lesion in the involved nerve, for which a central connection has been preserved. This may indicate the presence of a proximal nerve stump suitable for neurosurgical repair. The location of this sign and the area towards which it radiates, provide useful information about the site of the lesion and about which nerve has been injured postganglionically. If repeated examinations over time show distal migration of the point that elicits tingling, it indicates outgrowth of at least part of the severed nerve axons. Unfortunately, Tinel's sign does not necessarily appear in the case of a postganglionic injury. Thus the absence of this sign does not mean that postganglionic lesions are definitely absent. Palpation of the supraclavicular fossa may also indicate the presence of neuroma.

2.3.3 Neurophysiologic examination

The electrophysiologic evaluation of muscle function is most valuable in diagnosing brachial plexus injuries, since this allows the testing of muscles that are otherwise inaccessible and it may reveal findings that can not (yet) be detected by physical examination.

EMG

Electromyography (Licht, 1973) can be performed from approximately three weeks after the date of the injury, since the process of Wallerian degeneration is completed within that period. The EMG should be screened for:

- voluntary activity, revealing normal, mixed, single fiber or no action
Brachial plexus injuries

potentials, indicating the function of the muscle.
- denervation, spontaneous activity, the fibrillation potentials.
- reinnervation, the polyfasic signals.

As has been mentioned previously, examination of the deep cervical paravertebral musculature may reveal preganglionic injuries to the plexal roots C4 to C8 (Buffalini and Pescatori, 1969). However, due to the extensive overlap in the innervation of these muscles, the discrimination of which roots have been injured preganglionicly is impossible when using this test. Therefore its worth is only additive to the other examination procedures. Surface EMG is not considered, since it provides far diagnostic information.

nerve conduction

Apart from electromyography, nerve conduction studies may be performed. Since motor axons will degenerate in the case of preganglionic injury and in the case of postganglionic injury, motoric nerve conduction velocity determination can be used solely to establish first-degree injury (neurapraxia). Sensory Nerve Action Potentials, SNAPs, however, provide more useful information. Since in case of preganglionic injury the sensory axons remain intact, this method allows discrimination between pre- and postganglionic injuries to the plexal roots C6, C7 and C8 that innervate the hand (Zverina and Kredba, 1977; Jones, 1979, 1981; Gilliat, 1979; Benecke and Conrad, 1980; Landi et al, 1980; Warren et al, 1980). Although this examination is used extensively, the interpretation of the findings may be difficult:

- Overlap of dermatomes hampers the discrimination of roots.
- The presence of preganglionic as well as postganglionic injury in the same root may lead to misinterpretation. According to Sunderland (1978) the simultaneous presence of infraganglionic and postganglionic lesion in a root is likely in the case of traction.
- Quantification of findings is difficult, since intra individual left-right variations may amount to up to 50%.

SEP

Somatosensory Evoked Potentials, SEPs, may be used to establish whether
central conduction is still intact (Zalis et al, 1970; Zverina and Kredba, 1977; Jones, 1979, 1981). It should be noted, however, that theoretically, SEP will not provide any additional information to the combined application of sensory examination and SNAP, since in anaesthetic dermatomes SEP will remain absent, whereas it will be present in non-anaesthetic dermatomes. An important application is the use of SEP per-operatively, to determine whether neural stumps, amenable to grafting, are in continuity with the spinal cord.

axon reflex

Axon reflex testing (Bonney, 1954, 1959) relies on a similar phenomenon to SNAPs. They are used to determine whether sensory nerve fibers have been damaged central or distal to the dorsal root ganglia. Where there is preganglionic injury, the axon reflexes are preserved, in postganglionic injury they will be lost. Bonney proposed two tests, i.e. the histamine

![Figure 2.15 Myelographic findings due to traction injury of the brachial plexus (Reprinted from Seddon (1975)).](image-url)
response test and the cold vasodilatation test. Sunderland also mentions the skin-resistance test as a suitable method for axon reflex testing. Bonney's results proved to be good although he suffered from the same problems that have been described in relation to the SNAP test. Yeoman (1968) describes these problems in a comparison of cervical myelography and axon reflexes in 40 brachial plexus traction injuries.

2.3.4 Radiological examination

Cervical myelography is indispensable for examining patients with traction injuries. It was first described by Murphy et al (1947), thereafter numerous papers have appeared on the subject (White and Hanelin, 1954; Tarlov and Day, 1954; Yeoman, 1968). Water-soluble contrast media, which are in common clinical use nowadays, yield a high enough resolution to make the fila radicularia of the roots visible (Narakas, 1981a; Vielvoye, 1982). Seddon (1975) described the findings that may be encountered on a typical myelogram (Fig. 2.15):

- A traumatic meningocele may be present.
- A pouch may be present due to a rupture in the arachnoidea.
- A rupture of the dura may have healed invisibly.
- Distortion of the spinal cord may be encountered.

The most important finding, indicative of avulsion of the root, is the absence of its fila radicularia, even in absence of a traumatic meningocele. On the other hand, a meningocele may be present without avulsion of the root (Slooff, 1985). Variations in the anatomy of the brachial plexus, i.e. whether it is normal, prefixed or postfixed may hamper interpretation of the myelogram. Computed Tomography, CT, may contribute to the diagnosis, especially in depicting the fila radicularia visible. In future, Magnetic Resonance Imaging, MRI, may add information too. These methods are still improving.

Routine radiological examination of the shoulder region: clavicle, scapula, humerus and cervical spine should be performed to screen for bony injuries in the vicinity of the brachial plexus that make certain nerve injuries suspect (viz. Sect. 2.2). Radiography of the diaphragm may reveal a paralysis that can be attributed to the avulsion of root C4 or injury to the n. phrenicus.
2.3.5 Surgical exploration

It is generally agreed that the method of diagnosis proposed in the previous sections allows the establishing of a more or less accurate diagnosis and thereby the selection of patients amenable to neurosurgical reconstruction within 3 months after the trauma. Therefore, surgical exploration for diagnostic purposes alone is generally unnecessary (Van Dulken et al, 1982). If reconstruction is considered, however, exploration will reveal the details of the injury to the plexus. Cervical hemilaminectomy for direct inspection of the roots is potentially harmful, undesirable and unnecessary (Leffert, 1974; Sunderland, 1982; Narakas, 1985; Slooff, 1985; Thomeer, 1985).

2.4 MANAGEMENT

Brachial plexus injuries generally present a large amount of motor and sensory loss. The management of these injuries aims at optimal functional recovery. For a long time nerve repair was not considered a viable method of achieving this goal, and exploration was intended for diagnostic and prognostic purposes only (Bateman, 1949; Bonney, 1959). The reason for this was the large amount of scar-tissue that was found on operation (Stevens, 1934) and, as mentioned earlier, in those days the incidence of ruptures to the brachial plexus was much lower and, consequently, the prognosis for spontaneous recovery was better. Microsurgical techniques did not yet exist (Smith, 1964). Treatment was conservative, with the application of orthoses, or for the severe cases, late orthopedic reconstructive surgery was advocated (Barnes, 1949; Hendry, 1949; Tracy and Brannon, 1958), or shoulder arthrodesis and amputation with the fitting of prostheses (Yeoman and Seddon, 1961; Seddon, 1972; Fletcher, 1973; Ransford and Hughes, 1977). Although amputation was criticized early on (Hendry, 1949) and now seems to be generally rejected (Wynn Parry, 1984; Haselen, 1985; Narakas and Herzberg, 1985) this procedure is still advocated by some authors (Rorabeck, 1980; Malone et al, 1982; Shurr and Blair, 1984).

neurosurgery

The discussion on nerve repair was re-opened, when more severe traction injuries were found that might be amenable to surgical repair (Lusskin et al,
Brachial plexus injuries

1973; Millesi et al, 1973; Narakas, 1977). Now it is felt that neurosurgical reconstruction offers great potential in the treatment of brachial plexus injuries, and in the early stage it is vital to select patients that may benefit from surgery, i.e. patients with fourth- and fifth-degree injury (neurotmesis) (Narakas, 1981a, 1985; Sedel, 1982, 1984; Dulken et al, 1982; Sunderland, 1982b; Millesi, 1980, 1984; Wynn Parry, 1982, 1984; Dolenc, 1984, 1985). A general scheme for treating brachial plexus injuries has arisen. In sharp lesions such as stab wounds, surgical repair has to be carried out immediately. In all other cases, in the early stage, when an accurate diagnosis still has to be established, associated injuries, such as fractures, vascular injuries and head trauma are treated. Further, conservative treatment is started to prevent contractures and control pain and orthoses are provided. During this stage, by carrying out the diagnostic procedure that was described in the previous section, patients can be assessed for neurosurgical repair. Then, during the period while waiting for recovery to occur, either spontaneously when no repair has been done, or after surgical repair, conservative treatment is needed to mobilize joints, to reeducate reinnervating muscles and for psycho-social support. When most recovery has occurred, or when the prognosis can be clearly established, plastic-orthopedic surgery can be considered, like shoulder arthrodesis and tendon transfers. This general scheme, especially nerve repair and orthopedic reconstruction will be discussed more thoroughly in the next sections.

2.4.1 Traction and/or crush lesions

Within a few months after the trauma, patients may be selected for nerve repair. When there is doubt, it is possible to wait till about four months after the trauma for signs of recovery, such as a migrating Tinel's sign or polyfascic signals on the EMG. Surgery should not be postponed much longer, since experience has shown that the later the operation is carried out the worse the results (Sunderland, 1982b; Narakas, 1985; Dulken et al, 1982). If the diagnostic procedure reveals a mild trauma, i.e. first- to third-degree injury (neurapraxia or axonotmesis), the patient should not be considered for nerve repair but should be treated conservatively. Since the growth rate of axons is about 1 mm per day, spontaneous recovery after axonotmesis may take over two years.
nerve repair and orthopedic surgery

The possibilities of nerve repair depend on the site and the extent of the injury. Once these are known, a plan for reconstruction is made which takes into account the possibilities of late orthopedic reconstruction and hand surgery. Postganglionic ruptures with available proximal stumps are amenable to grafting, with autografts taken from the nn. surales and, in the case of avulsion of the lower plexal roots, C8 and T1, the n. cutaneus antebrachii medialis and the n. ulnaris (Narakas, 1985). Continuity of the nerves is restored by nerve grafting between the proximal stumps and the trunci, fasciculi or peripheral nerves of the plexus. In plexal root avulsions, the only possible means to restore continuity is by coaptation with neighboring nerves, either from within the brachial plexus, i.e. intraplexal nerve transfer, or from outside the plexus, i.e. extraplexal nerve transfer (Fig. 2.16). The aim of this procedure is to restore function by grafting healthy donor nerves which normally innervate muscles of less functional value. Many different donor nerves have been proposed for extraplexal transfers: the nn. intercostales (Dolenc, 1982, 1984; Narakas, 1981a; Nagano, 1987), the n. accessorius spinalis (Allieu et al., 1984; Narakas, 1985, 1987c; Vigasio, 1987)

![Diagram of nerve grafts]

Figure 2.16 Example of nerve grafts of the truncus superior and nerve transfers from the accessory nerve to the n. suprascapularis.
and nerves from the cervical plexus (Brunelli and Monini, 1984; Vigasio, 1987). The function obtained with intercostal transfers is not always integrated into the patterns of movements of the upper limb (Narakas, 1985). Notwithstanding this observation, Japanese surgeons have claimed stunning results from the use of this technique, which are much better than European surgeons have achieved (Nagano, 1987; Bonnard, 1987). On the whole, Japanese surgeons have very unorthodox views on the reconstruction of brachial plexus injuries and use multiple muscle transfers (Hara, 1987), or intercostal transfers combined with free transfers of the m. rectus femoris or the m. gracilis (Akasaka, 1987). Another important orthopedic operation in the management of brachial plexus injuries is the shoulder arthrodesis for the restoration of shoulder function (Hendry, 1949; Van de Kamp, 1982; Hara, 1987). An impressive range of possible reconstructive surgical procedures is presented by Hendry (1949), Leffert (1980) and Omer (1982a).

A final method of nerve repair is neurolysis, to relieve compression of extraneural or intraneural scar-tissue. It is indicated only in late cases and is a potentially hazardous procedure (Narakas, 1985).

Infraclavicular traction lesions are less frequent, but often have a better prognosis for spontaneous recovery which makes nerve repair undesirable (Leffert and Seddon, 1965). However, in some instances the infraclavicular injury may be more serious which demands neurosurgical repair (Alnot, 1984; Burge et al, 1985).

2.4.2 Other injuries

obstetric palsy

Obstetric brachial plexus injury, a subject on which a vast body of literature is still being published (Adler and Patterson, 1967; Tan, 1973; Bennet and Harold, 1976; Hardy, 1981; Rossi, 1982; Tada et al, 1984) is due to traction during delivery. The incidence of these injuries depends on the quality of obstetric care in the hospital, but is still between 0.1 - 4 */.. (Slooff, 1987). Most authors mention the good results of conservative treatment in these injuries and nerve repair is not mentioned as an alternative. However, also in obstetric injuries the same severe ruptures and avulsions can be found as in traction injuries in the adult (Narakas, 1981a) which makes these
injuries amenable to surgery (Brown, 1984). Nerve repair after the first three months is presently undertaken by some surgeons and yields good results (Tassin, 1983; Narakas, 1985; Kawabata et al, 1987; Siooff, 1987).

lacerations

Lacerations of the brachial plexus, caused by sharp objects such as knives or broken glass, usually present localized neurotmesis in which nerve repair is relatively straightforward. Direct repair can be considered. The results of repair will generally be good, except for repair of the truncus inferior or fasciculus medialis due to the long duration of axon regeneration in these injuries (Leffert, 1974, 1985; Narakas, 1981a, 1985).

gunshot wounds

In peacetime, gunshot wounds are relatively uncommon in Europe so that wartime experience (Brooks, 1949) still prevails in the treatment of these injuries. In the United States, these injuries are much more frequent, constituting 25% in the series of Kline (1987). In his experience, repair of these wounds proves valuable, between two to five months post-trauma, for patients with persistent loss of function or severe pain. Injuries to the truncus superior can be operated on even later. Patients with incomplete loss in elements of the brachial plexus are most likely to improve naturally and, consequently should not be operated on. Injuries to the lower roots, C8 and T1, have a worse prognosis than injuries to the upper roots. Patients referred to the neurosurgeon more than 14 months post-trauma should not be operated on, unless for treatment of pain.

injuries due to irradiation (actinic plexopathy)

Radiation therapy, especially for breast cancer, may result in brachial plexus injury 1 to 20 years post-radiation (Leffert, 1985; Narakas, 1985). Progressive loss of neurological functions results from scar and ischemia, and the patient may suffer from severe intractable pain. The use of exploration and decompression by means of neurolysis and revascularization using a free or pedicled omental graft remain controversial (Leffert, 1985). It is generally agreed upon that results are poor in regard to functional recovery,
at best, progression of functional loss can be stopped, but there are reports that the effect on pain is good (Clodius et al, 1984; Brunelli and Brunelli, 1985; Narakas, 1985, 1987; Vigasio, 1987). The operation should be carried out as early as possible after the onset of the symptoms, the indication being severe pain or rapid progression of motor and sensory loss (Narakas, 1987b).

2.4.3 Pain

Pain is a very common phenomenon in brachial plexus injuries. The complaints may be so disturbing, however, that they seriously hamper treatment of the brachial plexus injury and require specific attention. Severe pain seems to be associated with avulsion of the lower plexal roots, possibly due to their relatively large content of sensory fibers. Repair of the brachial plexus seems to have a beneficial effect on pain (Narakas, 1981b). Measures that specifically aim at treating the pain are, among others, stimulation of the posterior column, the thalamus or transcutaneous nerve stimulation, dorsal root entry zone (DREZ) coagulation, hypnosis and drugs. An overview of pain problems in brachial plexus injuries can be found in Narakas (1981b), pain syndromes of the upper extremity are dealt with in Goldner (1980a,b) and Omer (1984).

A very extensive overview on brachial plexus injuries and their diagnosis and management can be found in Leffert (1985).

2.5 THE NEED FOR SUPPORT

As has been described in the previous sections, brachial plexus injuries may present major problems of diagnosis and management. The injury often occurs after high-velocity trauma. In the early stage, associated injuries often require attention so that the brachial plexus injury is overshadowed or unrecognized. Particularly head trauma, which occurs most frequently, may obscure the injury to the brachial plexus. The diagnosis of brachial plexus injuries, i.e. determining the site, the extent and the severity of the injury, is severely complicated by the various possible combinations of motor and sensory deficits and the complex anatomy. A clear diagnosis is vital for the planning of the treatment for a specific patient. To gain insight into the
Table 2.3 Recovery of motor function, \( x \), of patients admitted to rehabilitation treatment before 1981.

<table>
<thead>
<tr>
<th></th>
<th>Upper roots</th>
<th>Lower roots</th>
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<tr>
<td></td>
<td>(shoulder function and elbow flexion)</td>
<td>(wrist, hand and elbow function, except elbow flexion)</td>
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<tr>
<td>admission</td>
<td></td>
<td>admission</td>
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<tr>
<td>( x \geq M3 )</td>
<td>9%</td>
<td>33%</td>
</tr>
<tr>
<td>( M1 \leq x &lt; M3 )</td>
<td>55%</td>
<td>45%</td>
</tr>
<tr>
<td>( x &lt; M1 )</td>
<td>36%</td>
<td>22%</td>
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Table 2.4 Results of treatment in a Dutch series, compared to those of other authors.

<table>
<thead>
<tr>
<th></th>
<th>Dutch</th>
<th>Narakas</th>
<th>Dolenc</th>
<th>Gussio</th>
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<tr>
<td></td>
<td>EF</td>
<td>SA</td>
<td>TOT</td>
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<td>Conservative</td>
<td></td>
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<tr>
<td>( n )</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>277</td>
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<td>( \geq M3 )</td>
<td>50%</td>
<td>38%</td>
<td>23%</td>
<td>&gt;91%</td>
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<tr>
<td>Nerve repair</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>( n )</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>135</td>
<td>135</td>
<td>14</td>
</tr>
<tr>
<td>( \geq M3 )</td>
<td>56%</td>
<td>78%</td>
<td>44%</td>
<td>&gt;64%</td>
<td>64%</td>
<td>79%</td>
</tr>
</tbody>
</table>

diagnosis and management of brachial plexus injuries in the Netherlands, a retrospective study was conducted on 136 patients that had been referred to the rehabilitation center De Hoogstraat, from 23 different hospitals all over the country. The etiology of these patients' brachial plexus lesions has already been presented in Tab. 2.2. In this series, 88% are caused by high-speed traffic-accidents involving car, motorcycle or moped, in 90% of the patients one or more associated injuries occurred that required treatment. These high figures indicate that the series under investigation is likely to consist of severe injuries. To gain insight into the diagnostic and treatment procedure applied to these patients, and especially into the effect of the
changing views on the management of brachial plexus injuries, this series has been divided in two, i.e. a series of 93 patients that had been admitted before 1981 and a series of 43 patients admitted between 1981 and 1985.

2.5.1 Recovery

From the series of patients admitted between 1981 and 1985, data were available from only 4 patients up to at least two years post-trauma, so that the result of treatment could not be assessed for this group. In the group that had been admitted before 1981, all patients were followed up for at least two years. Of these, for 49 patients sufficient data were available to assess the recovery of motor function. The results of the treatment for these patients is presented in Tab. 2.3. From this table it becomes clear that, as far as motor function is concerned, recovery in these patients is very limited. In the muscles innervated by the upper roots of the brachial plexus, C5, C6, C7, after at least two years of follow up, only 33% reached a function of M3 or better, whereas 22% still had less than M1. In the muscles innervated by the lower roots C7, C8, T1, 51% reached M3 or better and 20% remained worse than M1. For the upper roots, the average improvement was less than M1 (0.9), for the lower roots this was even worse, 0.7. Although the comparison of results is very difficult due to the different ways the results are scored, these results seem to be poor compared to those found in literature (Narakas, 1981a; Rorabeck, 1981; Sedel, 1982; Nagano, 1984; Wynn Parry, 1984). To allow a better comparison, in Tab. 2.4 the results of this Dutch series have been split up into patients that underwent neurosurgical repair (9 out of 49) and those who had been treated non-operatively. All patient injuries that had been operated on were reconstructed by nerve grafts. No nerve transfers were utilized. In the same table, these results are compared with Narakas (1981a), Dolenc (1982) and Gusso (1985). These data should not be strictly interpreted, since due to the different methods of scoring employed by the authors, errors may have been introduced by converting these results to a unity scale. For instance, the results of neurosurgery achieved by Narakas (1981a), which are comparable to those in his series presented in 1985, look worse than those of Dolenc and Gusso. It is important to note, however, that his series also contains patients for whom nerve repair was impossible or only very limited. Nevertheless, the table can serve to get a feeling of how the Dutch results
Table 2.5  Diagnostic tests performed on Dutch patients.

<table>
<thead>
<tr>
<th>Diagnostic test</th>
<th>number up to 1981</th>
<th>number after 1981</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of patients</td>
<td>93 (40%)</td>
<td>43 (60%)</td>
</tr>
<tr>
<td>EMG</td>
<td>37 (40%)</td>
<td>26 (60%)</td>
</tr>
<tr>
<td>SNAP</td>
<td>1 (1%)</td>
<td>3 (7%)</td>
</tr>
<tr>
<td>SEP</td>
<td>0 (0%)</td>
<td>5 (12%)</td>
</tr>
<tr>
<td>Axon reflex</td>
<td>7 (8%)</td>
<td>6 (14%)</td>
</tr>
<tr>
<td>Cervical myelography</td>
<td>17 (18%)</td>
<td>18 (42%)</td>
</tr>
<tr>
<td>CT-scan</td>
<td>0 (0%)</td>
<td>3 (7%)</td>
</tr>
<tr>
<td>Cervical hemilaminectomy</td>
<td>11 (12%)</td>
<td>7 (16%)</td>
</tr>
<tr>
<td>Diagnostic exploration</td>
<td>7 (8%)</td>
<td>4 (9%)</td>
</tr>
<tr>
<td>No supplementary tests</td>
<td>29 (31%)</td>
<td>9 (21%)</td>
</tr>
<tr>
<td>Insufficient diagnosis</td>
<td>45 (48%)</td>
<td>19 (44%)</td>
</tr>
</tbody>
</table>

relate to those of other series.

comparing Dutch results to literature

Although the number of cases is small, it may have become clear, that as far as nerve repair is concerned, results in the Dutch series tend to be a little worse than results in the other series. This can be due to a number of causes. First of all, none of the neurosurgical reconstructions in this series had been conducted in either one of the two expert neurosurgical centers for brachial plexus surgery in the Netherlands, i.e. the Leiden University Hospital and the De Wever Hospital. Neurosurgery in these hospitals, yields results that are comparable to those found in literature (Slooff and Thomeer, 1990). Moreover, two of the patients (22%) had been operated on more than six months after their trauma, and one (11%) had a follow up of only two years. This patient presented bad results, but seemed to have started to recover some elbow function.

The results of the patients that have been treated non-operatively seem to be much more out of line with the other series. A plausible explanation for this
is that in this series a large number of patients had severe injuries (Sunderland type 4 or 5), that would have been amenable to surgery. The same observation has been made by Wynn Parry (1984), concerning his own series of patients. This hypothesis is confirmed by the observation that of a total of 93 patients admitted before 1981 that, due to the high number of high speed accidents (88%), were likely to be serious injuries, only 12 (13%) have been repaired neurosurgically, whereas in Narakas's (1981) series this was 38%. Moreover, from the four lacerations only two have been operated on (50%). In the series of patients admitted between 1981 and 1985, the number of nerve repairs, though still less than 38%, is much higher: 11 (25%).

Before 1981, the patients in this series were referred to the rehabilitation center at a very late stage, i.e. on average 20 months post-trauma, whereas only 50% of the patients were referred to the rehabilitation center within 6.5 months after the trauma. This seems to have improved after 1981, since then the average time to admission is 12.5 months, with a median of 3 months.

The fact that few Dutch brachial plexus injuries that are treated outside the Leiden University Hospital and the De Wever hospital are neurosurgically reconstructed, and that patients are referred to a rehabilitation center at a late stage, may be due to ignorance on the part of the referring hospitals. To get an idea of the knowledge of the diagnosis and management in these hospitals, in the following section diagnosis and management will be reviewed.

2.5.2 Diagnosis and management

Table 2.5 shows the diagnostic tests that have been performed on 136 patients. As is clear from this table, before 1981 for 31% of the patients no diagnostic tests were conducted apart from motor and sensory examination, and this is still 21% after 1981. As a result, before 1981, in 48% of the patients, no diagnosis was recorded in the patient file concerning the site, the extent or the severity of the injury. After 1981, hardly any improvement could be noted, because then this percentage is still 44%. Very noteworthy also is the high percentage of cervical hemilaminectomies that is conducted: 12% before 1981 and 16% after 1981. It has been mentioned already that this operation must definitely be rejected as a diagnostic procedure. Also exploration of the brachial plexus as a diagnostic procedure was conducted in a fair number of patients: 8% before 1981 and 9% after 1981. Finally it should be mentioned
that although after 1981 the number of diagnostic tests, other than motor or sensory testing, has increased per patient from 0.9 to 1.7, the results of these tests are sometimes interpreted so poorly that they hardly contribute to a better diagnosis and management.

2.5.3 Conclusion

In the foregoing sections a number of problems in the diagnosis and management of brachial plexus injuries in the Netherlands that may be responsible for poor results have been mentioned. These are:

- In the early stage, associated injuries often demand attention so that the brachial plexus injury is left unattended.
- Diagnosis is very complex due to the possible combinations of deficits and possible anatomic variations.
- Diagnosis is often neglected by the referring clinic, due to ignorance of the neurosurgical possibilities, or to a pessimistic view on the results of neurosurgery.
- Patients are often referred late to the rehabilitation center.
- Few patients are treated by reconstructive procedures (17%).

From the above it may be clear that it is necessary to improve the diagnostics of brachial plexus injuries and to propagate the possibilities for operative as well as non-operative treatment. However, objective knowledge of the prognosis for different combinations of diagnosis and treatment is still hardly available. A specific function can often be restored in a number of ways, e.g. by neurosurgical repair, orthopedic reconstruction, hand surgery or the application of orthoses. A scheme for the evaluation of the results of neurosurgical repair has recently been developed by Narakas, so that assessment of these results is now called for. However, due to the lack of an information system for standardized data acquisition, results of different treatment schemes, can still not be compared. Therefore, in this domain an overall lack of knowledge can be observed as to the prognosis of different treatment schemes, and a lack of knowledge concerning diagnosis and management in a more global sense can be observed among non-experts.
Chapter 3
Data based support in medical decision making

3.1 INTRODUCTION

Many medical decision support systems somehow involve a prediction of a patient's future state that may be used in the decision making process. This prediction can be used to see whether medical intervention is necessary to control this state, e.g. by the prescription of drugs or through operative treatment. It can be used to assess the effect of such treatments in advance. Or it can be used to determine a therapy that is optimal in some sense, for instance a therapy that yields the best patient state, or that allows the soonest patient dismissal. To derive such detailed predictions, a static model will be insufficient and the data based classification systems relying on such models are useless. In these instances, there is a need for decision support systems based on dynamic models. As was made clear in Sect. 1.4.2, in the medical domain there are always uncertainties associated with the input and output of such models, so that deterministic models are usually inadequate to describe process behavior. Then, the process output can be considered a realization of a stochastic process.

In engineering and biology, techniques have been developed to derive dynamic models in cases where there is little or no a priori knowledge about the process available. Or in cases where this knowledge is inadequate, either because the models expressing this knowledge are too complex which demands a simplified description of the process, or the knowledge of parameter values of the model is missing. These characteristics certainly apply to the field of medical decision making. The important domain feature decisive for the similarities between many problems in engineering, biology and medical decision support problems is the unavailability or inapplicability of sufficient a priori knowledge of the process for knowledge based support. This poses the need for a data based approach, in which the necessary knowledge is derived from analyzing the process input and output signals. This approach is called system identification.

System identification is a large field on which a rich body of literature has been published. The aim of this chapter is to briefly discuss the aspects of system identification that are especially relevant in the application in
the medical domain. A more extensive discussion of the system identification problem can be found in Åström and Eykhoff (1971), Eykhoff (1974), Goodwin and Payne (1977) and Ljung (1987). System identification involves the acquisition of input and output data of the process, the choice of a set of candidate models that is believed to contain the 'real' model of the process, the choice of a parameter estimation method to determine the best model in the selected model set, and validation of this model to determine whether it suits its purpose. These aspects will be dealt with in the subsequent sections.

3.2 DATA ACQUISITION

As in all data based decision support systems, in system identification, support system knowledge is derived from analyzing data of the process. An important aspect of the theory of system identification concerns the experiment design to collect these data.

3.2.1 Experiment design

This includes the choice of input and output signals of the process to be measured, the choice of sampling interval, the prefiltering of the data and the choice of test signals. Basically, this is the most important part of the identification procedure, since the data that are collected determine what knowledge of the process can ultimately be derived. Therefore, the experiment that provides these data should be sufficiently informative to allow the distinguishing of different models and the determination the 'real' model of the process. Whether an experiment is sufficiently informative is closely related to the information content of the input signals. Therefore, choosing

![Figure 3.1. The closed loop character of the medical consultation process.](image)
optimal test signals to affect the process may be very useful in satisfying the necessary conditions for the information content of the input signals. It has been shown that these conditions are satisfied when persistently exciting input signals, i.e. input signals that affect the process in its entire bandwidth, are used. In open-loop experiments, these signals yield sufficiently informative experiments. In closed-loop experiments however, persistence of excitation is not a sufficient condition. Although at least theoretically problems related to closed-loop identification can generally be solved by the choice of the right identification method without the need of any specific measures (viz. Sect. 3.4), these aspects may severely hinder the correct identification of the real process model.

Another major problem is that medical processes, as all real-life processes, are non-linear and time-varying. If such a non-linear process is to be approximated by a linear model, it is of utmost importance that the input signals reflect the conditions the model is meant to describe. Despite the importance of the right input signals in the derivation of good quality models, in many areas the input signals to affect the process can not be freely chosen, either because it is physically impossible to manipulate the process inputs, as in economic or ecological processes, or because this is (ethically) undesirable as is the case in most medical applications. In these circumstances, the experimentation has to be carried out during normal operation when the process is excited only by the naturally occurring spontaneous fluctuations in the input signals. Then the information content of these signals may be low, seriously influencing the result of the identification. Therefore, the experiment designer faces three important problems in the identification of medical processes:

1. The process inherently operates in closed loop (Fig. 3.1).
2. The process is non-linear and time-varying.
3. The application of test signals is generally impossible.

These problems place high requirements on the remaining choices in data acquisition, to approximate, as well as possible, the case of a dataset that is sufficiently informative for identification of the process model. Remaining choices involve the choice of which data of the process input and output signals to collect and how to collect these. The data that are collected should reflect the process dynamics. As has already been described in Ch. 1,
apart from physiological variables, important factors influencing the medical process are psychological and social variables. These may be of great interest in deriving a reliable process model. However, data concerning treatments aimed at improving a patient's psychological or social well-being and the patient's state in connection with these aspects are hardly quantifiable. Therefore it may be impossible to explicitly incorporate these in the model as input and output signals. In this case its effects will become implicitly present in the quantifiable variables and in the stochastic noise terms in the model. Similarly, the necessary quantification of relevant signals concerning physical condition means a loss of accuracy. The fact that important input-output signals may not be measurable or poorly quantifiable severely restricts the choice of input and output signals of the model, and has a potentially negative effect on model accuracy.

3.2.2 Data acquisition

If it has become clear which data should be collected, the problem of actually acquiring these data remains. In many applications of medical decision support for processes of long duration such as rehabilitation, it is not possible to automate data collection as can often be done in modeling physiological processes, e.g. recording EEG or ECG signals, a patient's temperature etc. If this is so, the system designer has to rely upon the physician for data acquisition. Then two possibilities remain:

- Data retrieval from medical records.
- Data collection through standardized data acquisition systems.

medical records

Information processing is an important aspect of medical treatment. In medical decision making the physician relies upon information in the medical record. As has been made clear in Ch. 1, this is the more true in rehabilitation. Rehabilitation is a very complex process of long duration, in which many disciplines are involved. To achieve the intended results of the treatment, treatment team members and the patient have to be well informed about all aspects concerning the treatment and the patient's state. Retrospective
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studies have shown, however, that medical records can not sufficiently fulfill the demands of information exchange which makes them unsuitable for clinical research, epidemiological studies and probably even for sound decision making, especially in multi-disciplinary treatment (Elstrin, 1979; Hoogendoorn, 1983; Jaspers, 1984). The main imperfections found in medical records are:

- Data are often recorded in a non-uniform fashion.
- Relevant data are often missing.
- Data are very difficult to retrieve.

Therefore, data acquisition for decision making and modeling requires a well-structured system of information acquisition and information storage. Such a system guarantees the uniformity, completeness and accessibility of the relevant data. This does not only improve information exchange and coordination among treatment team members, it also makes these data available to research studies, such as epidemiological studies and the development of decision support systems. To fully benefit from such structured medical records, automated data processing becomes an obvious choice.

medical information systems

Critics of automation, mostly from the medical field, emphasize the problems of privacy protection and depersonalization of medical care which are associated with automated data acquisition. As far as the first argument is concerned, it can not be sufficiently stressed that traditional paper medical records are much more amenable to violation of confidentiality than a well-protected automated medical record. The potential abuse of these systems lies rather in their notion of completeness. It can often be observed that with the introduction of a medical information system there is a rapid increase in the amount of data that has to be recorded. This is particularly true if one system is to be used in several environments where the standardization of different opinions leads to the co-existence of similar variables in the system which results in an uncontrollable increase in system size and a proportional decrease in its usefulness (viz. Sect. 7.2.1). This will end in a poor motivation to use the system, or in the use of only those aspects that reflect the user’s opinions, which restores the undesirable previous situation of non-uniform, incomplete data collection. Apart from the number of process
variables that have to be recorded, another aspect places a great burden on the necessary effort for data acquisition.

sampling

If the data have to be suitable to derive a dynamic model of the process, they should reflect the process dynamics, so input and output signals have to be recorded over time. Since continuous registrations of signals can not be made nor be processed by digital computers, automated data acquisition requires that the data of interest are sampled. Sampling can mean a loss of information, since information about frequencies higher than half the sampling frequency will be lost. Moreover, if the continuous signal contains substantial energy above this frequency aliasing will occur, i.e. this energy will be interpreted as contributions from lower frequencies. The choice of sampling rate should be made so as to avoid both the information loss and the aliasing effect. In system identification, most methods assume that data have been sampled at equidistant instants since this greatly simplifies the analysis. According to Shannon's theorem, this uniform sampling should be done at a frequency that is more than twice the highest frequency in the continuous signal. Aspects to do with variance of parameter estimates and biasing towards the high frequencies by sampling which is too fast, leads to the recommendation of a sampling frequency that is about ten times the bandwidth of the system (Ljung, 1987). In the medical domain this may be prohibitive for many applications, since it places strong requirements on data acquisition. Only in very slow processes with time constants of several weeks or months, such as some rehabilitation processes, may a sampling frequency of this magnitude be viable. In the rehabilitation of spinal cord injuries, this led to a sampling frequency of once a week (viz. Sect. 7.2.1), which may still be unsurmountable in other applications. Also it may be very hard to get physicians to record patient data at prespecified instants. Especially if treatment processes are of long duration and part of the treatment is done outside the treatment center.

This observation leads to the conclusion that either sampling should be done at a lower frequency, or by sheer necessity, other ways of sampling have to be applied that are more natural in the domain. One such method is non-uniform sampling, which is the normal method in medical treatment. The physician examines the patient at not necessarily equal intervals when he expects
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certain findings or when signs of recovery or complications become manifest. However, methods to deal with non-uniformly sampled data are more complex than these for the uniform case.

Of course, apart from the sampling frequency, it should be ensured that the number of data points, i.e. the sample size, is sufficient to achieve an accurate model. This will be dealt with more thoroughly in Sect. 3.4. The variance of the parameter estimates is inverse proportional to the number of observed data, \( N \). Due to the strong requirements on data acquisition, in medical decision support this may cause problems in model accuracy.

3.2.3 Conclusion

In conclusion, it should be noted that data acquisition in rehabilitation medicine and other medical domains is potentially a bothersome task. First of all, it may prove very hard to record the amount of data required for reliable modeling, and to record these data in a manageable fashion, viz. quantifiability of data and sampling. Secondly, in general, it will be impossible to apply test signals to affect the process. The only choice remaining for the model builder is that of the natural input and output signals of the process. However, also this choice is severely restricted. Important signals affecting the process may be hard to measure, such as psychological or social factors. This may force a modeler to consider these factors that in rehabilitation may be very important, as disturbances affecting the process.

3.3 MODEL STRUCTURE AND PARAMETRIZATION

Once the necessary data are available, the second step in the identification process is the choice of the set of candidate models in which the 'real' model of the process is going to be sought. This is a very important step in system identification, since this choice determines whether the parameter estimation method will be able to find within this set a model of the process that satisfies the needs, to determine whether this is a unique solution and what computational effort is needed to derive this model. The relevant aspects for choosing a model structure, which are summarized by Goodwin and Payne (1977),
will be discussed in this section.

One of the reasons for the application of system identification for modeling medical processes is that very often the physi(olog)ical knowledge about these processes is not available or not applicable due to its complexity. Therefore, in choosing a model set it is impossible to construct a model from basic physiological laws, but a model builder has to resort to a standard model set in which the parameters will be estimated to fit the observed data of the process. Such models are commonly referred to as black-box models. They have no direct physiological significance. Modern system identification mainly deals with parametric models of linear time-invariant processes. However, real-life processes are non-linear and time-varying. The assumption that is often made in system identification then is that, around a certain operating point, these processes can be approximated by linear models. And often, time-varying properties are negligible. In some applications, however, this assumption may not be valid. For instance, it is questionable whether medical processes may be considered time-invariant. In these cases, the process to be modeled is subject to change due to the healing process that occurs as a consequence of the treatment. Also, it will be clear that medical processes are non-linear, e.g. doubling the intensity of the treatment will generally not result in a patient condition that is twice as good. Because of this, non-linearities and time-varying properties may be more important than in other problem domains. If so, non-linear time-invariant, linear time-varying or non-linear time-varying models may have to be chosen. However, from previous research there is no indication that linear time-invariant models would not apply to medical problems. Nevertheless, the effect of this modeling assumption should be investigated by means of simulation during validation of the model.

Most work on system identification in the medical domain has dealt with linear time-invariant models (Beneken et al., 1974; Blom, 1975; Stassen et al., 1980). In the following the discussion will be restricted to this class of models.

A linear time-invariant process, with scalar input $u(t)$ and scalar output $y(t)$ is described by (Ljung, 1987):

$$y(t) = \sum_{k=1}^{\infty} g(k)u(t-k) + v(t) \quad t = 0, 1, 2, \ldots$$

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Here $\sum_{k=1}^{s} h(k) e(t-k)$ is the impulse response of the process, and $v(t)$ are the disturbances affecting the output $y(t)$. These can be described as derived from a sequence of independent random variables with zero mean values:

$$v(t) = \sum_{k=1}^{s} h(k) e(t-k)$$

With the introduction of the backward shift operator $q^{-1}$ the Eqs. (3.1) and (3.2) lead to:

$$y(t) = G(q)u(t) + H(q)e(t)$$

A linear time-invariant model of the process (3.3) is then given by:

$$y(t) = G(q,\theta)u(t) + H(q,\theta)e(t)$$

3.4a

$f_{e}(x,\theta)$, the PDF of $e(t)$; \{e(t)\} white noise

3.4b

Here, $\theta$ is the vector of the model's parameters that have to be estimated and $e(t)$ is white noise with a probability density function $f_{e}(x,\theta)$. A one step-ahead prediction of $y$, given that $y(s)$ and $u(s)$ are known for $s \leq t-1$, is:

$$\hat{y}(t|\theta) = H^{-1}(q,\theta)G(q,\theta)u(t) + [1 - H^{-1}(q,\theta)]y(t)$$

3.5

Parametrization of this model structure requires a choice for the parametrization of the transfer functions $H(q,\theta)$ and $G(q,\theta)$. Two widely used families of parametrizations will be discussed, the input-output models (Box-Jenkins models) and the state-space models.

3.3.1 Input-output models

A straightforward parametrization of Eq. (3.5) would be the standard linear regression form, mentioned in Ch. 1. In the dynamic case this would be:

$$\hat{y}(t|\theta) = \theta_1 x_1 + \ldots + \theta_n x_n$$

$$= \theta^T x$$

3.6
Here $\mathbf{x}$ is a data vector of observations of the process, consisting of past inputs:

$$\mathbf{x}^T = [u(t-1), \ldots, u(t-n)]$$ \hspace{1cm} (3.7)

A more general case is constituted by the generalized regression model, in which $\mathbf{x}$ consists of both input and output observations:

$$\mathbf{x}^T = [y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, u(t-n_u)]$$ \hspace{1cm} (3.8)

In terms of Eq. (3.5) this can be written as:

$$\hat{y}(t|\theta) = B(q)u(t) + [1 - A(q)]y(t)$$ \hspace{1cm} (3.9)

$$A(q) = 1 + a_1q^{-1} + \ldots + a_{n_a}q^{-n_a}$$

$$B(q) = b_1q^{-1} + \ldots + b_{n_b}q^{-n_b}$$

---

**Figure 3.2** The ARX model.

---

**Figure 3.3** The general structure of input-output models.
This leads to the model set:

$$A(q)y(t) = B(q)u(t) + e(t)$$  \hspace{1cm} (3.10)

This is called an ARX model. It is a member of the family of equation-error model structures: The white noise term $e(t)$ enters as a direct error in the equation. The linear regression is a straightforward parametrization for linear models, the prediction $\hat{y}(t|\theta)$ is linear in the parameter vector $\theta$, which allows the application of simple estimation methods based on the least-squares criterion. However, from Fig. 3.2 it will be clear that this is not a very natural parametrization. The disturbances $v(t)$ that affect the process output are modeled to be derived from white noise filtered by the denominator dynamics of the process. To allow for a better description of this disturbance term, other parametrizations have been proposed, of which the ARMAX model is well known:

$$A(q)y(t) = B(q)u(t) + C(q)e(t)$$  \hspace{1cm} (3.11)

The ARMAX model is also of the equation-error type. A more natural way to model the disturbances however, would be to view them as disturbing the output of the model, as in output-error models:

$$y(t) = \frac{B(q)}{D(q)} u(t) + \frac{C(q)}{D(q)} e(t)$$  \hspace{1cm} (3.12)

In this so-called Box-Jenkins structure, $G(q)$ and $H(q)$ from Eq. (3.4) are parametrized independently, since they no longer share the polynomial $A(q)$ as a common factor. Both output-error and equation-error model structures are special cases of input-output models (Fig. 3.3).

Thus far, it has been assumed that the process to be modeled is a Single Input Single Output (SISO) process. The models described, however, can straightforwardly be applied to multivariable (MIMO) processes. In that case the input $u(t)$ and output $y(t)$ become vectors instead of scalars, the polynomials $A, B, C, D, F$ become matrix polynomials of appropriate dimensions.
3.3.2 State-space models

Another important family of model structures are the state-space models. They attracted attention especially from the field of control engineering. An important asset of this method for describing linear dynamic processes is that a priori knowledge of the process can be incorporated in the model relatively easily. For MIMO processes, in the state-space form the output \( y(t) \) is related to the input \( u(t) \) via a state vector \( x(t) \):

\[
\begin{align*}
x(t+1) &= Ax(t) + Bu(t) + Fw(t) \\
y(t) &= Cx(t) + Du(t) + Cv(t)
\end{align*}
\]

Here \( w(t) \) represents the process noise and \( v(t) \) represents the measurement noise. As was mentioned earlier, due to necessary model simplification, the suitability of a priori knowledge will often be very limited in medical applications. This dispose of the advantage of physiological interpretability of state-space model structures. In medical applications, state-space models also reduce to black boxes. In this case, except when input-output models prove to have bad numerical properties, simple input-output models may be a suitable representation of the process behavior.

Once a model structure has been chosen, the identification method searches for the best model within this model set by estimating the parameters of the model. The matrix representations described in this section do not necessarily define a unique description of the process. For instance, many different state-space representations determine the same input-output relations for the same process. In the identification of a model of this process, it is of interest to find that representation that has the minimum number of parameters: the minimal realization. This minimal realization can be derived from the canonical form of the model's transfer function. A detailed discussion on canonical forms is found in Ljung (1987) and Goodwin and Payne (1977).

3.3.3 Conclusion

The choice of a set of candidate models not only involves the type of model set but also the choice of the model's order in state-space models, or the
degree of the polynomials in input-output models and the choice of the parametrization are also important steps in this procedure. Well-founded a priori choices in this respect can often be made from careful preliminary data analysis. Generally, determining a final model structure is an iterative procedure of choosing a structure, computing a model, validating and comparing this to other models. This procedure is usually started with simple model structures like linear regression models to get a feeling of the problem. Whether possible shortcomings of simple structures can be solved by choosing more sophisticated model structures also depends on the available data of the process and the parameter estimation method.

3.4 PARAMETER ESTIMATION

To find the 'real' model in the set of candidate models that has been parametrized as described in the previous section, means the estimation of the value of these parameters. The parameter estimation methods commonly used in system identification for modeling dynamic processes are extensions of the methods used in statistics. In that framework, a parameter estimation method should preferably have the following properties:

- The expectation $E$ of the value of estimated parameters $\hat{\theta}$ should be equal to the real value of the parameters $\theta$: $E(\hat{\theta} - \theta) = 0$. In this case the estimator is unbiased.

- The variance of the estimated parameters should become smaller with the number of data, $N$: $\lim_{N \to \infty} E((\hat{\theta} - \theta)(\hat{\theta} - \theta)^T) = 0$. In this case the estimator is consistent.

As was mentioned in the previous section, the simplest estimation method is that based on the least-squares criterion in the ARX-model, the linear regression or least-squares estimator. The importance of this estimator is that its criterion can be minimized analytically. The equation error for this model can be written as $e = y - x^T\theta$. The cost function to be minimized in the least squares sense is:

$$J = [y - x^T\theta][y - x^T\theta]^T$$

3.14
This leads to the least-squares estimate

$$\widehat{\theta} = (x^T x)^{-1} x^T y$$

This estimator unambiguously leads to the right solution, since the cost function attains an absolute minimum only for $\widehat{\theta} = \theta$. The estimate is unbiased under the condition that the noise $v(t)$ and the matrix of observations $X$ are independent and $E(v(t)) = 0$. Under these conditions, the estimator is consistent also. However, in most practical situations these conditions are not fulfilled. The condition of independence between $v(t)$ and $X$ has already been violated in the generalized regression model 3.8. In this case $X$ contains the values of past outputs that are dependent on $v(t)$. Also for closed-loop processes these assumptions do not hold. Because of the feedback, the disturbances $v(t)$ affect the process, making $v(t)$ and $X$ mutually dependent and yielding biased estimates. Only in the case that the equation error consists of white noise are the assumptions valid and the estimator unbiased. This will generally not be the case. To solve this, iterative procedures have been developed that estimate the transfer function of the filter yielding the disturbances $v(t)$ from white noise. These methods are called prediction error methods. It has been shown that these methods can be applied straightforwardly for modeling closed-loop processes, in many cases with properties to do with identifiability as good as those in open-loop modeling (Ljung et al, 1974; Söderström et al, 1976; Ljung, 1976; Åström, 1980; Gustavsson et al, 1981). However, these methods pose some disadvantages also. Identification of the transfer function constituting the disturbances, increases the number of parameters to be estimated. Also, these estimates are only asymptotically unbiased. This calls for a larger number of data samples. In medical applications this poses the difficult trade-off between biased estimates due to the application of a simple estimation method in closed-loop identification, or biased estimates due to the use of an asymptotically unbiased estimator, or the need for many data. A detailed discussion on parameter estimation methods can be found in the literature cited earlier.

3.5 VALIDATION

Once the identification procedure has yielded a model, which according to
the criterion of the parameter estimation method is the best model in the chosen set of candidate models, it remains to be seen whether this model suits its purpose. This is the question of model validation. It includes such aspects as whether the model describes the observed data of the process sufficiently well and whether it is a good enough description of the true process. In validating the model, a priori choices regarding model structure, model order and parametrization are evaluated. For validation, a number of tools is available, such as Bode diagrams and simulation to check the model's input-output behavior and testing model residuals for whiteness. Comparing the behavior of different models will generally allow a choice as to a model that best suits the purpose.

3.6 CONCLUSION

The first identification problem of dynamic models of medical processes is the need for much data. This may often prove an important impediment in data based decision support in the medical domain. Not only is data acquisition an arduous task, data from medical processes is likely to be corrupted by substantial amounts of noise. This will greatly influence the result of the identification procedure since the standard deviation of the parameter estimate is a function of the signal to noise ratio. Again, the solution to this is to increase the number of data samples. The introduction of a medical information system may be helpful. In this case, close attention should be paid to the size of the system in order to prevent it from becoming unworkable. However, no matter how much attention has been paid to the conciseness of a system, its introduction will inevitably increase the task load of its users. On the one hand because of the seemingly unavoidable problems in the starting period, on the other hand because the system demands a complete collection of data for each patient. These considerations demand a directly demonstrated advantage of the use of the system to motivate physicians to use it. Long term objectives like 'improved patient care' or 'epidemiologic studies' are far too abstract to motivate the routine daily use of such systems. Direct benefits like automated generation of team reports, letters of discharge and simple data analysis are crucial to the successful introduction of an information system.

Two more properties of medical applications hamper easy identifiability, i.e.
the inherent closed-loop character of many processes and the impossibility of applying test signals to assure the acquisition of informative data sets. Notwithstanding these problems, system identification in medical domains may be feasible. Generally a model should be derived that is applicable not to a single patient but to a group of patients that have the same characteristics. Therefore, data obtained from large numbers of patients can be used to derive a model. Although this still requires a high enough sampling frequency for the data to reflect the process dynamics, it may be helpful to decrease the variance of the estimates. To allow for the estimation method to process these data, special extensions to these methods are required.

In general, the procedure to system identification of medical processes should be to:

1. Acquire as informative a data set as possible, preferably sampled at equidistant instants at a high enough frequency, which is at least several times the process bandwidth.
2. Analyze this data which will lead to a well-founded choice of input and output signals in the model.
3. Choose a model structure that is simple enough in relation to the data available and that is still able to describe the relevant properties of the process.
4. Estimate the parameters of the model in closed-loop identification preferably using a prediction-error method.

If, using this procedure, a high-quality model is derived, the resulting decision support system will still present a disadvantage compared to knowledge based decision support systems. Due to the black-box structure that is necessary to describe complex medical processes, the model will have no direct physiological significance. For potential physician users this may be an important objection to use the decision support system. On the other hand, this problem can not be easily solved by knowledge based systems, since very often the domain knowledge is insufficient to serve as a basis for modeling. This is the main advantage of data based systems. Since modeling the system dynamics is relatively easy in these systems, they are very well suited to use in gaining new insights in medical processes.
Chapter 4
Knowledge based support in medical decision making

4.1 INTRODUCTION

Knowledge based systems and expert systems have become popular products of the field of Artificial Intelligence, AI. For a clear comprehension of what is meant by these concepts in this thesis, they will first be briefly defined. In contrast to definitions of AI as being a part of cognitive science which focuses on theories of intelligence, in this thesis a very machine-centered definition of AI will be employed: 'AI is the study of ideas that enable computers to exhibit intelligent behavior'. Knowledge based systems are defined as being 'computer programs that contain knowledge coupled with methods of applying that knowledge in order to solve intellectually demanding tasks'. Expert systems, which have gained much attention in the past decade, are a subset of knowledge based systems. The knowledge present in expert systems has been derived from one or more experts in the domain, and the problem-solving behavior of these systems resembles that of human experts. The basic assumption underlying most present work on knowledge based systems is that intelligent behavior in a task domain can be achieved only by incorporating in the system a substantial amount of knowledge about that domain. This contrasts with the earlier work on AI, which mainly focused on general problem solving systems that did not contain domain-dependent knowledge. During the 1960s, however, it was recognized that these systems may greatly benefit from specific knowledge about the objects they deal with. This understanding led to a tendency to build special-purpose systems, containing expert knowledge, that could solve real-world problems in limited domains. This tendency is similar to what has since long been the practice in system identification in data based modeling. It should be realized that knowledge based modeling provides an alternative to data based modeling, to achieve a qualitative model that describes part of reality, instead of a quantitative model. What kind of technique is best applicable in which situation has already received some attention in previous chapters and will be treated further in the following.

The knowledge based approach brought about new problems in AI, to do with such issues as the acquisition and representation of knowledge. This chapter will briefly deal with these issues. In order to acquire some feeling for the kind of knowledge involved in the medical domain, an introduction to medical
decision making will be presented which will be followed by a review of methodologies found in AI for diagnostic systems and a discussion of techniques for acquiring and representing knowledge. A discussion on deep versus surface knowledge concludes this chapter. For more extensive discussion on AI, many text books are available, for instance Rich (1983), Winston (1984), Charniak and McDermott (1985) and Rauch-Hindin (1986). Also, an overview of the work on medical knowledge based systems can be gained from the following: Shortliffe (1976), Shortliffe et al (1981), Miller et al (1982), Pople (1982), Buchanan and Shortliffe (1984a), Clancey and Shortliffe (1984) and Reggia and Tuhrim (1985).

4.2 MEDICAL DECISION MAKING

As it has been alluded to already in Ch. 1, according to the definition in

![Diagram of the stages of clinical decision making](image)

**Figure 4.1** The stages of clinical decision making.
Knowledge based support in medical decision making

This thesis medical decision making involves diagnosis, selection of therapy and prognosis (Fig. 4.1). Among these, the diagnostic process has received most attention from researchers. Diagnosis is a key element in medical problem solving. Therapy selection depends greatly on the correctness of the diagnosis. Therapy selection seems to be a relatively straightforward decision making task which is often protocol driven, once a patient’s diagnosis has been established.

Many authors have indicated that medical diagnosis is an iterative process (Corry and Barnett, 1968; Schwartz et al, 1973; Elstein et al, 1978; Kassirer and Gorry, 1978; Pople, 1982; Reggia, 1982; Feltovich et al, 1984). The clinician, confronted with a patient complaining of some symptom, faces the problem of uncovering other manifestations by performing diagnostic tests and of determining whether sufficient data are available to diagnose a patient’s disorder. If not, he has to decide upon which new tests to perform to obtain additional information at a reasonable cost (cost in terms of patient discomfort, money etc.). It has been shown (Pauker et al, 1976; Elstein et al, 1978; Kassirer and Gorry, 1978) that the general problem-solving procedure physicians use to guide this diagnostic process is that of hypothesize and test. Cues in patient data suggest tentative hypotheses about the cause of observed manifestations. Subsequently, these hypotheses are tested against new information concerning the case. Feltovich et al (1984) emphasized the importance of a rich body of accurate, well-organized medical knowledge to back up this iterative process. Apart from common sense, medical knowledge in clinical problem solving involves structural knowledge of anatomical structures, causal knowledge of physiological processes, causal associations about how clinical manifestations relate to a certain disease and heuristic and strategic knowledge for efficient problem solving. It is the knowledge of disease models, i.e. knowledge of the pathophysiology of diseases and of the clinical manifestations that should be present in the case of a specific disease and the organization of this knowledge that distinguishes expert diagnosticians from the less experienced. Although the diagnostic strategies of experts may vary considerably, it has been found that in diagnostic performance this is often of secondary importance compared to their knowledge of medical facts (Elstein et al, 1978). The diagnostic process will be addressed in some detail so as to be able to draw on this description in subsequent sections.
4.2.1 Diagnostic process

The understanding of the expert's problem-solving process is critical to the design of knowledge based systems to assist physicians. Not only may systems based on this understanding achieve a high level of expertise, they also may be able to explain and justify their conclusions in a fashion closely related to the physician's way of thinking. Moreover, they may be efficient reasoners by employing expert problem-solving strategies and they may be capable of teaching these strategies to less experienced physicians. Therefore, the diagnostic process will here be expanded. The work of Kassirer and Gorry (1978) and Elstein et al (1978) serve as a basis. As they indicate, the diagnostic process is a sequence of hypothesis activation and evaluation which is based on gathering information (Fig. 4.2).
Diagnostic hypotheses are generated early in the diagnostic process when as

![Diagram](image1)

**Figure 4.2** The diagnostic hypothesize and test cycle.

![Diagram](image2)

**Figure 4.3** A diagnostic hierarchy for brachial plexus injuries.
yet very few data are available. Patient findings, causally related to hypotheses in the expert's long-term memory, activate these hypotheses which are subsequently transferred to his short-term memory. These hypotheses serve to focus attention, i.e. to bound the space of possible decisions. They identify relevant directions for further investigation. The more specific clinical findings are encountered, the more specific are the activated diagnostic hypotheses. This suggests that physicians' knowledge about disease models is organized hierarchically, as has been indicated by other authors (Gomez and Chandrasekaran, 1981; Feltovich, 1984). In this hierarchy, concepts concerning more general disease categories are placed at the top and particular diseases at the bottom (Fig. 4.3). As the diagnostic process proceeds, evaluation of hypotheses becomes more important. The general approach in hypothesis evaluation seems to be that of confirmation, elimination and refinement. In evaluating, a hypothesis can either be confirmed or eliminated, if necessary by default. For a hypothesis under consideration to be confirmed, it must be able to explain new data and a sufficient number of the expected findings for that hypothesis have to be present. Accordingly, a great deal of data may be needed to confirm a hypothesis. Sometimes the data may be costly to obtain, or unpleasant, or even potentially harmful to the patient. Therefore, the process of elimination of hypotheses is a powerful technique to bound the set of alternatives. By using the process of elimination, a physician may diminish the amount of data needed to discriminate among hypotheses, and sometimes a conclusion concerning the remaining alternatives may be reached without definitive confirmatory evidence. As observed earlier, physicians seem to possess a hierarchically organized set of disease categories. This hierarchy may be used to refine an originally general hypothesis to a more specific one when new information becomes available.

This diagnostic cycle continues until the physician is sufficiently certain of a diagnostic hypothesis, or that further investigation will have no serious implications for therapy and prognosis.

4.2.2 Concluding remarks

An important aspect of the diagnostic process described above is that new information is continually gathered, this either suggests (activates) new
hypotheses or aids in the evaluation (or refining) of hypotheses already under consideration. Since hypotheses are used to focus attention, much of this information gathering is hypothesis driven, i.e. hypotheses determine which information is most useful at a given point in order to narrow the scope of the problem. Sometimes, for the sake of completeness protocol-driven information is sought, to screen a patient for unexpected symptoms. The ability to obtain the right data distinguishes the expert from the novice. In gathering this information, a physician’s main concern is the reliability of the data. Often, physicians have to deal with discrepant information. Either new data may contradict information already available or it may be inconsistent with a hypothesis tentatively accepted. In these cases, confirmatory evidence may be sought via redundant procedures. If this discrepant information is validated, it may either be attributed to an additional hypothesis not yet under consideration, or it will cause the physician to reject his hypothesis and to develop an alternative one that explains all previously gathered information as well as the new fact.

Figure 4.4 The inference structure of the heuristic classification process.

Figure 4.5 Example heuristic association in the brachial plexus domain.
4.3 DECISION MAKING STRATEGIES IN AI

The rise of interest in knowledge based systems brought about a large number of problem-solving programs in the medical domain and in non-medical domains. Apparently, each of these programs has its own representation language and problem-solving strategy. Studies have demonstrated the advantages and disadvantages of different representation languages (Davis et al., 1977; Swartout, 1981; Clancey and Letsinger, 1981; Aikins, 1983; Clancey, 1983; Brachman et al., 1983). These will be discussed in Sect. 4.4. However, attempts to clarify the most promising strategy for a given problem seemed to break down in the overwhelming amount of systems, which made it hard to see the wood for the trees. An analysis by Clancey (1985) of expert system competence, independent of representation language and task, created some order in this chaos.

4.3.1 Heuristic classification

Clancey shows that these programs predominantly use a similar reasoning strategy, which he calls heuristic classification (Fig. 4.4). As in simple classification, in heuristic classification, after being abstracted, data may be matched to features of hierarchically organized classes to find a solution. Apart from this, however, in heuristic classification there may also be a direct non-hierarchical association with specific solutions or features characterizing a solution. Then, general solutions may be refined to more specific ones. Figure 4.5 shows an example of non-hierarchical association and refinement from the domain of brachial plexus injuries. In this classification process two kinds of knowledge are used: hierarchically organized (taxonomic) knowledge to connect members, subclasses and classes, and non-hierarchically organized knowledge to link (abstracted) data directly to causes, skipping over intermediate relations. These relations may be omitted either for reasons of efficiency, or because they are just not known, as may be the case in medical diagnosis as to the causal relations between symptoms and diseases. Based on the similar notion that a higher level of abstraction is needed than the implementation language level to reveal the tasks that knowledge based systems perform, Chandrasekaran (1986, 1988) identified a number of generic tasks for diagnostic, design and planning systems. These tasks should be the
building blocks for knowledge based systems. In his architecture also, the strategy of heuristic classification consists of three generic modules: a database component performing the data abstraction task, a hypothesis-matcher performing the heuristic match, and a classifier performing the refinement task.

From this description of the process of heuristic classification it may be clear that it bears a close resemblance to the physicians’ problem-solving strategy described in the previous section. How exactly do these relate? In comparing the two, the iterative character, which is so essential in clinical problem solving, is not as obvious in Clancey’s heuristic classification. However, both processes do employ a strategy to refine general solutions to more specific ones. The data abstraction phase that seems to be missing in the clinical problem-solving process is, of course, implicitly present in this process as well. In this phase, the physician, maybe unconsiously, translates data from questioning or from diagnostic tests into information, e.g. "If the patient has a motoric nerve conduction speed in the n. medianus of 28 m/s, the conduction speed is low", "If the patient is 22 years of age, he is a young person".

The only remaining difference to be explained between the physician’s strategy and the process of heuristic classification is that of the cyclic hypothesize and test process versus the heuristic match. For the heuristic match to correspond to the hypothesize and test cycle, it should consist of both hypothesis activation and evaluation as well as question generation. Though

![Diagram](image-url)

**Figure 4.6** Methods to assure monotonicity in reasoning.

a. Inheritance with exceptions.

b. Drawing an intermediate conclusion.
not specifically addressed in the inference structure of heuristic classification in Fig. 4.4, question generation is usually part of the process. As Clancey puts it (1985, p.323): "...the actual order in which assertions are made is often not strictly from left to right, from data to conclusions.". Heuristic classification programs typically employ focusing, including data gathering and hypothesis testing. The non-hierarchical associations used in heuristic matching are typical examples of hypothesis activation. This focused solution strategy, employing heuristic triggers, provides a very powerful means to efficiently limit the set of candidate solutions, especially in domains with large numbers of possible solutions. This will be discussed in more detail in Sect. 4.6.

As in physician reasoning, in opportunistic systems, hypotheses activated this way may be tested by gathering new data. This new data in turn may cause refocusing, which sometimes even results in non-monotonic reasoning.

4.3.2 Non-monotonic reasoning

In the domain of brachial plexus injuries, for instance, the presence of a meningocele or the absence of a root's fila radicularia on a cervical myelogram, suggests an avulsion of that root, unless the Tinel's sign is radiating towards the corresponding dermatome. Similarly, an infraclavicularly elicitable Tinel's sign suggests an infraclavicular injury, unless it is due to nerve recovery of an originally supraclavicular injury. In this way, a previously accepted hypothesis may have to be retracted, and all facts inferred from it, when it is invalidated by new evidence. Several formalisms have been proposed for such non-monotonic reasoning (Bobrow, 1980; McCarthy, 1986). Most systems, however, deal with problem solving in a monotonic way. Monotonicity can be assured by checking the necessary context before a hypothesis is accepted. Drawing an intermediate conclusion that can be refined to a final conclusion later, also keeps reasoning monotonic. Figure 4.6b presents an example of this from the domain of classifying animals. A number of object based representation methods (Sect. 4.5.3), allows exceptions to inheritance within networks (Fahlman et al, 1981; Brachman, 1983; Etherington and Reiter, 1985; Jonker, 1987; Rector, 1987). Fig. 4.6a shows an example of this. Inheritance will be treated in some detail in Sect. 4.5.3. Self-referencing rules (Clancey, 1983), i.e. production rules that conclude about
an object that is also mentioned in the condition, which are allowed in some rule-based systems, may be considered a form of non-monotonic reasoning.

4.3.3 Multiple faults

Thus far it has been implicitly assumed that solutions to a specific problem are single faults that can be pre-enumerated in the solution hierarchy, i.e. only one component of the process to be diagnosed can be faulty at the same time, or only a single disease is causing the symptoms. If so, the heuristic match and refinement procedures ultimately consist of selecting a node in that hierarchy. In some programs, however, solutions can not practically be enumerated because they have to deal with multiple faults. For instance, multiple diseases may be present, or a disorder itself may consist of a number of faults, e.g. a brachial plexus injury generally consists of multiple nerve lesions (viz. Sect. 2.2.2). This problem would make the space of candidate solutions grow exponentially and lead to a practically unmanageable number of solutions for the problem solving program to consider. In these cases a solution may be constructed from primitive solution components. A different class of generally applicable methods that elegantly address this problem has been proposed for diagnostic systems. These programs do not employ heuristic associations, but operate from first principles, reasoning their way through a problem using an understanding of the process to be diagnosed. Examples of these are Davis's system (1984), the Generalized Set Covering model (Reggia et al, 1983), the DART program (Genesereth, 1984), the General Diagnostic Engine (De Kleer and Williams, 1987) and Diagnosis from First Principles (Reiter, 1987). These methods are all, to a large extent, process independent and work from design descriptions of the process at hand rather than from heuristic associations. Although all these systems differ slightly in their definition of diagnosis and proposed algorithms their methods bear a close resemblance. In the remainder these systems will be referred to as diagnosis from first principles.

4.3.4 Diagnosis from first principles

Central to the approach of diagnosis from first principles is that a
description of the process to be diagnosed is available, consisting of a
description of its physical structure and models of the components which
constitute the process. The process and each of its components are assumed to
behave according to its model. If observations of the process conflict with
its intended (expected) behavior, it can be concluded that faults are present
in the process structure. This is called conflict detection. To explain these
inconsistent observations, also called symptoms or manifestations, candidate
solutions are generated, i.e. candidate generation. The diagnostic goal is to
determine those components constituting the process that function abnormally.

What is important in diagnosis from first principles is that it provides a
process-independent method to achieve this goal. Only models of the process
and its components are required, no models of possible faults or of
associations between symptoms and faults, the fault models, have to be
specified. This approach makes use of deep knowledge in contrast to the
surface knowledge of empirical associations often found in well-known systems
like INTERNIST (Pople, 1982) and MYCIN (Shortliffe, 1976). In Sect. 4.6 the
difference between the two approaches will be further addressed.

Reiter (1987) proposes a general formal theory for diagnostic reasoning, that
builds upon the work of De Kleer (1976) and Genesereth (1984). Here, this
theory will be elucidated with an example from the domain of the brachial
plexus. This example will be confined to a small part of the brachial plexus,
concerning the innervation of the m. biceps and the m. infraspinatus. Injuries
to the central nervous system are not considered. In this example it is
assumed that we are dealing with voluntary muscle contractions of maximum
activity. If there is an intention to contract this will be propagated through
the network. The m. infraspinatus is assumed to be innervated solely by spinal
root c5. The m. biceps is assumed to be innervated principally by roots c5 and
c6 and to a lesser degree by root c7. In this example, this is accounted for
by the value of the input signal to these roots. Note that it will become more
complicated to account for these variations in innervation when the network
is extended to incorporate other nerves and muscles. Now, using an electrical
analogon, this small network can be described simply in terms of conductors,
adders and amplifiers that are attached to one another via their inputs and
outputs (Fig. 4.7). A conductor typically has only one input and one output,
whereas an adder and an amplifier have two inputs and one output. On a lower
level of abstraction these modules may be described by a combination of
simpler components, but that would have little meaning for this purpose.
Nerves are assumed to either conduct electrical signals, or to add their input signals. For the sake of simplicity, muscles that actually transduce an electrical signal into a mechanical activity can be described as amplifying electrical nerve signals to electrical muscle activity as it can be measured by EMG-techniques.

Example
The normal behavior of the components in the process can be described by three axioms. Here, the unary predicate \( AB(x) \) is introduced, interpreted to mean \( AB\text{normal}(x) \):

1. \( \text{CONDUCTOR}(x) \land \neg AB(x) \supset \text{out}(x) = \text{in}(x) \),
2. \( \text{ADDER}(x) \land \neg AB(x) \supset \text{out}(x) = \text{SUM}(\text{in1}(x), \text{in2}(x)) \),
3. \( \text{AMPL}(x) \land \neg AB(x) \supset \text{out}(x) = \text{MULT}(\text{in1}(x), \text{in2}(x)) \).

The structure of the process and the inputs to the process can be specified as follows:

\( \text{COND(c5)}, \text{COND(c6)}, \text{COND(c7)}, \text{COND(suprascapularis)}, \text{COND(musculocutaneus)}, \text{ADD(tr.superior)}, \text{ADD(f.lateralis)}, \text{AMPL(biceps)}, \text{AMPL(infraspinatus)} \),

![Figure 4.7 Example network of part of the brachial plexus.](image-url)
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Out(c5) = In1(tr.superior),  Out(c6) = In2(tr.superior),
Out(c5) = In(suprascapularis),  Out(tr.superior) = In1(f.lateralis),
Out(c7) = In2(f.lateralis),  Out(f.lateralis) = In(musculocutaneus),
Out(suprascapularis) = In(infraspinatus),
Out(musculocutaneus) = In(biceps),
In(c5) = 2  V  In(c5) = 0,  In(c6) = 2  V  In(c6) = 0,
In(c7) = 1  V  In(c7) = 0,  In2(biceps) = 1,  In2(infraspinatus) = 2.5.
Endexample

As will be clear, in these axioms structural knowledge and behavioral knowledge about the process have been separated. To be able to diagnose the process, it must be possible to make observations of its behavior.

Example

If an intention to contract is observed and the resulting muscle activity of the m. infraspinatus is measured to be 0, then this observation indicates a fault in the process, since the activity was expected to be 5 (Fig. 4.7). This observation is represented by:

In(c5) = 2, In(c6) = 2, In(c7) = 1, Out(infraspinatus) = 0  4.1

A second observation might be that the value of the m. biceps is 3, represented by:

In(c5) = 2, In(c6) = 2, In(c7) = 1, Out(biceps) = 3  4.2
Endexample

The fact that the observation is inconsistent with the intended process behavior may be called detection of conflict. In general, for a process with components c1,...,cn, satisfying a process description PD and with observations OBS, this can be formalized by:

PD  U  {¬AB(c1),...,¬AB(cn)}  U  OBS  4.3

is inconsistent.

The objective of diagnosis is to explain the inconsistency (4.3) by specifying which components are faulty. Retracting all of the assumptions
-AB(c_1),..., -AB(c_n) will restore consistency to (4.3). This corresponds to the
diagnosis that all components are faulty. However, this explanation of the
inconsistency is not very appealing. Generally, human diagnosticians prefer
the simplest solution to a diagnostic problem. This will make them look for
some minimal set of faulty components to explain the inconsistency. The
Principle of parsimony.

Example

Observations 4.1 and 4.2 would lead to 13 potential diagnoses: (c5),
(c6, supraspapularis),..., (biceps, supraspapularis), (c6, infraspinatus),..., (biceps, infraspinatus).

Of course, all supersets of each of these potential diagnoses will explain
the inconsistency also (leading to 382 potential solutions), but these
would violate the principle of parsimony.

Endexample

Reiter presumes that if a component becomes faulty, the distribution of input
and output values becomes random. In the domain of the brachial plexus,
however, this is actually not the case. We know that in respect to motor
function the output of faulty adders or conductors will decrease from their
normal values.

In Reiter's theory, a diagnosis is determined by a smallest set of components
that, if it is assumed that these components are faulty together with the
assumption that all other components are not faulty, is consistent with the
observation and the process description. Proving the consistency of the
diagnosis with the observations becomes very inefficient for processes with
large numbers of components. The number of candidate diagnoses grows
exponentially with the number of components. Systems reasoning from first
principles often provide an inference mechanism to generate and test candidate
solutions in an efficient manner, to avoid the exponential growth of the set
of diagnoses as much as possible. De Kleer and Williams (1987) propose an
algorithm that entertains the idea of sequential diagnosis which is based on
the concept of conflict set and constraint propagation. In their algorithm,
whenever a new minimal conflict is discovered, any previous minimal candidate
which does not explain the inconsistency is replaced by one or more minimal
superset candidates that do explain the inconsistency. Reiter proposes a
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similar characterization of a diagnosis:

Definition 4.1 (Reiter 1987)

A conflict set for $(SD, COMPONENTS, OBS)$ is a set \( \{c_1, \ldots, c_n\} \subseteq COMPONENTS \) such that \( PD \cup OBS \cup \{-AB(c_1), \ldots, -AB(c_n)\} \) is inconsistent. A conflict set for $(PD, COMPONENTS, OBS)$ is minimal iff no proper subset of it is a conflict set for $(SD, COMPONENTS, OBS)$.

Proposition 4.1 (Reiter 1987)

\( \Delta \subseteq COMPONENTS \) is a diagnosis for $(PD, COMPONENTS, OBS)$ iff \( \Delta \) is a minimal set such that $COMPONENTS - \Delta$ is not a conflict set for $(PD, COMPONENTS, OBS)$.

Example

In the brachial plexus example, before any observation is done, there is no conflict, thus the diagnosis $\emptyset$ explains all observations. Then, when the symptom $Out(infraspinatus) = 0$ is discovered, the minimal conflict sets belonging to it are: $\{c_5\}$, $(suprascapularis)$, $(infraspinatus)$, leading to the same potential diagnoses. The conflict introduced by the observation $Out(biceps) = 3$, leads to the minimal conflict sets: $\{c_5\}$, $\{c_6\}$, $\{c_7\}$, $(tr.\ superior)$, $(f.\ lateralis)$, $(musculocutaneus)$, $(biceps)$,

Combining these with the previous diagnoses, leads to 13 new potential diagnoses: $\{c_5\}$, $(c_6, suprascapularis)$, $\ldots, (biceps, suprascapularis)$, $(c_6, infraspinatus)$, $\ldots, (biceps, infraspinatus)$.

Endexample

This example clearly illustrates that new observations may rapidly increase the number of potential diagnoses instead of limiting the number of solutions. Especially in processes consisting of a large number of components, this phenomenon may be dramatic. Note that a human diagnostican confronted with this problem would rapidly postulate the diagnosis $(c_5)$ to explain the symptoms and subsequently make new observations to confirm this diagnosis. De Kleer and Williams (1987) propose a method to identify the measurement that, on average, will lead to the discovery of the actual diagnosis in a minimum number of subsequent measurements.
The problem of the inefficiency of the diagnostic procedure presented here will be discussed in more detail in Sect. 4.6. A way to deal with these inefficiencies could be the application of parallel processing or Distributed Artificial Intelligence (DAI).

4.3.5 Distributed AI

DAI deals with systems that consist of a set of cooperating intelligent problem solvers. The aims of DAI are:

- To improve processing speed, by applying parallel systems.
- To improve reliability. If one system fails, its tasks can be taken over by the remaining systems.
- To improve transparency. A parallel architecture may make the total system more transparent.

DAI requires the problems of communication among and control of the parallel systems to be solved. A control architecture that has gained much attention in this respect, is the blackboard architecture (Hayes-Roth, 1985). Although the potential of DAI to improve knowledge based system efficiency, seems promising, it is still in the development stage. Therefore, in the following, it will not be considered further as a means to improve efficiency.

![Figure 4.8 The stages of knowledge acquisition and knowledge representation.](image-url)
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4.4 KNOWLEDGE ACQUISITION

Now that a general overview is available of how knowledge based systems can deal with diagnostic problems, two questions remain as to building such a system for a specific problem. These will be discussed briefly in the following sections:

1. How does one acquire the domain-specific knowledge to solve a problem?
2. How should this knowledge be represented in a system?

These questions are often referred to as the knowledge acquisition problem (Buchanan et al, 1983). In this thesis, the definition of knowledge acquisition will be limited to the process of extracting and interpreting knowledge from a source of expertise. In this definition the process of transferring this knowledge to a program is not part of the knowledge acquisition process, but of the knowledge representation problem, which is dealt with in Sect. 4.5. Instead, it is felt that an important aspect of knowledge acquisition should be the analysis and interpretation of the domain knowledge, which permits a deliberate choice of a representation formalism.

4.4.1 Stages in knowledge acquisition and knowledge representation

Figure 4.8 shows the stages of knowledge acquisition and representation as defined by Buchanan et al (1983). In this thesis, these stages are intended to involve the following aspects:

1. Identification. Identify the class of problems the system aims at, as well as the system goals. Get a global view of the subject matter. Identify the available resources.
2. Conceptualization. Uncover the important domain concepts and the relations among them. Special attention should be paid to the domain structure and to relevant problem solving strategies. Distinguish areas of completeness and incompleteness of knowledge.
3. Formalization. Specify choices regarding knowledge structure and levels of knowledge to be embedded in the system. Choice of system architecture and representation language.
4. Implementation. Encoding of knowledge in the chosen representation language.

5. Testing. Run representative test cases and, if necessary, tune the knowledge base.

It should be noted that problem identification is of primary concern in knowledge acquisition, since the way concepts are most conveniently represented and organized depends to a large extent on the purpose of the knowledge based system.

Knowledge sources that provide domain knowledge, may be, for instance, human experts, textbooks or databases containing example solutions. Often in constructing knowledge based systems, some of these sources are used simultaneously to acquire the desired expertise. From previous sections, it will be clear that the knowledge to be elicited from these sources depends heavily on the goal of the program to be constructed. Emphasis may be on empirical associations and strategies if the problem is well suited to be solved by heuristic classification, or on structural descriptions of the domain in the case of an approach through first principles. On the other hand, knowledge acquisition should similarly have an effect on the choice of problem-solving strategy and knowledge representation formalism. For complex devices, a diagnostic system based on empirical associations will become large. Hence, knowledge acquisition for such a system may be very difficult, whereas the acquisition of the underlying deep knowledge, consisting of device structure and physical laws, may be much easier. The purpose of knowledge acquisition is to provide an insight into the domain that allows well-founded design decisions, to do with problem-solving strategy and knowledge representation, and to elicit the knowledge necessary to achieve the desired expertise. Knowledge can be acquired in a number of ways, either through the intermediary of a human knowledge engineer, i.e. a person who interviews experts to acquire knowledge and who subsequently represents this knowledge in the system, or directly (Michalsky et al, 1983):

- Knowledge acquisition by being told.
- Machine learning:
  - Knowledge acquisition by learning from examples.
  - Knowledge acquisition by learning from analogy.
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- Knowledge acquisition by observation, discovery and experimentation.
- Knowledge acquisition by reasoning from deep structure.

Machine learning may considerably speed up the knowledge acquisition process, however, it is still in the research stage. The techniques for this approach are described well in Michalsky et al (1983).

4.4.2 Knowledge engineering

An important means of acquiring knowledge for most knowledge based systems is still acquisition from human experts, usually through the interaction of a knowledge engineer. This is one of the most tedious and time-consuming aspects of constructing knowledge based systems. At the same time it is most important, since the accuracy of the knowledge base determines the system's performance. Important questions a knowledge engineer has to deal with, are:

- How can the knowledge be extracted from the experts?
- Is there consensus among domain experts concerning the appropriate way to solve the tasks the system is constructed for?
- If inconsistencies occur among experts, can these be resolved? If not, who is right?
- Is a 'gold' standard available by which the system, i.e. the experts' knowledge can be tested?

In the identification and conceptualization stages (Fig. 4.8), a knowledge engineer should first become familiar with the concepts in the domain from text books and papers, before interacting with the experts. This allows the knowledge engineer to understand the experts' explanations and to ask the right questions. Then, he tries to discover experts' problem solving knowledge by means of interviews and by observing the experts solving a problem.

In the knowledge engineering approach, two extremes can be distinguished in knowledge acquisition and the building of knowledge bases:

1. Rapid prototyping.
2. Structured domain analysis.
In the first approach, after an early initial design and implementation of a prototype system, the size of the system is extended incrementally through subsequent testing and interviewing of the experts. Inherently, the choice of the problem-solving strategy and representation language has to a large extent already been made before sufficient domain insight has been gained. This approach especially emphasizes the importance of the feedback loops in Fig. 4.8. The second approach is based on a thorough analysis of the domain, resulting in a structured implementation of the system. This assures that a good insight into the problem domain is established, which provides strong design implications. Thus, the feedback in Fig. 4.8 plays a less predominant role than in the first approach. However, it also contains the danger that some problems in the domain are not revealed until the final stage of system construction. Partridge (1986) argues that structured programming (what he calls the SPIV paradigm: Specify-Proof-Implement-Verify) is not suitable to much of AI, but that there is a need for incremental development, which suggests a RUDE paradigm (Run-Understand-Debug-Edit). In practice, knowledge acquisition will lie between the two, as reflected in the scheme in Sect. 4.4.1. Starting from a thorough problem analysis, that guides design decisions concerning structure and levels of knowledge, a system is built that is improved incrementally (Chs. 5, 6). A useful notion from structured programming is to distinguish different knowledge acquisition stages, with their corresponding levels of knowledge, such as orientation, problem identification and problem analysis and the domain, inference, task and strategic levels in KADS (Breuker and Wielinga, 1988). Several other tools have been developed to aid in knowledge acquisition, like TEIRESIAS (Davis, 1977, 1979) and OPAL (Musen et al, 1987). A very insightful overview of knowledge acquisition methodologies in first generation knowledge based systems is presented in Neale (1988).

4.5 KNOWLEDGE REPRESENTATION

Throughout this chapter the importance of knowledge, instead of powerful inference methods for AI-systems, has run as a continuous thread. It has been made clear that simple inference methods like generate and test will suffice if they are used in combination with the right collection of knowledge. This observation calls attention to the issue of representing this knowledge to
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achieve expert performance in knowledge based systems. Woods (1983) describes
two issues to be considered in knowledge representation methods:

1. The expressive adequacy.
2. The notational efficacy.

Expressive adequacy concerns what a representation language can say, as well
as what it can leave unsaid. For example, in first-order logic the fact that
muscles are innervated by nerves may be expressed as in 4.4. Note that this
does not specify which nerve innervates which muscle.

\( \forall x \text{Muscle}(x) \supset \exists y \text{Innervates}(y,x) \land \text{Nerve}(y) \)  

The notational efficacy of a representation language has to do with how these
things can be said. It has to do with such issues as computational efficiency,
conciseness of representation and ease of modification. Levesque and Brachman
(1985) argue that there is always a fundamental tradeoff between expressive
adequacy and notational efficacy, what they call expressiveness and
computational tractability. For this reason, essentially no one formalism is
better than any other. It depends on the importance of each of the aspects
expressiveness and tractability. Generally speaking, anything that can be done
by one representation method can be done by the others also. However, each
representation takes a different position in the tradeoff. For a specific
problem, the method chosen should be expressive enough to represent the
necessary knowledge, and it should provide sufficient computational
efficiency.

In the following, the basic knowledge representation formalisms will briefly
be introduced. They will be compared along the lines of this tradeoff.

4.5.1 Logic

The oldest, and probably most disputed method of knowledge representation is
logic. The AI community seems to be almost split into one group that advocates
systems based on mathematical logic, and another which firmly opposes this
approach. First-order predicate calculus was the representation formalism
underlying most early work in AI on general problem solvers, whereas nowadays
PROLOG still is a prevailing language for many AI programs.
A logical formalism is determined by a syntax and a semantics that specify
the meaning of a certain notational convention which allows the determination
of the meaning of an expression in the language. Expressions in logic are
built up from primitives, propositions, that can either be true or false.
Normally, reasoning methods provided by logical representation systems are
based on deductive inference, according to inference rules such as modus
ponens, modus tollens etc. As example 4.4 has already made clear, logical
languages are well suited to describe incompletely known situations, for
instance by means of existential and universal quantification: Some muscles
can be tested by ENG (existential quantification), All normal muscles have
power 5 (universal quantification). The well-defined semantics and the
expressive power made this method very appealing in knowledge representa-
cion. Criticism on logic focused on the difficulty of breaking up real-world
knowledge into many small, independently true propositions (Minsky, 1981)
which make it hard to define more complex structures; the problem of capturing
the imprecise nature of human deduction; the inability to express control
information, leading to very inefficient systems. On relating these
observations to the two basic criteria described earlier, it can easily be
seen that the main problem with logic in representing knowledge lies in its
notational efficacy. In logic, a lot can be said but sometimes it is hard to
say it, and often it has high consequences on the computational efficiency.
Moore (1982) argues that the problem of expressing control information can be
and has been solved by extending logic. Moreover, he claims an important
class of problems can probably only be addressed by logic-based representation
languages. Israel (1983) argues that deduction is not necessarily part of a
logic language. In his view reasoning is distinct from representation, which

```
RULE
IF
root.axon_reflex = negative
AND
root.sensibility = anaesthetic
THEN
CONCLUDE root.postganglionic_lesion := TRUE
FI
ENDRULE
```

Figure 4.9 Example production rule from the domain of the brachial plexus.
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allows the specification of a set of transformation rules that do not necessarily have to constitute a sound deductive apparatus. To solve some of the problems encountered in representing knowledge in a logic formalism, extensions have been proposed, like fuzzy sets (Zadeh, 1968, 1976) to deal with imprecise knowledge and circumscription for non-monotonic reasoning (McCarthy, 1980, 1986).

4.5.2 Production rules

Another widely used method in knowledge representation is that of production rules. Ever since their successful application in MYCIN (Shortliffe, 1976), this formalism has received much attention. Production systems grew out of two different perspectives (Davis and King, 1984). First there is the psychological conjecture that human problem solving follows the rule based model. This resulted in efforts to model human problem-solving behavior by rule based systems. Although this led to promising results, viz. the PSG system (Newell, 1973), the conjecture that these systems are equivalent to human cognitive processes is fiercely disputed. Especially, it is argued that humans make use of a much more associational structure than is provided by the rule based method. The second approach is not concerned with similarities between rule based systems and human behavior. In this approach production rules are viewed as a suitable method for representing knowledge for systems to reach expert competence. Early knowledge based systems like MYCIN (Shortliffe, 1976) and DENDRAL (Buchanan and Feigenbaum, 1978) are examples of this approach.

Generally speaking, rule based systems consist of a knowledge base containing the rules and facts and an inference engine mostly providing a backward chaining or forward chaining of the rules.

Problem solving know-how is represented in a set of conditional rules in which the conditions form a Boolean expression and the action may be one or more conclusions or actions (Fig. 4.9). Essentially, production rules are a derivate of predicate calculus aimed at practical problem solving. In a specific situation, the application of a rule is based on matching specified goals against its actions, or by matching the pattern of its conditions against similar patterns in a database of evidence for that specific situation. These are the two kinds of inference methods available for rule
based systems:

1. Top-down or goal-driven inference.
2. Bottom-up or data-driven inference.

Top-down inference starts off with a known goal and tries to apply production rules that conclude about that goal in order to prove it. In this case, the conditions of a selected rule become new sub-goals. If these are proven, the rule's actions are executed, which may change the database of evidence. Bottom-up inference starts off with the database of evidence that is matched against the conditions of the production rules. If these conditions are satisfied the rule's actions are executed. If the inference method applies selected rules in the order they are present in the knowledge base, and if a rule's conditions are evaluated in the same order they have been specified in the rule, top-down inference is called backward chaining. Similarly, bottom-up inference is called forward chaining (Lucas and Van der Gaag, 1988).

Backward chaining is most efficient in diagnostic systems, in which the amount of evidence to be dealt with is relatively large, and the number of goals is limited. If a small amount of evidence has to be dealt with, but the number of possible outcomes is large, forward chaining may be called for. Sometimes, a combination of forward and backward chaining may be profitable. Such systems may work forward from an initial database of evidence to generate a goal, then reason backward to prove that goal, while propagating intermediate results through the knowledge base in a forward-chaining fashion.

Each rule represents a modular piece of knowledge, independent of other rules in the knowledge base. This facilitates adding new rules to the knowledge base or modifying already existing ones, for incremental increase in system performance or for dealing with changes in the domain knowledge. Also, production systems are capable of explaining their reasoning by presenting the trace of production rules that led to a certain conclusion (how?) or a question (why?). Since rule based systems are often used to represent experts' problem solving knowledge, they may leave out intermediate reasoning steps relating data to conclusions. This results in efficient problem solving, but may also hamper explanation of the system's behavior to less experienced users. The widespread use of this representation method has made clear that knowledge is often easily encoded in production rules. Experts generally find
it relatively easy to express their methods in a rule formalism. Especially when much of the knowledge to be represented in the system comes from empirical associations, rule based systems are very attractive. A nice analysis of the advantages, and some disadvantages of production rules for representing knowledge can be found in Davis et al (1977). However, more disadvantages have been ascertained. These are mainly due to the fact that production rules are well suited to represent judgmental problem solving know-how, but fail in representing descriptive know-what knowledge. It became particularly apparent that it is sometimes hard to represent knowledge explicitly in production rules, in particular for defining terms and describing objects and static relations among objects, e.g. knowledge about structures and taxonomies, such as the anatomical knowledge of the brachial plexus. This notion led to a new tendency in knowledge representation to use frame or object-oriented representation methods that provide a structured representation of an object or a class of objects.

4.5.3 Semantic networks and object based methods

Semantic networks (Woods, 1975; Brachman, 1979), representing knowledge in AI systems in a network of nodes and links, have long been a popular method. However, during the years the need became felt for higher level structures than single nodes and links. This led to the integration of network methods with work on object based representations, especially frames. Frame languages, which where first called attention to by Minsky (1975), shortly followed by Kuipers (1975), are especially useful in describing domain objects and structures. Each object is described by a frame that contains a set of attribute descriptions in slots and facets that describe attributes and attribute properties of the object represented by the frame. Frames can be organized in a taxonomic hierarchy of classes and subclasses. For this purpose, most frame languages have two kinds of taxonomic links, the membership link representing class membership, and the subclass link, representing specialization. These provide two interpretations of the IS_A link typically encountered in semantic networks, which allow a distinction between a definitional level and an assertional level. Figure 4.10 shows an example from the domain of the brachial plexus. Brachman (1985) provides a thorough discussion of the different meanings of the IS_A link in semantic
networks and frame systems.
What is important about Minsky's article on frames was the definition of defaults. That is, in the absence of better information, frames are thought to satisfy a prototype description, defined by default values for its slots. All modern frame languages support this notion of defaults and prototypes. For reasoning purposes, frame languages provide an inference method called inheritance. This method is used to propagate the value of attribute slots of more general frames to more specific ones, along the lines of the subclass and membership links. For example, the 'nerve' frame inherits the slots of the frames 'anatomical_structure' and 'status'. Often, inheritance is not sufficient for reasoning. In this case, the inference method has to be extended, which is the motivation behind developing hybrid representations. Whereas frame languages provide a rich structural language to describe objects, which is the main inadequacy of rule based systems, they are not as well suited to represent procedural knowledge of how to use the knowledge stored in the frames for problem solving in order to achieve expert-like problem solving behavior. A problem effectively handled by production rules.

Figure 4.10 Example frames from the domain of the brachial plexus.
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Brachman et al (1983) describe what they call the trouble with frames. In assertional frame systems, expressing incomplete knowledge or composite descriptions is very difficult, whereas descriptive systems only provide a package for manipulating symbolic data structures. This encouraged the integration of descriptive methods like frames and procedural methods such as production rules to form hybrid languages that combine the advantages of both.

4.5.4 Hybrid representations

The obvious solution to the tradeoff between expressiveness and efficiency is to combine different representation methods in one language. Bobrow and Winograd (1977) were among the first to acknowledge this:

"Any representation language that is to be used in modeling thought or achieving "intelligent" performance will have to have an extensive and varied repertoire of mechanisms."

In KRL (Knowledge Representation Language) they integrated procedural knowledge and a structured descriptive language, using what they call units for representing objects and predicates representing relations among objects, with attached LISP procedures for information about the deduction of such a predicate.

Since production rules are a very effective and popular method for describing how to use knowledge, the most natural formalism in hybrid representation seems the combination of frame and production rule languages, as in CENTAUR (Aikins, 1983, 1984), combining the advantage of structural descriptions and inheritance of frames with the inferential capabilities of production rules. Other approaches combine frame structures and logic to achieve systems that allow the definition of complex terms in combination with powerful assertional capability, e.g KRYPTON (Brachman et al, 1983, 1985), KL-TWO (Vilain, 1985) and LORE (Jonker, 1987).

Not only do these combinations increase the expressive adequacy of the representation system, they also allow a separation of different types of knowledge present in the system which provides a guiding structure for organization and more focused search. This may yield a more explicit representation of knowledge, potentially benefiting explanation and justification of the system's behavior.
4.5.5 Modeling uncertainty

Another issue receiving a great deal of attention in building knowledge based systems is reasoning under uncertainty. In practice, medical knowledge based systems have to deal with uncertain information and uncertain knowledge. First of all data acquired from (diagnostic) tests or patient interviews are not exact and are incomplete, but also knowledge represented in the system is incomplete, e.g. knowledge about prognosis of brachial plexus injuries, or uncertain, e.g. knowledge of the anatomy of a specific patient. A number of uncertainty models have been developed to deal with these uncertainties. These models consist of an uncertainty calculus for the representation of uncertainty, and an inference calculus to combine and propagate uncertainties through the inference process (Barker et al, 1988). In well-known uncertainty calculi, uncertainties are viewed as probabilities, degrees of belief, degrees of confirmation, or degrees of set membership (Prade, 1985; Henkind and Henderson, 1988). Inference calculi associated with these representations are Bayes' theorem, the Dempster-Shafer theory and the certainty factor method which are discussed in Buchanan and Shortliffe (1984b) and the theory of fuzzy sets (Zadeh, 1983, 1988).

```
RULE 1
IF
  c6.myelography = not_visible
AND
  c6.lesion
THEN
  CONCLUDE patient.diagnosis := preganglionic_lesion_c6  CF (0.9000)
FI
ENDRULE

RULE 2
IF
  c6.SNAP = absent
AND
  c6.sensibility = anaesthetic
THEN
  CONCLUDE patient.diagnosis := postganglionic_lesion_c6  CF (0.8000)
FI
ENDRULE

RULE 3
IF
  c6.axon_reflex = negative
AND
  c6.sensibility = anaesthetic
THEN
  CONCLUDE patient.diagnosis := postganglionic_lesion_c6  CF (0.8000)
FI
ENDRULE
```

Figure 4.11 Example use of certainty factors.
If domain knowledge is incomplete, none of these methods will be able to suitably model this. In these cases, the system designer will have to rely on the heuristic knowledge experts often develop to deal with this incompleteness. For the other kinds of uncertainty, these methods may be used. However, most of these methods have not been based on a formal mathematical foundation. Although Bayes’ rule is well founded on mathematical axioms, and has well-understood mathematical properties, the need to assess a large number of probabilities in this method usually leads to simplifying assumptions concerning independence of probabilities and to subjective estimation of probabilities in order to make it a useful method (viz. Sect. 1.4.3). Such independence assumptions which are necessary in the Dempster-Shafer theory and the certainty factor model also, or the estimation of probabilities (like the construction of membership functions in the fuzzy set theory and the choice of certainty factors in the certainty factor model), and the fact that in the Dempster-Shafer model and in the certainty factor model the combining functions are not theoretically justified make these models intuitive. Especially the choice of certainty measures based on intuition may lead to a substantial decrease in system performance (Leaper et al, 1972; Norusis and Jacquez, 1975). Other authors, however, indicate that the use of estimated probabilities does not hamper performance, or may even improve it (Gustafson et al, 1971, 1973).

**Numerical Models of Uncertainty**

To use intuitive methods for handling uncertainty is unadvisable since these are poorly interpretable and may largely blur a clear view on the line of reasoning a system may take in a specific case. Especially when physicians are allowed to use the same certainty measure to indicate their confidence in the measurements, which may already be partly accounted for in the certainty measures in the knowledge base, these intuitive methods make it very hard to control the line of reasoning a system will follow. To solve this, the uncertainty model could be extended, for instance, to incorporate different measures, each representing another source of uncertainty, i.e. a certainty measure for uncertain knowledge, one for the uncertainty in the data, and a credibility measure to represent the suggestive strength of the evidence to each hypothesis. It will be clear, however, that such a way of dealing with uncertainty will not benefit the transparency and the predictability of the
system. Although different sources of uncertainty can be distinguished in such
a system, the problem of the quantification of these uncertainties becomes
even worse, since now three measures are called for. Hence, system complexity
will increase accordingly.

For example, in the domain of the brachial plexus, the absence on the
myelogram of the fila radicularia of spinal root c6 suggests a preganglionic
lesion of this root. For the same spinal root, the absence of the SNAP is
suggestive of a postganglionic lesion. This may be implemented as in
production rules 1 and 2 in Fig. 4.11. Here it is assumed that both hypotheses
are mutually exclusive, which is taken care of by production rules elsewhere
in the knowledge base. The certainty factor accounts for the suggestive
strength of each symptom for a specific diagnosis. How should these certainty
factors be interpreted? Do they only reflect the suggestive strength of a
symptom if it is certain to be present, or do they also take into account the
chance of misinterpretation of a diagnostic test? (e.g. interpreting a
cervical myelogram is known to be difficult). The simultaneous presence of
both symptoms would lead to the diagnosis preganglionic_lesion_c6 (0.5),
postganglionic_lesion_c6 (-0.5).

What does this certainty factor mean? Is there a probability of 0.5 that the
patient has a preganglionic lesion of root c6? If so, what of the remaining
probability of 0.5? An axon-reflex test may confirm the SNAP data (rule 3).
This would lead to the opposite diagnosis postganglionic_lesion_c6 (0.6),
preganglionic_lesion_c6 (-0.6). Again this certainty factor is hard to
interpret. Moreover, something seems to be wrong, since a postganglionic
diagnosis is concluded, although we know the fila radicularia are not present.

Ad hoc adjustments of the certainty factors, which is very tempting, will
surely solve this for the moment, but will lead to similar problems in other
cases. The problem illustrated here is, first of all, that measurements are
not independent. Therefore, two weak indications for a diagnosis do not
necessarily combine to yield one stronger indication. In this case it is not
very surprising that SNAP and axon-reflex data yield the same results, since
globally they are based on the same phenomenon. This problem could be solved
by joining these dependent premises in one rule by disjunction (i.e. an OR
clause). As a result, however, the simultaneous presence of both symptoms will
have no effect at all on the certainty factor of the conclusion. Control of
the certainty factor could be restored by including in the rule's premise the context in which the rule applies. This will result, however, in an increase in the number of rules to keep the knowledge base complete. Secondly, this example reflects a misconception in the construction of the knowledge base which is facilitated by the use of an ad-hoc method to deal with uncertain information: combinations of symptoms may suggest a different diagnosis than each symptom alone. Also, in some domains two symptoms that each suggest the same hypothesis may exclude that hypothesis when present in combination. In the above example, the combination of the three symptoms might be explained by a preganglionic lesion that extends outside the foramen: pre_and_postganglionic_lesion_c6, which explains each of the three symptoms. On the other hand, evidence may be adequate to exclude a certain hypothesis, but be inadequate to prove another hypothesis. For instance, the presence of a meningocele on the myelogram excludes the hypothesis of a postganglionic lesion, but it is insufficient to prove that a lesion is preganglionic.

These observations call for a much more explicit method to model the sources of uncertainty.

explicit models of uncertainty

To deal with uncertainties in the data, the knowledge base should be made redundant, so that inconsistencies can be revealed by making different inferences that allow comparison and checking of the data. Uncertain knowledge has to be dealt with by modeling the knowledge at a high enough level in order to make the system robust.

The example of Fig. 4.11 made it sufficiently clear that it is impossible to calculate the belief in a certain hypothesis by summing up the disconfirmatory evidence and subtracting it from the evidence in favor of the hypothesis. Such an approach disguises how evidence suggests hypotheses and how hypotheses explain evidence. To model the suggestive strength of pieces of evidence for a hypothesis, a much more explicit method is required, than the ad-hoc numerical methods described earlier. To allow the reasoning process to be transparent and predictable, such a method should be non-numerical and explicitly model the credibility of each piece of evidence for each hypothesis. A more extensive discussion on different sources of uncertainty, and an approach to using more explicit methods to deal with uncertainties is discussed in Sect. 5.4.
4.6 DEEP VERSUS SURFACE KNOWLEDGE

In the preceding sections a recurrent subject has been that of what knowledge should be present in a knowledge based system, in what form, and how it should be reasoned out? In Sect. 4.3, it has been made clear that in modern AI systems two prevailing techniques can be distinguished. Systems either reason from empirical associations between data and hypotheses, using the knowledge underlying these associations in a highly compiled form, or they use deep knowledge structures, like systems reasoning from first principles.

In the following, for systems based on surface knowledge, the term surface system will be used. Systems based on deep knowledge will be called deep systems. Such deep systems are sometimes referred to as 'model based', as opposed to surface systems that would not be based on a model. In Ch. 1 it has been made clear, that all medical decision support systems are based on a model of the domain, whether this is data based or knowledge based, containing deep or surface knowledge. Therefore, the concept of model based systems should not just be restricted to systems containing deep knowledge.

4.6.1 System requirements

In Sect. 4.5, it has been indicated that production rules may be a suitable representation for surface knowledge, whereas deep knowledge may be represented more easily in an object based language. Which approach is better greatly depends on the desired system characteristics. Obvious goals knowledge based systems try to achieve are:

- To attain a high level of problem solving performance in the domain.
- To solve problems efficiently.

In addition, knowledge based systems might also aim at:

- explaining and justifying their behavior.
- acquiring new knowledge.
- understanding their own expert rules.
- knowing their own limitations.
- degrading gracefully at the boundary of their expertise.
Since knowledge based systems usually display expert-like behavior only in very narrow domains, the last two aspects especially are important issues in regard to these systems. In general, systems relying on surface representations are unable to really explain their behavior. The system knows an empirical association is present, but is unaware of the underlying knowledge. Also, these systems will not deal very well with problems at the boundaries of their knowledge. Instead, they may follow a bad chain of reasoning and make a wrong inference. Should the system use more fundamental knowledge and should it have knowledge about its limitations built in, it would be able to determine when a problem is beyond its capacity or it could qualify its own inferences. This would result in a graceful degradation at the boundaries of its expertise.

deep knowledge

It is generally felt that systems relying on deep knowledge are more likely to exhibit this desired behavior than systems using surface knowledge. The main argument in favor of this feeling concerning the inadequacy of surface knowledge is the observation that human experts themselves resort to deeper structures (first principles) when confronted with an especially difficult problem, for which their surface representation (rules of thumb) is no longer adequate. Another strong argument is that these systems, encompassing more or less complete knowledge of the domain, are no longer limited to a single application, but can be used for a number of different purposes. For instance, medical diagnostic systems may be used for teaching diagnostic problem solving behavior also, or may be used as a medical textbook. As an ultimate consequence of this approach, it should be possible to construct knowledge bases which are independent of an intended application.

Apparently, deep knowledge consisting of causal models, abstractions etc, provides a number of advantages over the surface knowledge inferred from it. This has been the motive for building deep systems (Patil et al, 1981; Pople, 1982; Steels, 1985; Koton, 1985). However, also in this issue all that glitters is not gold. The Achilles’ heel in deep systems is still the quality of the model of the domain knowledge. Also in deep systems simplifying assumptions are necessary, either because knowledge is incomplete, or to keep the model manageable. These assumptions may give rise to similarly wrong
inferences at the boundaries of expertise, although these boundaries may have been thrust back considerably. Moreover, here again we face a tradeoff between expressiveness and efficiency, which makes different positions in this tradeoff arguable.

surface knowledge

The major advantage surface knowledge offers compared to deep knowledge is the reasoning efficiency. In the problem-solving process surface systems can skip many of the steps needed in a deep system. Figure 4.12 shows an example of this from De Vries and De Vries Robbe (1985). As this example was originally meant to stress the advantage of deep over surface representation in explanation, it may serve to elucidate the possible viewpoints in the tradeoff.

Based on the observation that human experts do not use principles to drive the process of medical reasoning, several authors indicate that surface representations can be much more efficient for (diagnostic) problem solving than deep representations can be (Chandrasekaran and Mittal, 1983; Clancey, 1983). Also researchers constructing systems operating from first principles indicate that this is an important weakness in deep representations (Davis, 1984; Genesereth, 1984; Kton, 1985; De Kleer and Williams, 1987). They feel that somehow additional techniques should be incorporated to effectively deal with large devices. As Davis (1984, p.400) points out:

Figure 4.12 Deep knowledge and the inferred surface representation (After De Vries and De Vries Robbe, 1985).
Knowledge based support in medical decision making

"...it is clear that rules can serve useful roles. They might, for example, offer a form of memory to shortcut the process for problems previously encountered. This would clearly be an improvement on our current system, which will solve a problem from first principles every time, no matter how many times it is encountered."

Chandrasekaran and Mittal (1983) indicate that it certainly is a viable solution to compile the deep knowledge into surface representations that can handle exactly the same problems in a more efficient manner. Indeed, it can be seen easily that for a problem at the boundaries of expertise there is no way a deep system would be able to present a better solution than a surface system that has the same knowledge compiled into it. Deep systems will yield better solutions only on levels that the surface system derived from it was not constructed for. This idea seems to be shared by Genesereth, according to his observation concerning the inefficiency of design descriptions (1984, p.435):

"A more drastic way of dealing with inefficiency is to 'compile' design descriptions into MYCIN-like symptom-fault rules. If it is possible to diagnose a device automatically, it should be possible to create a set of diagnostic tests automatically. The cost of this approach can be formidable since it must take into account all possible faults. However, the savings can also be dramatic, and the approach warrants further investigation."

Or, as Clancey notices (1985, p.312):

"Indeed, from the perspective of knowledge transformation, it is ironic to surmise that we might one day decide that the 'superficial' representation of EMYCIN rules is a fine executable language, and something like it will become the target for our knowledge compilers."

4.6.2 Discussion

It may be clear by now that whether to represent knowledge in deep or surface structures depends greatly on the desired system characteristics. Deep knowledge will provide clean explanation and justification of the system behavior at various levels of detail. The system will be transparent, facilitating maintenance and system behavior will be well predictable. Moreover, the use of 'objective' domain knowledge allows a structured design and realization of the knowledge based system. Surface systems, if they are
constructed from a set of heuristics, will be less transparent, hampering maintenance. Their behavior will be hard to predict, which hinders testing the system performance and may lead to an infinite test-expand cycle. However, they will be more efficient problem solvers.

In contrast to the goal of what are commonly called expert systems, the intention to construct deep systems for problem solving seems to reflect an endeavour to not incorporate expert behavior, but imitate the approach of a novice who, to solve a problem, similarly struggles from first principles. In building knowledge based systems, the goal of the system and its intended application should play a predominant role in deciding what knowledge and which representation to use. In deep as well as in surface systems, there will be limits to the domain the system model is suited for. Therefore, it is much more important to explicitly state these limits, as well as the assumptions made in modeling, than to try to keep on extending the limits. Just as in 'classical' system identification (viz. Ch. 3), a knowledge engineer should strive for an efficient system, tailored for its intended application, without the burden of superfluous knowledge. For a diagnostic system this means that all relevant knowledge would be compiled into it in a form that keeps the resulting system transparent. For purposes of explanation, this surface knowledge could be backed up by deeper structures that generally are not used for reasoning.

When are encountered somewhat outside its area of expertise, which can not be solved by the surface representation, the system can switch to the deep representation for problem solving. This may be successful, as long as the assumptions done in modeling the deep knowledge do not prohibit the solving of this problem. By switching between surface and deep representations, diagnosis is performed at the highest possible level, assuring efficient problem solving. This leaves the question of identifying whether a certain problem is suited to be solved by the system's surface knowledge or whether deep representations will be needed. To make this possible, a criterion has to be defined against which the surface solution can be compared. In order to evaluate this surface solution, it has to be possible to perform a test to establish the actual diagnosis. In medical domains this will often call for invasive procedures, which are undesirable. In that case, deeper knowledge structures may be used to check the validity of the surface solution, which takes us back to the drawing-board. A final solution might be to make the surface knowledge base so consistent that it can detect its own limits itself.
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In that case it will not yield a solution for problems it was not designed for, but it will pass on this problem to the deep knowledge base instead. The classification of evidence that is introduced in Ch. 5, provides a means to achieve this.

Instead of dynamic switching between surface and deep knowledge, the sequential use of these knowledge structures to increase efficiency is conceivable. In this case, deep knowledge has to be organized hierarchically, whereas surface knowledge provides an efficient strategy for focusing search on a small part of this hierarchy, thus limiting the search space. Refinement of the hypotheses can then be handled by deeper knowledge. This reasoning strategy bears great resemblance to the reasoning of physicians (Sect. 4.2): In the early stage of reasoning, hypotheses serve to focus attention on a small part of hierarchically organized disease knowledge.

One could argue that the use of surface knowledge leads to an excessive amount of work, since for each problem in a domain a new system has to be constructed. As a counter argument, in my opinion each problem requires its own knowledge and its own form of knowledge representation. General medical knowledge bases, constructed independently from intended applications, may result in good medical textbooks but will be poor problem solvers due to the fact that task specific reasoning strategies are lacking. As is acknowledged by Iwasaki et al (1988), who are undertaking an endeavor to build one large general-purpose knowledge base to support multiple tasks in physics and engineering, it may not be possible in general to represent knowledge without implicit or explicit assumptions about its intended use. They claim, however, that the knowledge representation language should allow to make these assumptions explicit. Nevertheless, this requires a substantial effort to be put into implementing task specific strategies, if the system is to be used for a specific problem. This will probably only lead to sub-optimal systems regarding efficiency, since knowledge and its representation are not biased towards their use.

Although it has been stressed that for many problems the application of surface knowledge is important to focus reasoning and make reasoning more efficient, it is felt that the theory of diagnosis from first principles (Reiter, 1987) is a useful step to a theoretical foundation of general diagnostic reasoning.

One more observation concerning deep representations in the medical domain is
due here. Since in many areas in medicine, unlike in most technical domains, knowledge is still incomplete, the suitability of a diagnostic approach from first principles is often doubtful. Maybe, only subdivisions of the entire domain may lend themselves to this purpose, or worse, the approach from first principles may be totally unsuited for the entire domain which calls for a surface representation employing heuristic associations.

4.7 CONCLUDING REMARKS

The important concepts introduced in this chapter those of are transparency and efficiency in constructing knowledge based support systems. It has been asserted that the combination of hierarchical structuring of (if necessary deep) knowledge for transparency and domain-specific strategies for efficient search, provide the best possibility of balancing these aspects. Therefore, in system analysis and design, based on transparency and efficiency requirements, the desired use of deep and surface knowledge structures should be chosen. Clancey's (1987) ideas on heuristic classification and the work on generic tasks (Chandrasekaran, 1986, 1988) may provide a useful framework to guide these decisions. Attention should be paid to identifying those areas in which more or less complete knowledge is available, since this sets the limits to the possibility to use deep and surface knowledge. In knowledge acquisition the hierarchy in the disease knowledge of physicians has to be revealed also,
to provide clues for transparent and efficient organization of knowledge. The simultaneous identification of different levels of knowledge allows the development of techniques for efficient use of this knowledge. A simple but efficient technique is to use higher-level knowledge to focus on small, deeper knowledge structures.

In view of transparency, in knowledge representation, care has to be taken that an objective method is used for the explicit representation of uncertainty. Once these choices have been made, an appropriate representation language is chosen. These aspects (Fig. 4.13) will receive more attention in the following.
Chapter 5
Knowledge based support: PLEXUS

5.1 INTRODUCTION

As has been described in previous chapters, knowledge based modeling potentially offers substantial benefits in medical decision support. No large amounts of process data are required to derive a model. Also, the incorporation of domain knowledge can make these systems more closely related to human problem-solving behavior which allows a more natural conversation with the user and facilitates explanation and justification. For a specific application, however, a number of problems that have been addressed in Ch. 4 still have to be solved. Where should the necessary domain knowledge come from? Is this knowledge complete? How should it be represented in a knowledge based system? Should deep or surface representation or a combination of these be used? How can uncertainty be dealt with? These questions will be dealt with in this chapter for a system in the domain of brachial plexus injuries: PLEXUS. As has been elucidated in Ch. 2, in this domain a need for support is present in a number of areas:

1. Diagnosis of brachial plexus injuries is often poor, which seems due to a lack of knowledge of the right diagnostic procedure.
2. Management of these injuries is not always optimal, which seems to be caused by insufficient knowledge about the possibilities for treatment.
3. Prognosis of brachial plexus injuries is difficult to assess because
4. Evaluation of different treatment schemes still has to be done.

To improve diagnostics (1) and management (2), as well as to propagate that knowledge, and to permit the acquisition of knowledge of prognosis of these injuries (3) through the evaluation of different treatment schemes (4), the idea of a medical decision support system, PLEXUS, was conceived. This system should consist of knowledge based models for diagnosis, to determine the site and extent of brachial plexus injuries, and to ensure that the right diagnostic procedure be followed, and to determine the severity of the injury and a plan for treatment. Further, a database facility should be incorporated for the acquisition of process data necessary for data based modeling to assess the prognosis for different treatment plans. The interface permits communication between these modules and the user (Fig. 5.1). The problem
Figure 5.1 Global architecture of the medical decision support system PLEXUS.

Figure 5.2 Part of the domain of diagnosis and management of brachial plexus injuries.
domain was limited to traumatic and iatrogenic injuries, and to injuries due to irradiation. Obstetric injuries and injuries due to tumors and anatomical abnormalities are not considered.

The knowledge for the diagnostic and treatment modules has been acquired from two experts in the field of the diagnosis and management of brachial plexus injuries (Thomeer, 1986; Slooff, 1986) and from literature. The stages of knowledge acquisition and knowledge representation have been presented in Sect. 4.4.1. The design and implementation of PLEXUS will be discussed in more detail in the sequel. In Sect. 5.2, identification and conceptualization will be presented, aimed at the construction of a medical decision support system. Formalization and implementation will be discussed in Sect. 5.3. Special attention will be paid to solutions for dealing with uncertainty in Sect. 5.4. The evaluation and testing of PLEXUS will be dealt with separately, in Ch. 6.

5.2 IDENTIFICATION AND CONCEPTUALIZATION

In domain analysis, first the important concepts, relations and structures in the domain are identified. For the domain of brachial plexus injuries, these have already been described in Ch. 2. Part of this domain structure is presented in Fig. 5.2. Then, as pointed out in Sect. 4.7, to allow structured design and implementation of a knowledge based system, areas of complete domain knowledge have to be identified. Finally, sources of uncertainty are ascertained. A number of important properties and their implications for constructing a knowledge based system, for the diagnosis and management of brachial plexus injuries, will be summarized here.

Generally, a traumatic brachial plexus injury does not consist of a single, focal lesion. The nerve structure suffers from extensive damage in several locations. This is particularly true in the case of traction injuries, which constitute the majority of cases. In injuries due to motorcycle accidents, for instance, the brachial plexus injury may be caused by a sequence of events, each contributing to the injury. Two- or three-level injuries may occur. About 41 locations can be differentiated in the brachial plexus, therefore the possible number of combinations of injury is practically unlimited ($2^{41}$).
Figure 5.3 Task structure of the knowledge based system PLEXUS.

Figure 5.4 Detailed architecture of the medical decision support system PLEXUS.
Facts that can be established by diagnostic tests will generally point to several of these injuries, which makes determining a differential diagnosis difficult. Moreover, a large number of tests are available, but these will not always ensure reliable information, and their validity may even depend on the location of the injury. Often, only few diagnostic tests are performed and it may be hard to combine evidence acquired from these tests to a differential diagnosis due to anatomical variations. Once the diagnosis has been established, it may not always be clear which treatment scheme is optimal, since reliable data of the prognosis for different treatment schemes is not available. These domain properties present a number of problems in determining a diagnosis and treatment plan for a specific patient:

1. Necessary tests may not be done.
2. Tests may be done that do not supply valid information.
3. Test results are easily misinterpreted because of the frequent anatomical variations.
4. Combining test results to achieve a diagnosis may be hard due to the large number of possible diagnoses and the non-specificity of many findings.
5. To establish an optimal treatment plan may sometimes be impossible.

These problems indicate that a support system should check the consistency of test data (1), monitor the diagnostic procedure (2, 3), localize the injury (4), determine the severity of the injury and conceive a treatment plan (5). The resulting task structure of such a system is presented in Fig. 5.3. Figure 5.4 shows a more detailed architecture of the system, based on these tasks. Notwithstanding the problems mentioned above, knowledge concerning the localization of brachial plexus injuries is fairly complete and calls for a structured design approach although a large amount of uncertainty is associated with the anatomical variations that may occur, as well as with the suggestive strength of many findings from diagnostic tests. Knowledge of treatment planning, however, is rather incomplete which necessitates an approach using surface knowledge via heuristic associations.

5.2.1 Localization strategy

Diagnosing brachial plexus injuries consists of the determination of the
Figure 5.5 Supraclavicular dysfunction in the muscle matrix.

Figure 5.6 Infraclavicular dysfunction, 'checkerboard' pattern, in the muscle matrix.
location, the severity and the extent of the injury. Of these, the localization of the injury is critical since the determination of the severity and the extent of the injury, and the appropriate treatment plan depend on it. The network of locations of the brachial plexus and the associated motor and sensory symptoms represent deep level knowledge that is of interest to the brachial plexus localization problem. Localization may be viewed as the classification of a case in a limitless solution space. Therefore solutions can not easily be enumerated, but have to be constructed from a combination of the 41 possible locations of injury. In this view, localizing the injury means having to generate a classification hierarchy as defined by several authors (Gomez, Chandrasekaran, 1981; Chandrasekaran, 1983; Aikins, 1983) and to identify that combination of end-nodes that best explains the symptoms for a specific case (Fig. 5.2). Since a diagnosis very rarely consists of only one injury (i.e. one end-node), care has to be taken that all injuries are found. An exhaustive search of the diagnostic tree would solve this but is very inefficient. Therefore, as indicated in Sect. 4.7, to improve efficiency, somehow the search in this large solution space has to be focused by higher-level knowledge. The way to implement this may be derived from the physician's diagnostic strategy. This strategy has been revealed by interviewing the experts.

physician strategy

Proceeding from a first interpretation of patient history and physical examination, a physician will focus his attention on a part of the diagnostic hierarchy (e.g. the supraclavicular injuries). The more significant symptoms present, the better he will be able to limit the space of the remaining hypotheses. In this stage, information from muscle examination plays an important role in globally localizing the injury. Information concerning individual muscles is generalized to provide evidence on larger areas of normal or abnormal function. In this process of data abstraction, the matrix by Merle D'Aubigné and Deburge is important. If dysfunction is more or less complete, or is organized neatly along the lines of plexal root innervation, the hypothesis of a supra-clavicular injury is triggered (Fig. 5.5). If, however, dysfunction is along the lines of peripheral nerves, or presents a diffuse pattern, the 'checkerboard' pattern (Thomeer, 1987), then the injury is likely to be infraclavicular (Fig. 5.6). Following this, data of
neurophysiological and radiological tests are used for the confirmation or elimination of hypotheses. This limiting strategy makes use of causal associations between symptoms and hypotheses, heuristics and anatomical knowledge (Fig. 5.7). Then, the remaining hypotheses are refined to a final diagnosis, consisting of a combination of injuries.

The localization tasks described suggest a task structure of the knowledge based system, that consists of a combination of the heuristic match task which employs surface knowledge, and of a refinement task, based on deep knowledge.

5.2.2 Treatment strategy

As became clear in Ch. 2, the management of brachial plexus injuries is fully determined by the site and severity of the injury. The localization task was

Figure 5.7 Diagnosis and management for a specific patient.
discussed in the previous section. Assessment of severity of the injury and the appropriate treatment plan are described here.
It has already been mentioned that knowledge of treatment planning is very incomplete. Therefore, in the design of a knowledge based system for treatment planning expert heuristics will be very important. In practice, experts assess the severity of the injury, i.e. the possibility of natural recovery, from patient history, radiological examination and more recent physical and neurophysiological examinations. As described in Ch. 2, a migrating Tinel's sign, or reinnervation potentials on the EMG, supply information relevant in determining the severity of the injury. In cases that suggest serious injury, e.g. from patient history, from muscle function or from radiology, the expert physician may immediately decide upon neurosurgical repair of the injury. In cases that seem less serious, the physician may choose to wait for 3 or 4 months after the trauma for symptoms of reinnervation to occur, like polyfasic EMG signals or the migration of Tinel's sign. If these do not occur in that period of time, he is likely to decide upon operative treatment in order not to miss the chance of repairing a serious injury. Once site and severity of the injury are known, conceiving a treatment plan is relatively straightforward. Each injured location in the brachial plexus suggests a specific treatment (Fig. 5.7). The final treatment plan for the total injury is derived by evaluating the priorities for each treatment suggestion. The task structure for the treatment planning system corresponding to the described tasks is that of heuristic match and prioritization (refinement), based on surface knowledge.

5.3 FORMALIZATION AND IMPLEMENTATION

In the previous section the global inference structure of the localization and treatment planning modules of PLEXUS became clear (Figs. 5.8, 5.9). This structure facilitates the choice of a knowledge representation formalism for each task. It should be clear by now that different kinds of knowledge have to be incorporated in order to derive an efficient but still transparent system. Deep knowledge for the localization, surface strategic knowledge to focus localization reasoning, expert heuristics for treatment planning and data abstraction knowledge.
Figure 5.8 Inference structure of the 'data abstraction' and 'localize' tasks.

Figure 5.9 Inference structure of the task 'conceive treatment plan'. 
5.3.1 Data abstraction

Data gathered from patient history and examinations can not be matched directly to a solution. Solution features are inferred by data abstraction. In this process, before the actual abstraction from data to evidence, the consistency of the data may be checked by applying redundant procedures to validate inconsistent data. This is taken care of in the consistency task. Abstracted symptoms of which the consistency has been checked supply more reliable evidence for further reasoning about the location of the injury and treatment planning. To keep data abstraction efficient, intermediate concepts that do not significantly contribute to the system transparency are left out. Data abstraction knowledge has been very conveniently represented in production rules in Delfi2+ (Goedhart, 1988). Figure 5.10 shows an example of this factual knowledge.

Also in the first stage of the reasoning process, the diagnostic procedure

```plaintext
SET fib_poly
   TRANSLATION "EMG results fibrillations and polyfasic"
   DOMAIN TEXT
   VALUE ["fibrillations", "polyfasic"]
ENDSET

RULE 334
IF
[ biceps.power = 5 ]
AND
[ ONEOF(biceps.EMG, fib_poly) ]
THEN
CONCLUDE biceps.status := "partial_defect" CF (1.000)
FI
ENDRULE

RULE 3
IF
[ [ myelography.not_visible = "c6" ]
OR
[ CT_scan.not_visible = "c6" ]
OR
[ MRI.not_visible = "c6" ]
AND
NOT[ c6.radiology_visible ]
THEN
CONCLUDE c6.radiology := "root_not_visible" CF (1.000)
FI
ENDRULE
```

Figure 5.10 Example of data abstraction rules.
followed by the user can be screened. As was mentioned before, and as it is clear in the task structure of PLEXUS (Fig. 5.3), sometimes the usefulness of diagnostic tests depends on the results of other tests, or on the actual location of the injury. This might necessitate the retraction of conclusions that have already been established, which calls for a form of non-monotonic reasoning. However, this can be easily avoided by the introduction of an extra level of reasoning, as is made clear in Fig. 5.11. An example of knowledge of checking the consistency of symptoms and screening of the diagnostic procedure is shown in Fig. 5.12.

**muscle function**

A second level of data abstraction has been introduced based on the observation that in the early phase of diagnostic reasoning, the phase of hypothesis activation, human experts do not rely on detailed information concerning muscle function but tend to generalize information of individual muscles to larger areas of normal and abnormal function. In PLEXUS, these areas have been derived from the same source human experts use, i.e. the matrix by Merle D'Aubigné and Deburge. From this matrix, in combination with

```plaintext
RULE 1233
IF
[ c8.radiology = "root_not_visible" ]
AND
[ c8.postganglionair_lesion ]
AND
NOT[ c8.exclude_pre_postganglionair_lesion ]
THEN
CONCLUDE c8.pre_postganglionair_lesion := TRUE CF (0.900)
FI
ENDRULE

RULE 1383
IF
[ c8.SNAP = "not_present" ]
AND
[ c8.sensibility = "an_dermatome" ]
AND
NOT[ c8.contradiction_SNAP_axon_reflex ]
THEN
CONCLUDE c8.postganglionair_lesion := TRUE CF (1.000)
FI
ENDRULE
```

Figure 5.11 Dealing with 'non-monotonic' evidence.
SET single_mixed_normal
TRANSLATION "EMG results single_fiber_pattern, mixed, normal"
DOMAIN TEXT
VALUE ["single_fiber_pattern", "mixed_pattern", "normal"]
ENDSET

RULE 420
IF
[ infraspinatus.EMG = "notdone" ]
AND
[ ONEOF(supraspinatus.EMG, single_mixed_normal) ]
AND
[ supraspinatus.power = 0 ]
THEN
CONCLUDE supraspinatus.EMG := "non_zero" CF (-0.900)
EXECUTE plexusremark(patient.name,420)
WRITE "******************************************************************************"
WRITE "* Since there is no information available about the EMG of the      *
WRITE "* m. infraspinatus, I can not decide whether the measured signal in *
WRITE "* the m. supraspinatus is due to real muscle activity, or to an *
WRITE "* artefact from the m. trapezius. Therefore, I decided by default *
WRITE "* that the latter is the case. If you do have information about the *
WRITE "* EMG of the m. infraspinatus, however, please revise your answer, *
WRITE "* so that I can improve my diagnosis.                *
WRITE "******************************************************************************"
FI
ENDRULE

RULE 430
IF
[ infraspinatus.EMG <> "notdone" ]
AND
[ infraspinatus.EMG <> "non_zero" ]
AND
[ ONEOF(supraspinatus.EMG, single_mixed_normal) ]
AND
[ supraspinatus.power = 0 ]
THEN
CONCLUDE supraspinatus.EMG := "non_zero" CF (-1.000)
EXECUTE plexusremark(patient.name,430)
WRITE "******************************************************************************"
WRITE "* Because of the fact that there is no activity in the m. infra- *
WRITE "* spinatus, I decided that the measured activity in the m. supra- *
WRITE "* spinatus is due to an artefact from the m. trapezius.        *
WRITE "******************************************************************************"
FI
ENDRULE

Figure 5.12 Knowledge concerning consistency checking and monitoring the diagnostic procedure.
the plexal root innervation assumed in this thesis (Fig. 2.11), three groups of muscles have been identified that, globally, are innervated by the same plexal roots (Meinders, 1989). First of all, there are the muscles innervated by roots C5 and C6, i.e. the truncus superior, then the muscles that receive a major contribution from root C7, i.e. the truncus medius, and finally the roots that are mainly innervated by roots C8 and T1, i.e. the truncus inferior. From the same matrix, in each of these clusters on the level of plexal roots, peripheral muscle groups can be identified, which leads to a

<table>
<thead>
<tr>
<th>Muscle function</th>
<th>$f_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>intact</td>
<td>1</td>
</tr>
<tr>
<td>partially denervated</td>
<td>0.5</td>
</tr>
<tr>
<td>totally denervated</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 5.1 Scoring of muscle function in data abstraction.

![Diagram of muscle function clusters](image)

Figure 5.13 The cluster model of motor function.
total of 16 muscle fields (Fig. 5.13). The function of the 38 muscles that are
routinely tested in muscle function examination can thus be abstracted to 16
muscle field statuses.

Muscle function, as established in the first data abstraction phase, can
either have the value 'normally innervated', 'partially denervated' or
'totally denervated'. In the second data abstraction phase, these functions
are quantified. The resulting functions, \( f_i \), are scored as indicated in Tab.
5.1. Further, the relative importance of a muscle to its corresponding field,
as indicated by its area in the muscle matrix, is expressed by a weighing
factor \( w_i \), that has been chosen in such a way that for each field the sum of
its \( N \)
weighing factors equals 1, i.e. \( \sum_{i=1}^{N} w_i = 1 \).

Accordingly, the field status \( F_k \), i.e. the amount of muscle function in the
field, can be easily calculated as follows:

\[
F_k = \sum_{i=1}^{N} (f_{ik} \cdot w_{ik})
\]

These field statuses, \( F_k \), are used for further surface reasoning based on
muscle function. An important aspect of this is the recognition of patterns
of supra-or infraclavicular dysfunction, i.e looking for the checkerboard
pattern, or other clearly infraclavicular patterns. This pattern recognition
strategy is a procedural task that reasons about individual objects, such as
specific combinations of peripheral nerves and fasciculi (Fig. 5.14).

Therefore, it proved to be more suitable to represent this pattern recognition
strategy in production rules than in an object-based method (Meinders, 1989;
Ter Haar, 1989).

```
RULE 2528
IF
NOT[ cluster.c5c6 = "damaged" ]
AND
NOT[ cluster.c8t1 = "intact" ]
AND
[ field.thoracodorsalis_c6c7c8 = 0 ]
THEN
CONCLUDE cluster.c7 = "damaged" CF (0.200)
CONCLUDE cluster.dorsalis_c7 = "damaged" CF (0.200)
FI
ENDRULE
```

Figure 5.14  An example pattern recognition rule.
5.3.2 Localization

The suitability of knowledge representation methods for neurological localization problems has been investigated by other authors also. Reggia (1978) indicated that a physician's neurological knowledge is organized in a frame-like fashion. In addition, he believes physicians use a conceptual, visually oriented representation of the nervous system, which makes neurological localization knowledge hard to express in production rules. The inference structure of the 'localization' task of PLEXUS (Fig. 5.8) suggests that this might be true for the 'refinement' task, where deep knowledge of the anatomy of the brachial plexus plays a predominant role in establishing the final location of the injury. This suggests a representation in a network-like method, as is also proposed by other researchers (Hertzberg et al, 1987). However, interviews with experts in brachial plexus localization revealed that these apply a surface strategy to limit the space of potential solutions previous to their refinement of the global solution. Moreover, as was mentioned earlier, to increase the efficiency of the knowledge based system, a higher-level diagnostic strategy is needed to focus reasoning. Therefore the knowledge representation method should also be expressive enough to model this surface strategic knowledge which will be incorporated in the 'heuristic match' task.

heuristic match

In Sect. 4.5.2, it was made clear, as it has been described by other authors also (Davis et al, 1977; Gomez, Chandrasekaran, 1981; Clancey, 1983), that production rules are very suitable means to represent the surface knowledge based on empirical associations that constitutes the heuristic match task. It has become evident, however, that a representation in production rules requires that much attention be paid to knowledge organization, in order to keep the knowledge base transparent. The inference structure presented in Fig. 5.8 provides a global framework for the organization of production rules. The system's reasoning strategy can be made more transparent by explicitly representing it on a higher level of abstraction, instead of it being present implicitly on the implementational level (Chandrasekaran, 1986, 1988). For this purpose, four types of rules have been identified for each hypothesis in the hierarchy of Fig. 5.2:
TRIGGERING RULE

RULE 2939
IF
[ patient.extraforaminar_truma ]
AND
[ patient.location_extraforaminar_truma = "supraclavicular" ]
THEN
CONCLUDE lesion.supraclavicular := TRUE  CF (1.000)
FI ENDRULE

PRUNING RULE

RULE 2450
IF
[ patient.Horner ]
THEN
CONCLUDE tl.exclude_extraforaminar_lesion := TRUE  CF (1.000)
FI ENDRULE

EVALUATION RULE

RULE 1123
IF
[ c8.radiology = "root_not_visible" ]
AND
NOT[ c8.exclude_avulsion ]
THEN
CONCLUDE c8.avulsion := TRUE  CF (0.900)
FI ENDRULE

CONFIRMATION RULE

RULE 1153
IF
[ c8.avulsion ]
AND
[ cluster.c8tl = "damaged" ]
THEN
CONCLUDE c8.avulsion := TRUE  CF (0.500)
FI ENDRULE

Figure 5.15  Example of classification of evidence into objects, attributes and production rules.
- Triggering rules
- Pruning rules
- Evaluation rules
- Confirmation rules

Triggering rules look for positive evidence that is sufficient to activate and confirm a hypothesis. Pruning rules, on the contrary, look for negative evidence to exclude a hypothesis. With the combined forward- and backward-chaining inference mechanism of Delfi2+, triggering and pruning rules constitute the actual focusing strategy by the activation and direct confirmation or ruling out of hypotheses. Often, hypotheses can not be directly confirmed or ruled out, but evidence in favor of the hypothesis has to be gathered and weighted against evidence against that hypothesis. This is taken care of in the evaluation rules. If no sufficient exclusionary evidence is available to rule out a hypothesis, and sufficient positive evidence is present, the hypothesis is postulated to be processed further in the refinement stage. Once the diagnosis has been established after refinement,

---

**Figure 5.16** Triggering strategy in PLEXUS for the hypotheses 'supraclavicular lesion' and 'infraclavicular lesion'.
the confirmation rules explain remaining symptoms on the basis of this diagnosis. An example of these rules is presented in Fig. 5.15. To be able to construct these rules, for each hypothesis the evidence has been classified into one of five categories:

- **Triggering facts.** These very specific facts activate and confirm a hypothesis, regardless of the presence of necessary or exclusionary facts.
- **Necessary facts.** For a specific node its necessary facts must be present to postulate that hypothesis.
- **Exclusionary facts.** The presence of one or more of these facts excludes a hypothesis.
- **Corresponding facts.** Once a specific end-node has been established as part of the diagnosis, these facts may be confirmed by it.
- **Irrelevant facts.** For a specific hypothesis some facts may be irrelevant.

This classification of evidence makes it possible to very specifically identify the contribution of each piece of evidence to the establishment or rejection of a hypothesis, again benefiting transparency. This classification, in combination with the 'check consistency' task, assures that all symptoms found in a specific patient are accounted for. This can be taken care of, either in the diagnosis, or in messages informing about inconsistencies in the evidence, possibly due to improper application or interpretation of diagnostic tests or to anatomical variations. An example of the resulting triggering strategy concerning the hypotheses of supraclavicular and infraclavicular lesion is presented in Fig. 5.16. As can be seen in this figure, not only has evidence been classified in categories, but also within the category of triggering facts, a hierarchy of evidence has been established for some hypotheses. For instance, evidence of a supraclavicular lesion based on the location of extraforaminar trauma to the brachial plexus, e.g. stab wounds, has higher priority than triggering evidence of an infraclavicular lesion based on the pattern recognition rules.

refinement

After the focusing strategy of the heuristic match task has been applied, a number of competing hypotheses may be present, that constitute a number of mutually exclusive sets of hypotheses that can each account for the observed
symptoms. For example, in the absence of triggering or pruning evidence, a loss of muscle function can often be explained at several levels in the brachial plexus, for instance at the roots, the trunks or the peripheral nerves (Fig. 5.17). This is mainly due to the fact that the anatomy of the brachial plexus is represented only very globally in the heuristic match task, which is merely intended to focus the search. In the refinement task, deep knowledge is used to evaluate these remaining candidate hypotheses. Deep knowledge that is suitable to discriminate between these sets of hypotheses is provided by the anatomy of nerves and muscles. Since knowledge about the structure of the brachial plexus is important in this stage, an approach from first principles is very suitable. In such an approach, knowledge of the structure of the process and of the behavior of its components is incorporated in the system, and an algorithm is added for generating solutions.

In determining the location of a nerve injury based on muscle-function results, knowledge about the behavior of components is simple. Provided it can be assumed that muscles function correctly, i.e. there is no additional muscle disease or muscle trauma besides the brachial plexus injury, and that nerves are either intact or defect, an injured nerve will not conduct action potentials. This manifests in muscle function: a muscle that receives normal

![Diagram of the Brachial Plexus](image)

**Figure 5.17** Brachial plexus Injuries causing similar dysfunction: injury to a. roots c8 and t1, b. truncus inferior, c. fasciculus medialis, d. n. ulnaris and radix medialis n. medianus.
action potentials will exhibit normal power, reduced action potentials will result in reduced power, whereas muscle power will be zero if no action potentials reach the muscle. Based on this behavior, knowledge about the structure of the brachial plexus can be used to localize the injury. The representation of this knowledge is very difficult in production rules so that a different representation is called for. Representation in a network-like method seems obvious. The structure of the brachial plexus consists of the intraneural network of axons that arise from the plexal roots and innervate the muscles. However, general knowledge of the anatomy of this axonal network is not available so that this structure can not be used for reasoning. Also, it is very likely that at this microscopic level anatomic variations are so frequent that no general model of this anatomy can be found. At a higher level, axons join in funiculi. Funicular networks have been presented in literature, viz. Fig. 5.18 (Kerr, 1918). However, also at this level anatomic variations are frequent (Narakas, 1978) which makes this deep knowledge

![Diagram of Funicular network of the brachial plexus](image)

**Figure 5.18** Funicular network of the brachial plexus. Reprinted from Kerr, 1918.
unsuitable for a diagnostic model. Therefore, human experts perform deep localization at the level of nerves (Fig. 5.19). The network presented in Fig. 5.19 can easily be represented in binary relations of muscles and nerves. For example, the fact that the m. biceps is innervated by axons from plexal roots C5, C6 and C7 through the truncus superior (tr_sup) and truncus medius (tr_med) and their anterior divisions, via the fasciculus lateralis (f_lat) and the n. musculocutaneus (n_musc), can be represented as follows:

$$P_{biceps} = \left[ \left( \frac{2}{5} \cdot C5 + \frac{2}{5} \cdot C6 \right) \cdot tr\_sup \cdot a\_div\_tr\_sup + \frac{5.2}{1/5} \cdot C7 \cdot tr\_med \cdot a\_div\_tr\_med \right) \cdot f\_lat \cdot n\_musc$$

The power of a muscle, $p_i$, is thought to be the summation of the activity in the parallel nerve pathways. These binary relations can be constructed for all 38 causal nerve-muscle relations. The relations constitute a network consisting of a series of paths. They represent structural as well as behavioral knowledge. Since behavior of the components of the brachial plexus is very simple, the collection of 38 nerve-muscle relations can be considered a structural model of the brachial plexus. In this example, the contribution of each spinal nerve to the innervation of the m. biceps is represented by the weighing factors $2/5$ for roots C5 and C6 and $1/5$ for root C7, just as in the example in Sect. 4.3.4. These weighing factors have been based on the anatomy.

Figure 5.19 Brachial plexus network of nerves.
Knowledge based support: PLEXUS

of the brachial plexus, as described in Ch. 2. In the behavior of the network, they are interpreted as follows:

- If all axons from plexal roots with a large contribution to a muscle's innervation are intact, and those of a root with a small contribution are damaged, it will not be noticeable in muscle function.
- If all axons from plexal roots with a large contribution to a muscle's innervation are defect, and those of a root with a small contribution are intact, the muscle will have some function remaining.

To achieve this behavior from the nerve-muscle relations, values of \( p_i \) greater than or equal to 0.75 are said to correspond to an intact muscle. Values less than 0.1 are said to correspond to a totally denervated muscle, whereas values between 0.1 and 0.75 are said to correspond to a partially denervated muscle. In the case of the m. biceps, injury to the truncus superior would thus result in a power of 0.2, i.e. partially defect, whereas injury to the truncus medius would result in a power of 0.8, i.e. intact. At this macroscopic level, however, some nerves are that large, that injury does not always result in a total defect of these nerves, as was assumed about the behavior of nerves, but also partial defects may occur. This is especially true for the trunks, fascicles and large peripheral nerves: truncus superior, truncus medius, truncus inferior, fasciculus lateralis, fasciculus dorsalis, fasciculus medialis, n. radialis, n.ulnaris and n. medianus. To keep the behavioral knowledge of the brachial plexus as simple as described before, which allows reasoning based on structure only, instead of the need to incorporate a separate behavioral model, this phenomenon can be described by an extension of the network with partial locations for these large nerves (Fig. 5.20). This makes it necessary to convert the binary representation of the nerve-muscle relations to incorporate partial locations (part\_x), parallel to the complete nerves (x). Nerve-muscle relations can be thought of as representing the value of the current, \( p_{i} \), through the network. In this electrical analogon, the locations represent the inverse resistance of each part of the network. For each part, this resistance can be either \( \infty \) (location = 0 \Ø defect) or 1 (location = 1 \Ø intact). The total resistance of parallel, complete and partial locations is 1. Then, the resistance of the partial location is thought to be 10 times the total resistance. For the m. biceps this can be implemented as follows:
<table>
<thead>
<tr>
<th>#</th>
<th>Loc. name</th>
<th>#</th>
<th>Loc. name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>truncus inferior</td>
<td>2</td>
<td>t1 preganglionair</td>
</tr>
<tr>
<td>3</td>
<td>t1 preganglionair</td>
<td>4</td>
<td>c8 preganglionair</td>
</tr>
<tr>
<td>5</td>
<td>c8 preganglionair</td>
<td>6</td>
<td>c7 preganglionair</td>
</tr>
<tr>
<td>7</td>
<td>c7 preganglionair/tr. medius</td>
<td>8</td>
<td>truncus superior</td>
</tr>
<tr>
<td>9</td>
<td>c6 preganglionair</td>
<td>10</td>
<td>c6 preganglionair</td>
</tr>
<tr>
<td>11</td>
<td>c5 preganglionair</td>
<td>12</td>
<td>c5 preganglionair</td>
</tr>
<tr>
<td>13</td>
<td>ant. division tr. inferior</td>
<td>14</td>
<td>post. division tr. inferior</td>
</tr>
<tr>
<td>15</td>
<td>post. division tr. medius</td>
<td>16</td>
<td>ant. division tr. medius</td>
</tr>
<tr>
<td>17</td>
<td>post. division tr. superior</td>
<td>18</td>
<td>ant. division tr. superior</td>
</tr>
<tr>
<td>19</td>
<td>fasciculus medialis</td>
<td>20</td>
<td>fasciculus dorsalis</td>
</tr>
<tr>
<td>21</td>
<td>fasciculus lateralis</td>
<td>22</td>
<td>n. suprascapularis</td>
</tr>
<tr>
<td>23</td>
<td>n. pectoralis lateralis</td>
<td>24</td>
<td>n. musculocutaneus</td>
</tr>
<tr>
<td>25</td>
<td>radix lateralis n. medianus</td>
<td>26</td>
<td>radix medialis n. medianus</td>
</tr>
<tr>
<td>27</td>
<td>n. medianus</td>
<td>28</td>
<td>n. axillaris</td>
</tr>
<tr>
<td>29</td>
<td>n. radialis</td>
<td>30</td>
<td>n. subscapularis</td>
</tr>
<tr>
<td>31</td>
<td>n. thoracodorsalis</td>
<td>32</td>
<td>n. ulnaris</td>
</tr>
<tr>
<td>33</td>
<td>n. pectoralis medialis</td>
<td>34</td>
<td>truncus inferior partial</td>
</tr>
<tr>
<td>35</td>
<td>truncus medius partial</td>
<td>36</td>
<td>truncus superior partial</td>
</tr>
<tr>
<td>37</td>
<td>fasciculus medialis partial</td>
<td>38</td>
<td>fasciculus dorsalis partial</td>
</tr>
<tr>
<td>39</td>
<td>fasciculus lateralis partial</td>
<td>40</td>
<td>n. ulnaris partial</td>
</tr>
<tr>
<td>41</td>
<td>n. radialis partial</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5.3 Network of the brachial plexus, with partial locations.
Knowledge based support: PLEXUS

\[ Pbiceps = \{(2/5 \cdot C5 + 2/5 \cdot C6) \cdot tr\_sup \cdot (part\_tr\_sup + 0.1 - 0.1 \cdot part\_tr\_sup) \cdot a\_div\_tr\_sup + 1/5 \cdot C7 \cdot tr\_med \cdot (part\_tr\_med + 0.1 - 0.1 \cdot part\_tr\_med) \cdot a\_div\_tr\_med) \cdot f\_lat \cdot (part\_f\_lat + 0.1 - 0.1 \cdot part\_f\_lat) \cdot n\_musc\} \]

5.3

Now, a partial injury to the fasciculus lateralis will result in a power of 0.1, i.e. partially denervated, instead of the total denervation of the m. biceps, that occurs in case of a total injury to the fasciculus lateralis. In this way, the structure and behavior of the brachial plexus is represented on the deepest possible level in 38 relations. To use this knowledge in deep reasoning, an algorithm has to be added to generate and evaluate potential solutions.

hypothesize and test

Several hypothesize and test algorithms have been proposed, viz. the algorithm based upon the Set Covering Model by Reggia (1983) and the algorithm DIAGNOSE (Reiter, 1987), based upon the theory of diagnosis from first principles. As has been described in Ch. 4, these algorithms are often rather insufficient for searching the entire solution space. Therefore, it is interesting to look for more efficient algorithms. De Kleer and Williams (1987) described how the conflict recognition strategy of their algorithm GDE was refined to improve efficiency. Unlike the problems that domain-independent diagnostic algorithms like GDE are usually presented with, i.e. diagnosing analog or digital circuits, in medical domains knowledge of structure is often not certain, due to anatomical variations. Some of the variations of the brachial plexus have been described in Ch. 2. By representing the structure of the brachial plexus at the level of nerves these variations are minimized, so that often they will not seriously influence diagnosis. In this case, automated diagnosis is viable as long as the diagnostic algorithm is sufficiently robust. Localizing the injury then means the determination of the solution that best explains the symptoms. This optimal solution can be found if the algorithm has the possibility of ascertaining that a specific solution possesses qualities that are unmatched by any other possible solution in the candidate space which makes diagnosis an optimization problem. To assure efficiency of the diagnostic algorithm, heuristics may be incorporated, as has been proposed for many heuristic search algorithms (Pearl, 1984). In general, a diagnosis for
a brachial plexus injury is a multiple fault diagnosis, i.e. solutions consist of combinations of injuries. Therefore, the optimization algorithm will have to construct solutions from basic solution components. In PLEXUS, the A* algorithm, adapted for trees instead of graphs (Rich, 1983), was implemented (De Lindt van Wijngaarden and Furth, 1987; Meinders, 1989). Similar to the algorithms based on diagnosis from first principles, in this Algorithm for Knowledgeable Trees ($A^K$), diagnosis also consists of candidate generation and evaluation of potential solutions. The incorporation of heuristics to guide the search for the optimal solution is important.

candidate generation

Candidate generation is the process of generating potential solutions that subsequently will be evaluated. This process starts from an initial state, from which successors are generated. In the domain of the brachial plexus localization problem, an obvious choice for this initial state is that in which all locations of the brachial plexus are intact. The way in which new solutions, the children, of this parent node are generated, depends on the strategy of the search procedure. The simplest strategy is to generate all

![Diagram](image_url)  
**Figure 5.21** Example solution tree.
children of the parent. After these children have been evaluated, they themselves become parent nodes the children of which will be generated, etc. This procedure is called node expansion. In large problem spaces, however, this procedure will be very inefficient. In the domain of brachial plexus localization, for instance, this might mean that all $2^{41}$ potential solutions to a problem have to be generated. For these problems it is useful to guide the search in more promising directions. Search is directed by the search strategy.

To keep search effective, it is important that every child can only be generated once. In PLEXUS, this is taken care of as follows. The brachial plexus has been represented in a one-dimensional array, the elements of which each represent one of the 41 locations of the brachial plexus. Each element can either have the value 1 (intact) or 0 (defect). In the initial state, the array is filled with 1's, representing the state that all locations of the brachial plexus are intact. From this parent, children are generated by changing the value of one of the array elements from 1 to 0. For successive children, a higher element in the array is changed, i.e. for the first child, the first element in the array is changed to 0, for the second child the second element, etc. Once these children have been evaluated, one of them is selected for further exploration. If for this node, the position of the zero element is $i$, only children will be generated that have new zero elements in positions $j$, with $j > i$ (Fig. 5.21). In this way that children are only generated once is taken care of. As can be seen in Fig. 5.21, each node in the tree actually represents a state of the brachial plexus. Initially this solution tree is generated breadth-first. Then, the direction of search is guided by the search strategy.

search strategy

A search strategy is said to be systematic (Pearl, 1984) if:

- Every possible solution is evaluated.
- Every solution is generated only once.

The first requirement, called completeness, guarantees that the desired solution will be found, if it exists. The second requirement, that has already
been discussed in candidate generation, is necessary for efficiency. To guide the direction of the search, some measure has to be available to assess the quality of the solutions generated thus far. This is represented by the evaluation function, $g$. This evaluation function projects a solution to a number that is a measure for the quality of that solution. In simple search algorithms, for each node, the value of this function is used to rank candidates to determine the best direction for further search. In heuristic search algorithms, like $A^\infty$, a heuristic function, $h$, is added to estimate the expected improvement of the solution if it is explored further. This heuristic function projects a solution to a number that is a measure for the expected quality of the children of that solution. From these two functions, a function, $f$, can be determined that predicts the value of the evaluation function of the goal node, when a node will be explored further:

$$f = g + h$$  \hspace{1cm} 5.4$$

The value of $f$ determines the direction of the search. In the brachial plexus localization problem, the evaluation function can be determined from the difference between the actual muscle functions and the muscle functions that would result from the solution under consideration:

$$g = \sum_{i \in M} \text{abs}(\text{muscle}_i.\text{function}_{\text{actual}} - \text{muscle}_i.\text{function}_{\text{solution}})$$  \hspace{1cm} 5.5$$

Then the optimal solution is that solution which has the smallest value of $g$, making this a problem of minimizing the value of the evaluation function. In this case, $h$, can be used to estimate the improvement of $g$ in the case of further exploration of a node:

$$f = g - h$$  \hspace{1cm} 5.6$$

To make sure the search strategy will be complete, in the case of a minimization problem, it is required that $h$ overestimates the improvement. In the brachial plexus localization problem the heuristic function has been chosen as the summation of the difference for each muscle of the maximum muscle function that can be achieved by further exploring the node, as long as this function is not better than the actual function of that muscle, i.e. the optimal muscle function, and the computed muscle function for the solution...
under consideration. This is the improvement of the solution that can be achieved by further exploring a node:

\[ h - \sum_{i=1}^{38} (\text{muscle}_i\text{.function}_{\text{optimal}} - \text{muscle}_i\text{.function}_{\text{solution}}) \]

This heuristic overestimates the improvement of \( g \), or is at best a precise estimate for this improvement.

In the evaluation function as presented on page 142, a positive difference between the actual muscle power and the muscle power calculated for a specific solution is weighted similar to a negative difference. Since the goal of the search strategy is to provide a robust means to find all injured locations of the brachial plexus, it is better to weigh solutions with a negative difference, i.e. the case that not all dysfunction is explained by the solution, higher than solutions with a positive difference, i.e. the case that too much dysfunction is explained. In this way it can be assured that all injuries will be found. For instance, assume the n. suprascapularis (n\_sup) has been injured, resulting in a partially denervated m. supraspinatus and m. infraspinatus. For these muscles, the nerve-muscle relations are:

\[ P_{\text{supr}} - P_{\text{infra}} = C_5 \cdot tr_{\text{sup}} \cdot (\text{part\_tr\_sup} + 0.1 + 0.1 \cdot \text{part\_tr\_sup}) \cdot n_{\text{sup}} \]

For an intact n. suprascapularis this will result in a value for the evaluation function of \( \text{abs}(0.5 - 1) + \text{abs}(0.5 - 1) = 1 \).

For a defect n. suprascapularis this is \( \text{abs}(1 - 0.5) + \text{abs}(1 - 0.5) = 1 \).

Due to the fact that the value of the evaluation function is the same for both solutions, the solution in which the n. suprascapularis is intact will be chosen. When negative differences, i.e. the intact case, are weighted with a factor 2, the defect case will have a lower value for the evaluation function and will thus become part of the final solution.

**principle of parsimony**

If no focusing and pruning would be employed in the heuristic match task, in the refinement task the status of 41 locations had to be determined from 38 muscle functions. This redundancy in the network structure of the brachial plexus may cause a problem in determining a single best solution. Despite the
Figure 5.22 Locations to which the parsimony rule of the AKT algorithm applies.

Figure 5.23 Example result of the focusing stage.
incorporation of the weighing factor, eventually some solutions may present
the same value for the evaluation function. In practice, due to the strategy
employed before the $A^K_T$ algorithm, these generated solutions are similar in
the sense that, at most, they differ in, that one solution may contain a
central node from the solution tree, whereas another may contain all its
peripheral children instead. Since these solutions are essentially the same,
the principle of parsimony has been added to the $A^K_T$ algorithm (Fig. 5.22).
Now, instead of generating all essentially equal solutions, only the diagnosis
containing the parent node will be generated. Laboratory test sessions with
expert physicians revealed that they apply this rule as a matter of course.
Moreover, these experts felt annoyed if this same principle was not applied
by the system. For instance, dysfunction of the group of muscles innervated
by the fasciculus dorsalis is more likely to be due to a lesion of this
fasciculus, than to lesions of the individual nerves. Hertzberg et al (1987)
also found that clinical neurologists apply this rule. However, in PLEXUS it
is very well seen to that all relevant information, including heuristics and
combinations of symptoms, is applied first for efficient pruning of the
hypothesis space so that the parsimony rule only applies to the remaining,
actively similar hypotheses.

The parsimony rule has been simply implemented by selecting the order of the
locations in the array of the brachial plexus. Since a nerve location can only
be set defect if its predecessor is defect already, it can be seen to that
solutions with more central locations set to defect are evaluated before
solutions with more peripheral locations defect. The locations to which the
parsimony rule applies are depicted in Fig. 5.22.

discussion

The resulting diagnostic strategy of the localization task consists of three
stages. As data become available, data processing and consistency rules are
applied. When the occurrence of inconsistent evidence is traced by the
consistency rules, these rules reason about the justification for this
evidence by means of additional information. In this way conclusions about
the validity of the evidence can often be achieved, so that certain pieces of
evidence can either be discarded or accounted for by anatomical variations.
If this is not possible, however, the system will come to a conclusion by
default.
The next stage resembles the physician's focusing on a part of the diagnostic tree. Therefore, both triggering and pruning rules are employed to efficiently limit the hypothesis space. As a result of this stage, for each location in the brachial plexus, it has been determined whether it is intact, defect or unknown to be either intact or defect (Fig. 5.23). The unknown locations constitute a number of candidate solutions.

These remaining candidate solutions are evaluated by means of a heuristic hypothesize and test method. As it has been indicated by many authors (Elstein et al., 1978; Kassirer and Gorry, 1978), hypothesize and test appears to be the guiding force in human diagnostic reasoning. Recently, diagnostic algorithms have been proposed based upon this notion, viz. the algorithm based upon the Set Covering Model by Reggia (1983) and the algorithm DIAGNOSE (Reiter, 1987), based upon the theory of diagnosis from first principles. In the approach taken by both Reggia and Reiter, solution trees are generated breadth-first and pruned successively. The approach in PLEXUS distinguishes itself from this approach in that a very efficient pruning of the search space is accomplished by means of the diagnostic strategy, based on the classification of evidence, i.e. the triggering and pruning rules, prior to generating a solution tree. Following this, in the refinement stage, at the first level

![Diagram]

**RULE 8430**

**IF**

\[
\text{[ patient.conservative_treatment ]}
\]

**AND**

\[
\text{NOT[ patient.time_being_3_months ]}
\]

**AND**

\[
\text{NOT[ patient.surgical_treatment ]}
\]

**AND**

\[
\text{NOT[ patient.time_being_4_months ]}
\]

**THEN**

**CONCLUDE**

\[
\text{patient.treatment := "conservative_treatment" CF (1.000) FI}
\]

ENDRULE

Figure 5.24 Priorities in determining the final treatment plan.
of the tree, potential solutions are generated breadth-first which are then evaluated by means of an evaluation function and a heuristic estimator for the expected improvement of the solution in each branch of the tree. These functions guide further search, so that new solutions are sought best-first.

5.3.3 Treatment

As has been described in Sect. 5.2, knowledge concerning the treatment of brachial plexus injuries is rather incomplete. Therefore, treatment planning largely relies on heuristic knowledge. After data abstraction, for each injured location the severity of the injury is determined from the cause of the injury and the results of diagnostic tests via heuristic matching. Once location and severity of the injury are known, for the injured supraclavicular locations as well as for the infraclavicular locations, the optimal treatment plan is determined by heuristic match from diagnosis to treatment. In some cases it is impossible to establish an optimal treatment plan due to differences in opinion among the experts. In these cases alternative treatment schemes are established. After data have been abstracted, both heuristic match tasks are relatively straightforward. Therefore, for these hypotheses, no classification of evidence has been implemented, but evidence directly suggests a specific hypothesis.

Once a treatment plan has been established for the supraclavicular and for the infraclavicular part of the injury, the final treatment plan for the total injury is derived by evaluating the priorities for each treatment scheme according to the priorities in Fig. 5.24. Prioritization has been implemented in an extra reasoning level, at which inferred treatment plans are compared. Heuristic match and prioritization have all been implemented in production rules.

5.3.4 Concluding remarks

In the previous sections, all knowledge based modules of the PLEXUS system have been described. The way these modules interact is presented in Fig. 5.25, which depicts the architecture of PLEXUS. In the final realization as described in this chapter, PLEXUS consists of two separate modular knowledge
bases, one for localizing brachial plexus injuries, totaling 1141 production rules, and one for determination of severity and treatment planning, totaling 1218 production rules. The number of rules would have been much lower, i.e. about 500 for each knowledge base, had the Delfi2+ shell really supported the use of multiple instantiations, instead of the limited possibilities it presently offers. In Fig. 5.25, PLEXUS architecture as well as the database and interface are shown. These external modules that take care of communication and data storage and retrieval do not rely on domain knowledge. These will receive attention in Ch. 6.

In the localization system, the heuristic match task, based on surface knowledge, and the successive refinement task, based on deep knowledge, provide a task specific control structure for diagnostic reasoning. Moreover, the classification of evidence provides an explicit representation of the inference structure of the heuristic match task. Heuristic match prunes the solution space thus that only a small set of potential solutions remains. Then, in refinement this set is searched by the A*' algorithm for the minimal set of hypotheses that best explains the evidence.

Figure 5.25 Architecture of the knowledge based system PLEXUS.
Due to the combination of surface and deep knowledge in the localization system, this system may be suitable for use in a wider domain than it was originally intended for. Obstetrical injuries, as well as injuries due to tumors or anatomical abnormalities may be well localized also. However, the treatment of these injuries substantially differs from those the system was intended for thus that it lacks the necessary extra knowledge. Therefore, in testing the system, these injuries were not considered. Pages 150 through 152, present 2 examples of system reasoning. The first concerns a patient with a two-level injury, the second concerns a patient with an infraclavicular injury.

5.4 MODELING UNCERTAINTY

Uncertainty plays an important role in most medical knowledge based systems. It manifests in a number of different ways.

5.4.1 Kinds of uncertainty

A very deep source of uncertainty in medical domains is the incompleteness of knowledge. This phenomenon has been extensively described in previous chapters concerning management and prognosis of brachial plexus injuries. This source of uncertainty seriously hampers the design of a knowledge based system, since it washes out the structured design of a transparent system relying on 'objective' domain knowledge. If this incomplete knowledge becomes an important cause of uncertainty, it calls for a system based on expert heuristics, which hinders structured system design.

A second source of uncertainty is that of knowledge that is indeed complete in a general sense, but that can not be represented in a knowledge based system to reason with certainty about individual cases. An example of this uncertain knowledge is constituted by the anatomy of the brachial plexus. The general anatomy of this nerve structure has been extensively described in literature along with its variations. However, to represent all possible variations in a knowledge based system would be very inefficient. Moreover, even if one would succeed in achieving this, there is no conceivable way a reasoning system, whether this would be a human expert or a knowledge based
Patient 79: A patient with ruptured and avulsed roots, in combination with a costoclavicular crush injury.
Knowledge based support: PLEXUS

RESULT OF FOCUSING AFTER EVALUATION, I.E. INPUT TO REFINEMENT (AKT)

- status defect
- status intact
- status unknown

resulting array after focusing

? 1 1 ? 1 ? 1 0 1 1 ? 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

---

EXAMINATIONS
- fractured clavicle
- Tinel supraclavicular
- Tinel infraclavicular

LOCATION
- costoclavicular
- sup med infra
- postganglionic roots
- p02
- c5p67c8 11

SEVERITY
- conservative
- operative
- nerve graft transfer neurolysis

TREATMENT

Patient 79 (continued).
RESULT OF FOCUSING, AFTER DATA ABSTRACTION 2 AND EVALUATION, I.E. INPUT TO REFINEMENT (AKT)

LOCATIONs

EXAMINATIONS / REASONING

DATA ABSTRACTION

EVIDENCE

TRIGGER/PRUNE

no specific evidence

DATA ABSTRACTION 2: CHECKERBOARD

infraclavicular lesion

EVALUATION

status defect

status intact

status unknown

resulting array after focusing

| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | ? | ? | ? | ? | ? | ? | ? | ? | ? | ? | ? | ? | ? | ? |

LOCATION AFTER REFINEMENT

SEVERITY

TREATMENT

Patient 61: A patient with an infraclavicular injury.
system, could decide upon the actual anatomy of an individual without exploring the plexus. This source of uncertainty is very common in medical domains since anatomical variations are very frequent. The only possible solution to this problem is to somehow increase the robustness of the system. The best known method to achieve this is to incorporate a numerical uncertainty model, like the certainty factor method, to model these uncertainties. In Ch. 4, the disadvantages of ad hoc methods like this have already been discussed. The most important disadvantage is that they can make a system's reasoning process totally unpredictable. Therefore a more explicit method is called for. Such a method will be discussed in the sequel, in relation to methods to deal with another source of uncertainty, i.e. uncertain information.

Apart from uncertainty in the knowledge, the data the system reasons with may be uncertain also, for instance due to the fact that a certain examination is difficult to perform correctly, or the results are hard to interpret. These errors lead to a kind of measurement noise on the data. This may be illustrated by an example of cervical myelography in brachial plexus injuries. First of all, correctly performing the myelography requires the greatest care in patient position and camera angle to achieve optimal resolution. Then, the interpretation of the myelogram requires a great deal of experience to distinguish present and absent fila radicularia.

5.4.2 Quantifying uncertainty

As illustrated in Sect. 4.5.5, to deal with this kind of uncertainty, ad hoc numerical methods are not very suitable. On the contrary, there is a need for making the uncertainty of input data explicit, instead of the intransparency of quantifying the uncertainties. This can best be illustrated by the example of the myelographic examination of the cervical spine.

If on the myelogram the fila radicularia of a root are visible, it is practically certain that this root is not avulsed. If at the level of a root a meningocele is visible, the root may be avulsed, although cases have been documented of meningoceles without avulsions (uncertain knowledge). If the fila radicularia of a root are not visible, this root is very likely to be avulsed, if the myelography was performed correctly (uncertain information). Using the certainty factor method to quantify uncertainty, this knowledge
would typically be expressed in the rules of Fig. 5.26. As will be clear from these rules, in such a representation it becomes impossible to distinguish different sources of uncertainty which makes the system intransparent. Even worse, however, is the effect of this phenomenon on the system’s predictability, especially if a third source of uncertainty is taken into account, i.e. the physician’s quantification of his uncertainty in the interpretation of findings. In this example, part of this interpretative uncertainty has been represented already in the certainty factors. For instance, if we were certain the fila radicularia of a root are not visible on the myelogram, i.e. they are absent, the conclusion of a root avulsion could be made with absolute certainty. However, since the rule-writer knows the invisibility of the fila radicularia may as well be due to a poor X-ray picture, he chose for a lower value of the certainty factor.

```
RULE 1
IF
[ c6.myelography = "root_not_visible" ]
AND
[ c6.lesion ]
THEN
CONCLUDE patient.diagnosis := "avulsion_c6" CF (0.700)
FI
ENDRULE

RULE 2
IF
[ c6.myelography = "root_visible" ]
AND
[ c6.lesion ]
THEN
CONCLUDE patient.diagnosis := "extraforaminar_lesion_c6" CF (0.900)
FI
ENDRULE

RULE 3
IF
[ c6.myelography = "meningocele" ]
AND
[ c6.lesion ]
THEN
CONCLUDE patient.diagnosis := "avulsion_c6" CF (0.500)
FI
ENDRULE
```

Figure 5.26 Production rules describing the associations between myelographic findings and root avulsion, using the certainty factor method to quantify uncertainty.
Knowledge based support: PLEXUS

The unpredictability of system behavior as illustrated above partly results from the fact that rules 1, 2 and 3 are not independent chunks of knowledge, although that is the underlying assumption of the certainty factor model. Independence of these rules can be achieved, however, if, instead of the simple arguments represented in the premises of these rules, also the context in which these arguments apply is added. Not only will this result in an increase in the number of clauses in rule premises, it may also cause a combinatorial explosion of the number of rules in the knowledge base, since supersets of rules 1, 2 and 3 would have to be included to keep the knowledge base complete. Another problem associated with the certainty factor method or other such methods appears if the problem requires that a single best diagnosis is found, instead of a clustering of possible solutions. Selecting the best hypothesis on the basis of the certainty associated with it by such an ad hoc method can be doubtful (Buchanan and Shortliffe, 1984b). This is illustrated by the results Hertzberg et al (1987) describe of their system for neurological localization.

5.4.3 Explicit representation of uncertainty

The disadvantages of ad hoc methods for dealing with uncertainty necessitate the use of a method to more explicitly model this uncertainty instead of quantifying it. As described in the foregoing, such a method should deal with uncertain knowledge as well as uncertain information.

uncertain knowledge

Dealing with uncertain knowledge either requires the incorporation in the knowledge base of all possible variations from 'standard' knowledge, or it requires robustness to these variations. The first option is often not viable, since it would result in an unmanageable increase in the size of the knowledge base and, as was illustrated for the anatomy of the brachial plexus, often this knowledge is unsuitable to use to reason about individual cases. If so, the obvious way to deal with uncertain knowledge is to increase the system's robustness to it. Two aspects are important to achieve this. First of all, it must be ensured that the domain is modeled at a high enough level to minimize this kind of uncertainty. Secondly, data processing should aim at revealing
inconsistencies in the data that may be due to variations from standard knowledge. In the domain of diagnosing brachial plexus injuries, the first aspect has been realized by modeling nerve-muscle relations at a higher level in the muscle fields, and by modeling the anatomy in the AKT algorithm at the highest level possible for the refinement task. The second aspect is taken care of, of course, in the tasks for consistency checking and checking of the diagnostic procedure.

uncertain information

The methods discussed above play an important role in dealing with uncertain information also. Data abstraction in the checkerboard task, as well as consistency and procedure checking are important for converting uncertain data to more reliable evidence. One more aspect concerning uncertain information is crucial. Already in the stage of data acquisition, to a large extent the reliability of the data is determined by the questions asked of the user and the answers allowed. In this stage, in order to obtain data which is as reliable as possible, uncertainty of input data should be made explicit to the greatest degree possible. For illustration, let us look at the example of acquisition of data from cervical myelography. The easiest way to obtain this information is to ask the physician for his interpretation of the myelogram,
with certainty measures associated with his findings, as in the example of Fig. 5.26. From this example it has become clear, however, that it is not at all obvious how to reason with this information. The cause for this is the poor interpretability of the quantified certainty measures, partly due to the fact that a single measure represents the summation of several sources of uncertainty. This same problem can be avoided by qualification of the information. For instance, the physician could be asked for which spinal roots he is definite the fila radicularia are visible, and for which the fila radicularia are definitely not visible. The former allowing straightforward evaluation of rule 2 (Fig. 5.26), the latter similarly permitting the increase in the certainty factor of rule 1 to a value of +0.90 or even 1, making the system more transparent. A third category, e.g. 'Which spinal roots are dubiously visible?', could be used for reasoning along alternative lines, for instance by looking for additional information to indicate or contradict an avulsion of the spinal root.

combining evidence

The methods discussed here, which have been implemented in PLEXUS, aim at reliably converting data to evidence. Once this evidence has been gathered, the uncertainty in the suggestive strength of each piece of evidence for each hypothesis remains to be modeled explicitly. This uncertainty can be modeled in a way similar to the objectification of uncertain information by making the uncertainty explicit instead of quantifying it. For that purpose, in PLEXUS all evidence has been classified for each hypothesis, objectively fastening down the evoking or disconfirming strength of the evidence for each hypothesis. In this domain, a classification into five categories proved to be sufficient to explicitly model the uncertainty:

1. Triggering facts.
3. Exclusionary facts.
4. Corresponding facts.
5. Irrelevant facts.

Figure 5.27 shows how a piece of evidence may be adequate to exclude a certain hypothesis, whereas it is inadequate to prove other hypotheses.
In this classification, not only the evoking strength of single pieces of evidence has been scored, also relevant combinations of symptoms, which may constitute evidence for a different hypothesis than each symptom alone, have been classified. For example, loss of function in the region of spinal roots C8 and T1 in combination with a clavicle fracture suggests a costo-clavicular crush lesion of the lower trunk when exclusionary evidence is absent for this hypothesis, instead of extraforaminar injury to the roots. In this way the predictability of the system's behavior is much improved compared to systems relying on ad hoc numerical methods. Also, the transparency of the system benefits from this classification of evidence, since it clearly shows the relation of each piece of evidence to each hypothesis. More specific clinical findings suggest more specific hypotheses and rule out others, which has been shown to be an important part of expert physician decision making (Sect. 4.2.1). The resulting diagnostic strategy of activation and evaluation of hypotheses in combination with the refinement task bears good resemblance to the physician's reasoning strategy. A classification as in PLEXUS serves the purpose of the necessary structuring of medical diagnosis. Due to this structuring, uncertainty has been made more explicit compared to ad hoc measures.

5.4.4 Discussion

In this section, different methods have been proposed to deal with each of the sources of uncertainty: incompleteness of knowledge, uncertain knowledge and uncertain information. An excellent monograph on non-numerical models of uncertainty has been published that extends the ideas presented in this section much further (Cohen, 1985). Cohen describes the representation of uncertainty in endorsements, as well as the propagation of these endorsements through inference. An AI program, SOLOMON, based on these concepts is introduced. A subject related to uncertainty is that of how to deal with incomplete information. For every reasoning system, there is a minimum amount of information required to be able to achieve a conclusion. In the reasoning process it has to be assured that this minimum is indeed available, or the system should not present a conclusion. In PLEXUS this is taken care of by the 'check procedure' task. Dependent on the findings in a specific case, this task determines what information is necessary to achieve reliable advice.
Chapter 6
Results of the knowledge based approach to decision support

6.1 INTRODUCTION

Evaluation and testing of the medical knowledge based system PLEXUS are important to determine whether the theories that underlie the system's design work and to assess the level of expertise that is reached by the system. Since in most knowledge based systems knowledge has been separated from the inference engine they allow separate testing of both system parts. In this chapter, evaluation and testing of the PLEXUS knowledge base and the choice of the Delfi2+ shell will be executed. As described in Ch. 6, the phenomenon of incompleteness of domain knowledge often leads to the use of heuristics. This is a specific feature of knowledge based systems compared to traditional software. This incomplete knowledge hinders the specification of system requirements, which in turn hampers testing of the system. The incorporation of this incomplete knowledge in the form of heuristics makes predicting the system's behavior very difficult. Therefore, a system's knowledge content and knowledge representation have their effect also on the evaluation of the system. In Ch. 8 of 'Building Expert Systems', Gaschnig et al (1983) stress the importance of evaluation in building expert systems. They summarize the aspects to evaluate:

1. The quality of the system's decisions and advice.
2. The correctness of the reasoning techniques used.
3. The quality of the human-computer interaction.
4. The system's efficiency.
5. The system's cost-effectiveness.

After Wyatt and Spiegelhalter (1989), the quality of advice can be thought to involve the following questions:

- Can the system detect cases which are odd or beyond its margins?
- Does the system make serious mistakes within its domain?
- Compared to current practice, how accurate are the system's judgments?

The correctness of the reasoning techniques is important for the explanatory capabilities of the system. If the system aims at teaching problem-solving
strategies to the user, it may even be necessary that it mimics expert problem-solving reasoning.

In this chapter, an endeavor will be made to achieve a structured evaluation of PLEXUS.

In evaluating medical knowledge based systems, tests of the system's functionality are related to the desired quality of the system. Therefore, what aspects to evaluate and how to evaluate them, depends to a large extent on the role the system is meant to play in medical consultation.

The aim of PLEXUS in the management of brachial plexus injuries has been derived from the need for support in this domain (Sect. 2.5). The resulting role of the system in medical consultation has been elucidated in Sect. 5.2. Briefly, the aim is to improve treatment of brachial plexus injuries by supplying diagnostic and treatment advice to non-expert physicians, and especially aiding the diagnostic procedure by assuring that the right examinations are performed and by preventing the execution of superfluous or dangerous diagnostic tests.

In assessing the results of PLEXUS two areas will be distinguished:

1. Acceptance and maintainability properties.
2. The level of expertise.

Acceptance and maintainability properties of a knowledge based system, such as efficiency, transparency, predictability etc., to which attention has been called in Chs. 4 and 5, roughly correspond to aspects 2 - 5 from Gaschnig et al (1983).

In order for a medical knowledge based system to be accepted by its users, it should meet requirements in four different areas (Van Daalen, 1988):

1. There has to be a demonstrated need for support in the domain the system is designed for, and this need has to be recognized by its potential users.
2. The system should meet user-friendliness requirements, concerning issues such as the course of interaction with the system, the speed of a consultation and explanation facilities.
3. In dealing with the problems in its domain, the performance of the system should be good.
4. Legal, psychological and financial factors have to be considered.

These issues will receive attention in the subsequent sections. First, attention will be given to the need for support in the brachial plexus domain (Sect. 6.2). Acceptance issues concerning user friendliness will be separated into transparency aspects (Sect. 6.3) and efficiency aspects (Sect. 6.4). Results concerning the level of expertise reached by the system, corresponding to aspect 1 from Gaschnig et al, will be discussed in Sect. 6.5. Clearly, a system may be very efficient and transparent, however, it will be of no value if it fails to give accurate and reliable advice, or fails to present that advice in a cost-effective manner, or if it fails to convince intended users of its quality.

Legal and psychological, as well as financial aspects are somewhat outside the scope of this thesis. They will be discussed briefly in Sect. 6.6. A more thorough discussion can be found in Van Daalen (1988).

Maintainability of a medical knowledge based system requires a well structured, modular design with a good transparency and predictable system behavior. Whether PLEXUS meets these requirements will be discussed in Sect. 6.3.

All aspects presented here have to be assessed at two levels, i.e. in a laboratory or paper test, as well as in a field trial. Presently, such field trials are being conducted in the Leiden University Hospital and in the De Wever Hospital in Heerlen. For those aspects that can already be assessed, preliminary results of the field trial will be presented in the subsequent sections.

6.2 NEED FOR SUPPORT

The need for support in the domain of brachial plexus injuries has been demonstrated in Sect. 2.5. To reveal whether this need is recognized by the potential users, an inquiry was conducted among 69 Dutch neurologists managing brachial plexus injuries (Grolman, 1989). The response to this inquiry was poor, of 69 neurologists, 22 (31%) returned the questionnaire. As a consequence, the results of this inquiry have to be interpreted with the
Table 6.1 Results of an inquiry among 69 Dutch neurologists.

<table>
<thead>
<tr>
<th>Question</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>very/</td>
</tr>
<tr>
<td></td>
<td>fair/</td>
</tr>
<tr>
<td></td>
<td>poor/</td>
</tr>
<tr>
<td></td>
<td>no</td>
</tr>
<tr>
<td></td>
<td>not</td>
</tr>
<tr>
<td></td>
<td>answered</td>
</tr>
<tr>
<td>Number sent out</td>
<td>67</td>
</tr>
<tr>
<td>Number of respondents</td>
<td>22 (31%)</td>
</tr>
<tr>
<td>Decision support system useful</td>
<td>14 (64%)</td>
</tr>
<tr>
<td>Would use decision support system</td>
<td>13 (59%)</td>
</tr>
<tr>
<td>Computing experience</td>
<td>8 (36%)</td>
</tr>
<tr>
<td>Expects problems for introduction</td>
<td>2 (9%)</td>
</tr>
</tbody>
</table>

greatest care. Respondents do not constitute a random selection of Dutch neurologists. However, results may still provide some indications for further research. Answers indicate that potential users seemed to be mildly aware of the need for support in the management of brachial plexus injuries (Tab. 6.1). Neurologists tended to find the management of these injuries very complex. Of 22 respondents, 14 (64%) indicated that a decision support system would be very or extremely useful. They felt such a system in improving diagnosis and treatment of these injuries and in guiding the diagnostic procedure has good potential. Three respondents (14%) found a decision support system useful. Four (18%) found it only moderately useful, or even awkward to use. One respondent (5%) did not answer the questions related to this subject. Respondents that found a decision support system only moderately useful or awkward, indicated that brachial plexus injuries do not occur frequently enough to justify the use of such a system, or they already treated these injuries in a multidisciplinary team, making the need for a decision support system less essential.

Thirteen respondents (59%) indicated that they would probably make use of a decision support system for diagnosing brachial plexus injuries, whereas 7 (32%) said they would not use it. An important reason for the reserve in connection with using a decision support system may be the fact that only 8 respondents (36%) had experience in working with computers. Twelve respondents (55%) expect difficulties with the introduction of a decision support system in daily practice. The most important difficulties expected are:
Results of the knowledge based approach to decision support

- It will be hard to get used to working with computers.
- A decision support system must not hamper a physician's independence.
- Use of a decision support system would be time consuming.
- The quality of the knowledge in the system must be assessable and it must be possible to trace where the knowledge comes from.

To overcome these problems, it requires the following acceptance requirements concerning the human-computer interaction to be fulfilled (Van Daalen, 1988):

1. Flexibility of the dialogue, possible by means of graphical I/O facilities.
2. Efficient dialogue that is not very time consuming.
3. Possibility for the user to generate his own solutions.
4. Good explanation facilities on several levels of detail.

The first two of these requirements can partly be overcome by incorporation of a database facility that allows the consultation system to run in the background, as in the case of PLEXUS. From the global architecture presented in Fig. 5.24, it will be clear that interaction with the PLEXUS system is guided by the user interface. This is a simple I/O interface that allows the inspection of patient files, the editing of patient files or the making of new patient files through structured questioning and answering. Also it takes care of the communication for consultation of the system and explanation to the user, based on the well-known 'why' and 'how' facilities of the Delfi2+ shell. Compared to the acceptance requirements presented by Van Daalen (1988) these possibilities are rather limited. This is also clearly indicated by physicians cooperating in the field trial, who find user friendliness still unacceptable. Presently, work is being conducted on making this interface more flexible, incorporating graphical I/O facilities (Grolman, 1989), better explanation facilities (Van Daalen and Jaspers, 1989a), and possibly allowing critiquing (Ter Haar, 1989). A prototype graphical interface has been finished (Fig. 6.1). Its merits have already been assessed in preliminary tests by the experts cooperating in the project. However, this prototype still needs to be tested in a clinical evaluation. Man machine interfaces for medical knowledge based systems are a research subject on their own (Van Daalen et al, 1989b). Nevertheless, the possibilities for improving the interaction, speed of consultation and explanation, depend to a large extent on the transparency and
Figure 6.1 Example screens from the prototype graphical interface.
Results of the knowledge based approach to decision support

Figure 6.1 (continued).
efficiency of the knowledge based system. These issues will be discussed in Sects. 6.3 and 6.4.

6.3 TRANSPARENCY

The transparency of the system has to do with its architecture, its knowledge content and with the way knowledge is represented and is used for reasoning. The modular architecture of PLEXUS (Fig. 5.25) facilitates a good insight into its structure. Knowledge content involves structural knowledge, e.g. the anatomy, causal relations represented in nerve-muscle relations, for instance, and strategic knowledge represented in production rules.

anatomical knowledge

Brachial plexus anatomy has been represented in two different ways in the knowledge base. It is present as a global model of three nerve clusters in the second data abstraction task, and as a binary network in the refinement task. The representation of muscle fields in the cluster model, instead of individual muscles, is closely related to the experts' data abstraction based on the muscle matrix (Sect. 5.3.1). Also, it makes the first localization stage robust for individual variations in brachial plexus anatomy. In the refinement task, anatomy has been represented in a matrix of detailed nerve-muscle relations. This matrix is very suitable for use as a basis for deeper explanation of the anatomical knowledge. Both kinds of anatomical knowledge have been represented in external tasks of the knowledge base. However, for explanation on both deep and surface levels, they can easily be made explicit.

causal nerve muscle associations

Just as the anatomical knowledge, causal nerve muscle associations have been represented at two different levels, i.e. at a global level of causal associations between muscle fields and nerve clusters in data abstraction, and at a deep level of causal associations between individual nerves and muscles. Again, the global level makes the system more robust for anatomical variations. In the refinement task, however, the deep level is necessary in order to allow the determination of a more specific diagnosis.
Results of the knowledge based approach to decision support

diagnostic strategy

The diagnostic strategy is determined by the classification of evidence in the heuristic match task and the search strategy of the AKT algorithm in the refinement task. After data abstraction, first triggering rules will activate hypotheses about the global location of the lesion, i.e. whether the lesion is supraclavicular or infraclavicular. In this stage, two-level lesions are not triggered. As mentioned before, the redundancy in the brachial plexus anatomy makes it impossible to simultaneously localize injuries at two levels in this early stage when the number of possible solutions is still very large. Once the global level of the main injury has been determined, smaller injuries at the other level may be concluded by means of additional evidence. This strategy is consistent with experts' localization strategy as revealed in interviews. Inherently this means that, similar to the experts' results, PLEXUS can not always localize all two-level injuries. This problem can not be avoided, however, since the anatomy of the brachial plexus and the nature of the available diagnostic examinations make it impossible to pre-operatively localize all two-level injuries. Injuries more distally in the brachial plexus will be masked by more proximal injuries. Thus these can only be revealed by exploration of the plexus.

After the global level of the injury has been determined, the number of possible solutions is decreased further by exhaustive application of other triggering and pruning rules. This leads to a number of locations that are potential candidates for the final diagnosis. In the refinement task, the AKT algorithm subsequently evaluates these potential locations at a deeper level to determine the actual diagnosis. A typical example of this reasoning process and the resulting diagnostic and treatment advice and some messages to the user are presented in Fig. 6.2 for patient 47.

treatment strategy

The location of the brachial plexus injury, which has been determined in the diagnostic module is recorded in the patient file at the end of a consultation. In the treatment module of PLEXUS, this location which consists of a combination of injuries that may be both on the supraclavicular and on the infraclavicular level is the basis for treatment planning. Often, infraclavicular injuries are comparatively mild and show a good natural
Patient 47: An example of the reasoning process and the resulting advice.
Results of the knowledge based approach to decision support

NEUROANATOMY

examinations

physical examination

radiology

motor function

myelography

not visible

supraclavicular

trigeminal

trochlear

tinnel

EXAMINATIONS

supraclavicular

Horner

defect

confirm

RESULT OF FOCUSING AFTER EVALUATION, I.E. INPUT TO REFINEMENT (AKT)

11 12 10 7 5 3

22 36 8 35 34 1

18 16 17 15 14 13

23 59 21 28 38 20 31 37 19 52

24 25 29 26 40

27

× status defect
□ status intact
○ status unknown

resulting array after focusing

1 0 1 0 1 0 ? 1 ? 1 ? 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

LOCATION AFTER REFINEMENT

trunks

postganglionic

avulsed
troots

sup

med

inf

4–5

SEVERITY

TREATMENT

conservative

nerve graft

transfer

neurolysis

Patient 47 (continued).
FACTS ADDED BY PLEXAKT
the diagnosis for supraclavicular lesions:
- avulsion_c7
- avulsion_c8
- avulsion_tl
- truncus_superior
the diagnosis for peripheral supraclavicular lesions:
- none
the diagnosis for infraclavicular lesions:
- none
the examinations which are required for an exact diagnosis:
- check_sign_of_Tinel
has a not exactly diagnosed avulsion....: FALSE
has a not diagnosed postganglionair lesion : FALSE
the plexus brachialis.................: according_to_standard_anatomy
has a two_level lesion................: FALSE

REMARKS MADE BY PLEXAKT

Because of the fact that there is no activity in the m.infraspinatus, I have decided that the measured activity in the m.supraspinatus is due to an artefact from the m.trapezius.

The side towards which the Tinel-Hoffman sign is radiating is an important clue for the location of the postganglionair lesion. I would advise you to check again towards which side the Tinel-Hoffman sign is radiating.

FACTS ADDED BY TREAT
the treatment:
- supraclavicular_surgical_treatment
- supraclavicular_conservative_treatment
the operation:
- nerve_graft
the recommended time for operation: as soon as possible
the nerves that show natural recovery:
- none
- not_truncus_superior
the nerves that may recover:
- none

Remarks made by TREAT

A nerve graft will be recommended in this case. The results of this operation will not be very good, although there is a chance that some function may return. It is, however, a major operation [Narakas].

Conservative treatment will also be recommended, because some surgeons consider the chances of any function returning too small to attempt an operation [Thomeer].

Patient 47 (continued).
Results of the knowledge based approach to decision support

recovery, whereas supraclavicular injuries are mostly more severe. Because of this, these different types of injury often require different treatment (Leffert and Seddon, 1965). Therefore, in PLEXUS, these injuries are dealt with separately. The site of the injury derived from the diagnostic support module has already been split up into a supraclavicular and an infraclavicular part. For each part, in the treatment planning module, the severity of the injury and the possibilities for natural recovery are determined, based upon information from more recent tests. Once site and severity are known, in the heuristic match task each part of the injury suggests an optimal treatment plan. In some cases it is impossible to establish an optimal treatment plan, due to differences in opinion among the experts. This is particularly true for a subset of the supraclavicular injuries, i.e. those cases that solely present nerve root avulsions. In these cases alternative treatment schemes are established. Once a treatment plan has been established for the supraclavicular and for the infraclavicular part of the injury, the final treatment plan for the total injury is derived by evaluating the priorities for each treatment scheme in the prioritization task. Of course, the final treatment plan may still consist of alternative treatment schemes, due to differences in opinion.

conclusions concerning transparency

From the foregoing it will have become clear that the PLEXUS knowledge base has been very modularly organized (Fig. 5.25), which very much facilitates transparency. Also, it is felt that the way the different tasks have been designed and implemented makes this knowledge base transparent and results in a strategy that is closely related to the physician's reasoning strategy. Another aspect concerning system architecture and knowledge content is of importance. The heuristic match task and the successive refinement task, not only make the reasoning process mimic physician reasoning, they also provide a reasoning strategy on a higher level of abstraction than that of the implementation language level, benefiting transparency. Even more important may be that the classification of evidence explicitly lays down the associative strength of each piece of evidence for a certain hypothesis. This important transparency aspect may prove very valuable in the explanation of the system's reasoning and the justification of its advice.
Strategic surface knowledge can be very transparently represented in production rules, whereas this representation method is very unsuitable to represent structural knowledge, e.g. anatomical knowledge. Representing this anatomical knowledge in nerve-muscle relations again makes refinement transparent.

This combination of surface strategy and deep knowledge allowed a structured design of the system. Experience with surface systems has shown that the incremental growth of the knowledge base for improving system performance is practically unending due to the ongoing acquisition of surface heuristics to make the knowledge base complete. Because of the combination of these heuristics with deep level knowledge, the criterion for ending this process is not the quality of the system's advice but system efficiency, so it can be stopped whenever efficiency is found satisfactory. Also, limiting the amount of surface knowledge reduces the problem of interaction of knowledge, which is very beneficial to the maintainability of the system. Adding new knowledge in surface systems can have detrimental effects on performance due to unanticipated interactions of knowledge. The objective classification of evidence in PLEXUS and the use of surface heuristics for focusing only, make this problem less urgent.

The treatment planning module solely consists of surface heuristics derived from human experts and from literature. In this case, the process of acquiring this knowledge has been rather limited, since treatment planning is relatively straightforward compared to localization.

It should be mentioned here, that the CHECKERBOARD module of the PLEXUS knowledge base, consisting of pattern recognition rules, is not very transparent as yet. These rules relate global muscle function to a global location of the injury. As was mentioned in Sect. 5.3.1, the nature of this very procedural task makes it hard to find a more transparent representation. Two more aspects concerning the rule based parts of PLEXUS need to be reconsidered concerning the transparency issue. First of all, it should be realized that the diagnostic hierarchy of hypotheses (Fig. 5.2) plays a very important role in the diagnostic strategy. However, nowhere in the knowledge base, is this diagnostic hierarchy explicitly present. Also, the classification of evidence that strongly relies on this implicit hierarchy is only implicitly represented itself in triggering, pruning and evaluation rules as well as in object definitions (Fig. 5.14). These observations
Results of the knowledge based approach to decision support

indicate the major weaknesses concerning the transparency of this representation of brachial plexus management knowledge. In Sect. 6.6 what has been done to improve the knowledge base in this respect will be indicated.

6.4 EFFICIENCY

As has been made clear in foregoing chapters, the efficiency of a knowledge based system is determined mainly by the level at which the domain has been modeled in the knowledge base, the way deep and surface knowledge structures interact and the size of the knowledge base. From the efficiency point of view, the application of surface knowledge is to be preferred over deep knowledge. However, for the sake of structured design, transparency and maintainability of the knowledge base, as well as the predictability of system behavior, the incorporation of deep knowledge is necessary. An important concept underlying the design of PLEXUS has been that the combined application of deep and surface knowledge will be capable of yielding the right balance between expressiveness and efficiency. Expressiveness issues have been discussed in the previous section. However, it remains to be shown whether this concept suffices for efficiency. For that purpose, three different systems for localizing brachial plexus injuries will be compared.

First of all, the results of a system solely relying on surface knowledge represented in production rules will be presented. This system, which in the following will be called the surface system, is essentially the same as the PLEXUS system described in the previous chapter except that it lacks the refinement task and the heuristic triggers based on the second data abstraction stage, i.e. the checkerboard triggers. In this system, the determination of the final diagnosis is taken care of at a surface level also, in production rules.

Secondly, a deep system was conceived of, solely consisting of the 38 nerve-muscle relations that have been presented in Ch. 5. This system does not apply any surface strategy or hierarchy apart from the localization strategy represented in the $A^{KF}$ algorithm, but solely reasons with motor function results to find a solution. It is very similar to the small system of the example of Fig. 4.7 (Sect. 4.3.4).
Table 6.2  Efficiency results for the surface and the hybrid system.

<table>
<thead>
<tr>
<th>Specificity of evidence</th>
<th>Number of cases</th>
<th>Mean time for consultation [s]</th>
<th>Std.dev. [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount of dysfunction/ Site of lesion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SURFACE SYSTEM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>little dysf, supraclav.</td>
<td>0</td>
<td>1</td>
<td>21.0</td>
</tr>
<tr>
<td>medium dysf, supraclav.</td>
<td>1</td>
<td>23.0</td>
<td>2</td>
</tr>
<tr>
<td>much dysf, supraclav.</td>
<td>0</td>
<td>2</td>
<td>23.5</td>
</tr>
<tr>
<td>little dysf, infraclav.</td>
<td>1</td>
<td>19.0</td>
<td>0</td>
</tr>
<tr>
<td>medium dysf, infraclav.</td>
<td>3</td>
<td>21.7</td>
<td>1.7</td>
</tr>
<tr>
<td>HYBRID SYSTEM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>little dysf, supraclav.</td>
<td>0</td>
<td>1</td>
<td>47.0</td>
</tr>
<tr>
<td>medium dysf, supraclav.</td>
<td>1</td>
<td>52.0</td>
<td>2</td>
</tr>
<tr>
<td>much dysf, supraclav.</td>
<td>0</td>
<td>2</td>
<td>45.5</td>
</tr>
<tr>
<td>little dysf, infraclav.</td>
<td>1</td>
<td>50.0</td>
<td>0</td>
</tr>
<tr>
<td>medium dysf, infraclav.</td>
<td>3</td>
<td>51.7</td>
<td>2.6</td>
</tr>
</tbody>
</table>

Efficiency results for these two systems will be compared to PLEXUS, which will be called the hybrid system since it combines surface strategy with deep reasoning in the refinement task. In contrast to what has been described in Ch. 5, both in the hybrid system and in the deep system, for purpose of efficiency, deep knowledge has been represented slightly differently. Instead of reasoning from an initial state in which all locations are intact, which seems to be the most natural choice, candidate generation strategy has been chosen such that in the initial state all locations are defect. Successively, children are generated that have one or more locations intact. Due to the parsimony rule and the heuristic function that have been incorporated it
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benefits efficiency, since in serious cases with many parsimonious locations defect, like injured roots, trunks or fascicles which constitute the majority of cases in the Dutch series, evaluation can be stopped early. In these cases it will be found that further exploration of the solution will not improve it so the search path can be cut off. This is the more true for the hybrid system, where the surface strategy focuses on only a few locations that remain to be evaluated by means of deep knowledge. In practice, a relatively large number of these remaining locations prove to be injured so that reasoning from an initial state with all locations defect is more efficient.

The surface system localization knowledge base consists of 1154 production rules in Delfi2+. This system applies the same classification of evidence that has been described in Sect. 5.3.2 in combination with the forward and backward chaining inference mechanism of Delfi2+. The hybrid system knowledge base is about the same size, containing 1141 rules, plus the 38 nerve-muscle relations. The number of rules is this high because an extra data abstraction stage has been incorporated for reasoning with motor function results and the trigger strategy has been extended with the matching checkerboard triggers to increase efficiency. The Delfi2+ shell allows the compilation of the rule bases to intermediate code to improve efficiency. This feature has been employed in the efficiency tests. The deep system knowledge base is very small, consisting of 38 nerve-muscle relations with the matching reasoning strategy implemented in the A^T algorithm.

Efficiency tests have been run on a SUN 3-60 workstation with 8 MB RAM. In the following discussion, the results of the surface system will be used as a standard to compare the efficiency results of the other two systems.

Table 6.2 shows the results of the surface and the hybrid system on a retrospective test of 10 patients from the Leiden University Hospital. These patients had been selected to represent many different kinds of injury, i.e. supraclavicular as well as infraclavicular, either with many specific diagnostic findings or without specific findings and with different levels of motoric dysfunction. If the patient had been operated on, the system's advice was compared with the peroperative diagnosis. Due to the different realization of the refinement task in each system, sometimes differences occurred in the final diagnosis presented by the systems. In these cases the advice of the hybrid system always corresponded better to the expert's diagnosis. This
Table 6.3 Efficiency of the deep refinement task.

<table>
<thead>
<tr>
<th>Dysfunction</th>
<th>Mean time for consultation [s]</th>
<th>Std.dev. [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of cases</td>
<td>little</td>
</tr>
<tr>
<td>SUPRACLAVICULAR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>INFRACLAVICULAR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

phenomenon will be illustrated in Sect. 6.5. However, most often both systems arrived at similar advice.

6.4.1 Comparing the surface and the hybrid system

From Tab. 6.2 the effect of the different implementations of the refinement task becomes clear. First of all, the surface system proves to be about 2.5 times faster than the hybrid system. Moreover, it can be seen that the surface system is not very sensitive to the specificity of the available evidence or the amount of motoric dysfunction.

The hybrid system, on the contrary, shows some sensitivity to the amount of
dysfunction and to the specificity of the evidence. This can be easily understood. The specificity of the evidence determines the number of potential locations which remain to be evaluated by the deep refinement task. The more locations remaining after focusing, the less efficiently the system operates. In this test series, the number of locations that remained to be evaluated after focusing had taken place ranged from 2 to 18 locations of the total number of 41 locations present in the nerve-muscle relations (Tab. 6.3). Regarding the sensitivity to the amount of motoric dysfunction a similar explanation holds. As described at the beginning of this section, in view of efficiency, the deep refinement task has been implemented in such a way that it starts from an initial state in which all locations that have to be evaluated are defect. This improves efficiency for those cases that have a large amount of motoric dysfunction, and thus have many defect locations. However, this also means that the efficiency decreases for those cases in which only few of the remaining locations are defect.

Although the hybrid system takes substantially longer to evaluate a patient the increase seems to be within acceptable bounds. It should be noted that the results presented in Tab. 6.2 refer to the total time necessary for a consultation. This includes I/O, e.g. reading the patient file and writing the advice, data abstraction, consistency checking etc. This accounts for a large part of the increase in time in the hybrid system, since due to the fact that data abstraction and refinement have been implemented in external modules, separate from the rule base, much more time is needed for communication among these modules.

6.4.2 The deep system

The results of the deep system could not be scored for a large number of patients. To diagnose a device as complex as the brachial plexus, with its 41 locations, by means of deep reasoning is known to be very inefficient due to the combinatorial explosion of the number of potential solutions to be evaluated. Therefore, instead of consulting the deep system for 10 patients, the effect of the number of locations, 1, to be evaluated, which is a measure for the number of potential solutions, S(1), has been tested:
It is well known that the combinatorial explosion of the number of solutions has to be avoided by introducing a hierarchy in the search space to focus reasoning. In the hybrid system this focusing is taken care of by surface strategy. The effect of abandoning this surface strategy can be seen in Fig. 6.3. Here the time required to evaluate a certain case with varying numbers of unknown locations is depicted. From this figure it is clear that this time rapidly increases with the number of unknown locations. If deep localization would be performed by a search algorithm that does not employ a heuristic function, this time would be doubled each time an extra location has to be evaluated. However, due to the poorly predictable effect of the heuristic function in the search strategy, this time is less than doubled. For this specific patient, this effect is demonstrated nicely in the area between 18 and 22 unknown locations. Here the cpu-time needed for a consultation remains constant, due to the fact that the last five unknown locations are peripheral nerves that are innervated via the same fasciculus. From Fig. 6.3 it can be calculated that the time necessary to evaluate all 41 locations of the brachial plexus network would be somewhere in the range of 2 to 250 days.

![Figure 6.3 Efficiency of deep refinement, plotted against the number of unknown locations.](image-url)
6.4.3 Conclusion

When we compare the results of the deep system to those of the hybrid system, we see that the efficiency effect of focusing is dramatic. This becomes evident from Tab. 6.3. In this table, the number of unknown locations after focusing and the actual cpu-time required for deep reasoning in the hybrid system, without I/O etc., for two classes of motoric dysfunction in supraclavicular injuries, and for infraclavicular injuries, measured for 19 real patients is depicted. For supraclavicular injuries the number of unknown locations is small, 3-6, except for one patient, for whom no specific evidence was present which resulted in 10 unknown locations. For infraclavicular injuries such specific evidence is hardly ever present. Therefore, in deep reasoning all 18 infraclavicular locations have to be evaluated. In these cases the effects of the parsimony rule and the heuristic function again become evident. In one patient, the right solution is achieved rapidly (0.9 s.), due to the fact that this solution only consists of one location. This solution can easily be found by the evaluation strategy because of the application of the heuristic function that soon cuts off the search process. From these results it becomes clear that the deep refinement task is important especially in the cases that do not provide much specific evidence to be used for focusing, particularly the infraclavicular injuries. Another aspect of the deep system, and of the refinement task in the hybrid system, that can be evaluated is the idea that these systems are more efficient for cases with much motoric dysfunction. This effect is demonstrated in Tab. 6.3 also, for supraclavicular and for infraclavicular injuries.

As has been discussed in Ch. 5, treatment planning knowledge necessarily has to be on surface level due to the fact that this knowledge is very incomplete. Therefore, evaluation of efficiency for different levels of knowledge, as has been done for localization reasoning, is impossible. The treatment planning system consists of 1218 production rules. In Tab. 6.4 the efficiency results for the treatment planning surface system are presented.

6.5 QUALITY OF ADVICE

A need for support in the domain of managing brachial plexus injuries has been
Table 6.4 Efficiency results for the treatment planning system.

<table>
<thead>
<tr>
<th>Number of patients</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean time for consultation [s]</td>
<td>Std.dev. [s]</td>
</tr>
<tr>
<td>18.9</td>
<td>1.6</td>
</tr>
</tbody>
</table>

Figure 6.4 The system life-cycle in classical software development.

demonstrated. Also, it has been shown that the PLEXUS system developed for this purpose is sufficiently transparent and efficient to make it acceptable and maintainable. A remaining question is whether this system achieves its goals, i.e. will it make a significant contribution to improving diagnosis and treatment of brachial plexus injuries?

In classical software development, the system life-cycle (Fig. 6.4) plays an important role in system development. It provides a framework for developing a system but is not at all sufficient to assure that the resulting system will meet its requirements. Especially for complex systems, it is necessary to emphasize testing and evaluation of the system in each stage of development, and to have feedback in the development process for the early recognition of and recovering from faulty design or implementation decisions. This calls for an iterative life cycle instead of a sequential method as shown in Fig. 6.4. The KADS system mentioned in Sect. 4.4 provides a framework for developing knowledge based systems. However, this methodology also aids in analysis and design in particular and does not support testing and evaluation of the system under development.
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Wyatt (1987) proposes a cycle for medical knowledge based system development in which evaluation plays a predominant role (Fig. 6.5). In his view there are certain similarities between the evaluation of new drugs and that of medical knowledge based systems. The proposed life-cycle reflects this view. The evaluation of PLEXUS' quality of advice has been conducted in a way similar to that described by Wyatt. Therefore, the results of this evaluation will be presented along the lines of this cycle. First, the results of the training set used in system development will be demonstrated, subsequently that of two different test series and finally a field trial will be given attention.

Figure 6.5 Cycle of medical knowledge based system development (Wyatt, 1987).
6.5.1 The gold standard

From evaluations of MYCIN (Yu et al, 1979), two important lessons can be learned. First of all, there is the need for an objective 'gold' standard to which the results of the system can be compared. Usually in evaluating medical decision support systems, the real objective standard is the result of invasive procedures, like exploration of the brachial plexus. Often, these standards are not available. In these cases human experts are chosen as the standard to which the system is compared. Then, a second lesson from MYCIN's evaluations becomes even more important. To avoid biasing in such an evaluation study, care has to be taken that a blind study design is provided for.

In scoring the results on the training set and on the first paper test set, the standard was defined to be the operative findings, if an exploration of the patient had been carried out. If the patient had not been operated on, a less objective standard had to be turned to. Then, the expert's diagnosis and treatment plan were taken to be the correct standard. In these two tests evaluation was done retrospectively on patients that had been treated in the Leiden University Hospital.

Unlike many other systems, PLEXUS only presents one advice so as not to leave the decision as to the actual diagnosis or the best treatment plan to the user. Because of this assessing the quality of advice is much easier than assessing it for systems that present a number of alternatives.

To get a better insight into the level of expertise reached by the system in comparison to the human experts, a new evaluation study was devised. In this test, a blind comparison, i.e. a Turing Test (Turing, 1950), was conducted in which both the human expert and the knowledge based system were presented the same patient data and their advice was judged by the second expert. O'Keefe et al (1987) indicate that validating a system by comparing its results to those of the experts on whose knowledge it was built is of dubious value. When validating PLEXUS, however, no other test cases were available than those of the experts'. In view of this observation more extensive evaluation of the system is called for, possibly by using international test cases. However, knowledge from international experts, extracted from literature and from personal communication, has also been incorporated in the system. Moreover, knowledge from Dutch experts does not seem to deviate
Results of the knowledge based approach to decision support substantially from that of international experts (Lausanne, 1987). Nevertheless, further validation of the system remains a point of concern.

6.5.2 Performance results

In the training series and the first test series the first question concerning the quality of advice: 'Can the system detect cases which are odd or beyond its margins?' was not formally addressed. The classification of evidence, i.e. the avoidance of the use of ad hoc certainty measures and the consistency checking of the input data, make the system robust to changes in these data as well as to slight change in the knowledge content. The checking of the diagnostic procedure takes care of determining whether determining a diagnosis and treatment plan, based on the input data is possible. The first test series showed that it functions well. A more detailed discussion will be presented in the section on results of the Turing Test.

results on the training series

The training series consisted of 1 injury due to irradiation and 34 traumatic brachial plexus injuries. Of these, 28 were supraclavicular injuries, 17 of which had been neurosurgically reconstructed, 3 were infraclavicular, 1 of which had been operated on and 3 were two-level injuries, which had all been operated on. The results of these patients have been presented in Tab. 6.5. The following criteria have been used:

- The system's advice is judged good if it corresponds to the standard.
- The system's advice is judged fair if it only slightly deviates from the standard or if, in the case of treatment planning, it presents deviations that were implemented on purpose.
- In all other cases the advice is judged poor.

From Tab. 6.5 it becomes clear that concerning localization, the system's advice is good in all cases, except for two of the three two-level injuries which are diagnosed only fairly. As has been described in previous chapters, these two-level injuries can often not be diagnosed pre-operatively due to the
Table 6.5 Results on the training series.

<table>
<thead>
<tr>
<th>Quality of advice</th>
<th>poor</th>
<th>fair</th>
<th>good</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kind of injury/Treatment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>PLEXUS LOCALIZATION</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supraclavicular operative</td>
<td></td>
<td></td>
<td>17 (49%)</td>
</tr>
<tr>
<td>conservative</td>
<td></td>
<td></td>
<td>11 (31%)</td>
</tr>
<tr>
<td>Infraclavicular operative</td>
<td></td>
<td></td>
<td>1 (3%)</td>
</tr>
<tr>
<td>conservative</td>
<td></td>
<td></td>
<td>2 (6%)</td>
</tr>
<tr>
<td>Two-level operative</td>
<td>2 (6%)</td>
<td>1 (3%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2 (6%)</td>
<td>32 (94%)</td>
<td></td>
</tr>
</tbody>
</table>

| **PLEXUS TREATMENT** |      |      |      |
| Supraclavicular operative | | | 17 (49%) |
| conservative | | | 3 (9%) |
| Infraclavicular operative | | | 8 (23%) |
| conservative | | | 1 (3%) |
| Two-level operative | | | 1 (3%) |
| Total | | | 4 (12%) |
| | | | 30 (88%) |

redundancy in the brachial plexus. In this respect it should be noted that the expert diagnoses two-level injuries per-operatively.

Concerning treatment planning, from the same table it is clear that here also the results are rather good. Differences between PLEXUS and the expert's treatment plan occur in cases for which the expert adopts a more conservative strategy, whereas PLEXUS chooses for a more progressive, i.e. operative approach (Tab. 6.6). This difference has been deliberately implemented in the PLEXUS system, because it had to be assured that each patient that might be considered for neurosurgical repair be seen by the expert. Advising a surgical
Results of the knowledge based approach to decision support

Table 6.6 PLEXUS treatment advice on the training series compared to the human expert.

<table>
<thead>
<tr>
<th></th>
<th>HUMAN EXPERT</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>operative</td>
<td>conservative</td>
</tr>
<tr>
<td>PLEXUS</td>
<td>21</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>21</td>
<td>13</td>
</tr>
</tbody>
</table>

Crude 'accuracy' = 30/34 = 0.88
False negative rate = 0 = 0
False positive rate = 4/13 = 0.31
Predictive value pos. = 21/25 = 0.84

treatment for these patients may guarantee that the neurologist treating this patient will send him to an expert neurosurgeon.

results on the first test series

The first test series consisted of 15 traumatic brachial plexus injuries. Of the traumatic injuries, 8 were supraclavicular injuries, 4 of which had been operated upon, 4 were infraclavicular injuries of which 2 had been operated on and 3 were two-level injuries, that had all been operated upon. The results of this test have been scored similarly to the training series. The results show the same tendency as those of the training series (Tab. 6.7, 6.8).

comparing the surface and hybrid system

In the previous section, efficiency measures for the hybrid localization system PLEXUS have been compared to a system based purely on surface knowledge. As had been indicated, the surface system proved to be the more efficient. In Sect. 6.3, advantages of the hybrid system concerning transparency and maintainability have been described. A particular advantage, as mentioned there, is the fact that in building systems which rely on a
Table 6.7 Results on the first test series.

<table>
<thead>
<tr>
<th>Kind of injury/Treatment</th>
<th>Quality of advice</th>
<th>poor</th>
<th>fair</th>
<th>good</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PLEXUS LOCALIZATION</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supraclavicular operative</td>
<td>1 (7%)</td>
<td>3 (20%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>conservative</td>
<td>4 (27%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infraclavicular operative</td>
<td>2 (13%)</td>
<td>2 (13%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>conservative</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-level operative</td>
<td>2 (13%)</td>
<td>1 (7%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 (20%)</td>
<td>12 (80%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PLEXUS TREATMENT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supraclavicular</td>
<td>4 (27%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>operative</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>conservative</td>
<td>2 (13%)</td>
<td>2 (13%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infraclavicular</td>
<td>2 (13%)</td>
<td>2 (13%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>operative</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-level</td>
<td>3 (19%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>operative</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 (13%)</td>
<td>13 (87%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Combination of deep and surface knowledge, in contrast to surface systems, surface knowledge does not have to be complete. This facilitates a more structured approach to design and implementation of the knowledge base. To achieve a similarly good quality of advice in surface systems would necessitate a much lengthier Run Understand Debug Edit process, to make the knowledge base complete. To test this idea, it is interesting to compare the quality of advice of both the surface and the hybrid systems, as described in the previous section. The results of the surface system in the training series and in the first test series are presented in Tab. 6.9. As can be seen in this table, in the training series, apart for two of the infraclavicular injuries,
the results of the surface system do not seriously deviate from that of the hybrid system. The poor advice for the two infraclavicular injuries, is due to the lack of the checkerboard pattern matching and triggers, which could easily be remedied by expanding the surface system with these triggers. On the first test series, however, serious differences manifest and the surface system seems to be much worse than the hybrid system. These differences appear to be mainly due to imperfections in the surface refinement task. Whereas no serious differences occur in the hybrid system’s results between the training series and the first test series, these differences are considerable for the surface system. This indicates the effect of the deep knowledge in the hybrid system, which makes system behavior more predictable. To improve the quality of the surface system would thus require the incorporation of extra heuristics in the refinement task in order to complete this part of the knowledge base. However, in attempting to do so, one might encounter unanticipated interaction of knowledge, which is likely to be present in complex surface systems as this. This means that the same knowledge that is added to correct system behavior may have a harmful effect on the behavior for cases that were previously handled correctly. This effect in itself makes the RUDE process still longer.
Table 6.9 The quality of advice of the surface system.

<table>
<thead>
<tr>
<th>Kind of injury/</th>
<th>Quality of advice</th>
<th>poor</th>
<th>fair</th>
<th>good</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>poor</td>
<td>17 (49%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>fair</td>
<td>11 (31%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>good</td>
<td>1 (3%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 (6%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 (6%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 (3%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRAINING SERIES</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supraclavicular</td>
<td>operative</td>
<td>1 (7%)</td>
<td>3 (20%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>conservative</td>
<td>1 (7%)</td>
<td>3 (20%)</td>
<td></td>
</tr>
<tr>
<td>Infracavicular</td>
<td>operative</td>
<td>1 (7%)</td>
<td>1 (7%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>conservative</td>
<td>2 (13%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-level</td>
<td>operative</td>
<td>1 (7%)</td>
<td>2 (13%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>4 (27%)</td>
<td>4 (27%)</td>
<td>7 (47%)</td>
<td></td>
</tr>
<tr>
<td>FIRST TEST SERIES</td>
<td>Supraclavicular</td>
<td>1 (7%)</td>
<td>3 (20%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>conservative</td>
<td>1 (7%)</td>
<td>3 (20%)</td>
<td></td>
</tr>
<tr>
<td>Infracavicular</td>
<td>operative</td>
<td>1 (7%)</td>
<td>1 (7%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>conservative</td>
<td>2 (13%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-level</td>
<td>operative</td>
<td>1 (7%)</td>
<td>2 (13%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>4 (27%)</td>
<td>4 (27%)</td>
<td>7 (47%)</td>
<td></td>
</tr>
</tbody>
</table>

results of the Turing Test

In the Turing test, 10 cases of each of the two cooperating human experts were presented to the knowledge based system. The same 10 cases of one expert, which were the latest 10 cases that had been operated on, were presented to his colleague. Because of the neurosurgery that had been performed, a good standard was available against which to assess the quality of diagnosis of the knowledge based system and of the expert.

In this respect, it is important to note that even this standard is not perfect, as was stated by the experts, at operation, the shape of the
Table 6.10 Results of the Turing Test.

<table>
<thead>
<tr>
<th>HUMAN EXPERT</th>
<th>Total</th>
<th>Expert wgh.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>pos. total</td>
</tr>
<tr>
<td>--</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>PLEXUS 0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>+</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>++</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Plexus weighted positive total</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

Crude agreement = \( \frac{8}{20} = 0.4 \)
Plexus positive rate = \( \frac{7}{20} = 0.35 \)
Plexus negative rate = \( \frac{5}{20} = 0.25 \)
Plexus weighted pos. rate = \( \frac{9}{20} = 0.45 \)
Plexus weighted neg. rate = \( \frac{6}{20} = 0.30 \)

Incision, i.e. the part of the brachial plexus that is brought into view for visual inspection, is determined to some extent by the pre-operative diagnosis. For instance, roots that are likely to be avulsed will often not be explored. Because of this, it may still be the case that certain injuries are not found during operation because they are not looked for. Since only patients who had been operated on had been selected for this test the quality of treatment planning could not be assessed. It should be mentioned, however, that in all 20 cases the knowledge based system and the expert fully agreed upon the treatment plan. In 18 out of 20 cases, both the expert and the knowledge based system advised the performance of neurosurgical repair immediately, whereas in the remaining two cases the advice was to wait for a few weeks before repairing the plexus. These advices corresponded to the actual treatment that had been carried out.

The quality of the diagnostic advice was assessed on a five-point scale by the
expert who had operated on the patient. He was presented with both the advice of the expert and of the knowledge based system in such a way that it was impossible to tell from which source the advice originated. The results of this test are presented in Tab. 6.10. This table shows that the agreement rate between the knowledge based system and the human expert was 8/20. In 7 out of 20 cases the knowledge based system's advice was judged better than that of the human expert. In 5 out of 20 cases the expert's advice was judged better. If these rates are weighted by the deviation between knowledge based system and human expert the PLEXUS positive rate is 9/20, the negative rate is 6/20.

Concerning the detection of odd cases, in this test one difficult case occurred. Both the expert and the knowledge based system concluded that in this case the findings from radiology and physical examination were contradictory and that the radiology should be checked.

One important remark remains to be made. Although to a great degree PLEXUS relies on deep knowledge concerning localization of nervous injuries, the Turing Test revealed that surface knowledge in the system still made for a biasing towards the expert that was the main source of this knowledge. As a result, fewer differences occurred between PLEXUS and this expert, as with the other expert. These differences originate from the interpretation of radiological information to determine whether a plexal root has been avulsed or is injured extraforaminally. Deep localization reasoning can not resolve this.

results of the field trial

The field trial was conducted to reveal 'errors' in system performance, efficiency and user friendliness. This test revealed some obscurities in the system's questions that could be easily resolved. Moreover, it proved the importance of a good user-interface. The interface of the original prototype was found to be totally unsatisfactory. The prototype graphical interface (Fig. 6.1) has only been tested briefly. Preliminary results indicate a good potential.

As mentioned earlier, thus far the number of test cases run through the system has been relatively small (69), therefore further evaluation of the system is called for. Wyatt and Spiegelhalter (1987) and O'Keefe et al (1987) present
Results of the knowledge based approach to decision support

an insightful guide to devising well-controlled evaluation experiments. Nevertheless, results thus far indicate that PLEXUS' advice is at expert level. From Ch. 2, it should be clear that a success rate of 80% is a considerable improvement on the present situation in Dutch hospitals.

6.6 CONCLUDING REMARKS

The results presented in this chapter, give credit to some of the observations made in Ch. 4. The application of surface knowledge in medical knowledge based systems leads to efficient systems. Much attention has to be devoted, however, to the organization and representation of this knowledge in order to keep the system transparent. The classification of evidence employed in PLEXUS serves this purpose very well. It yields a transparent representation of the evoking strength of symptoms which is a very explicit representation of this kind of uncertainty, it offers a good starting-point for knowledge organization, and it increases reasoning efficiency through the embedded strategy of triggering and exclusion of hypotheses (Ch. 5). In combination with the refinement task, this classification of evidence provides a task specific diagnostic strategy of focusing on candidate solutions and successive refinement of these solutions, that is natural to the heuristic classification strategy. The problem of exhaustive acquisition of the surface 'symptom-fault' knowledge to keep the knowledge base complete, has been avoided in PLEXUS by the combination with deep knowledge. Normally, deep knowledge makes for transparent but inefficient reasoning which limits its applicability to the diagnosis of simple devices. In view of the efficiency results presented in this chapter, the combination with the domain-specific 'exclusion' strategy of the classification of evidence, together with a heuristic search algorithm, offers a good solution to this problem.

acceptance

Transparency is an important issue in acceptance. As described in Sect. 6.3, transparency of the PLEXUS knowledge base has been accomplished by its modular architecture, the explicit way of dealing with uncertainty and the clear-cut combination of surface strategy and deep reasoning. This combination makes the system's reasoning process very similar to that of human experts. Apart from
this, concerning acceptance, also issues with respect to the interface require a formal evaluation. However, still a lot of work has to be done on improving this interface and therefore it can not yet be evaluated. Presently work is being conducted on explanation (Van Daalen and Jaspers, 1989) and critiquing (Ter Haar, 1989), whereas prototype graphical I/O facilities have been created (Grolman, 1989). The efficiency of the system and its transparent architecture benefit this work. In the last section, measures will be discussed that may further enhance transparency in order to facilitate explanation.

System transparency and the predictability of system behavior are important assets which also benefit system maintainability. These issues are closely related. A transparent, well structured, modular design is apt to yield behavior which is better in respect to predictability than a system based on a spaghetti-like structure.

A number of aspects concerning the system's architecture facilitated a structured design and they are very beneficial to system maintainability. The combination of surface strategy and deep reasoning limited the number of iterative cycles in the RUDE process. Since deep-level knowledge takes care of determining the final solution of the localization problem, which is the most difficult part of the problem-solving process, surface heuristics in the knowledge base, which are only meant for focusing the search, do not have to be complete. The absence of deep knowledge, as in the surface system of Sect. 6.4, would require much more complete heuristics to yield similarly good advice, as has been indicated by the results in Sect. 6.5. This would lead to incremental growth of the knowledge base and an (infinitely) lengthy RUDE process.

psychological, organizational, financial and legal factors

In the acceptance of computerized medical decision support systems, apart from transparency, efficiency and quality of advice, a number of aspects play an important role that to a certain extent are outside the power of a system designer. These concern the legal aspects of using medical decision support systems, as well as psychological, organizational and financial aspects. Legal aspects involve the question of liability when errors occur due to incorrect advice by the decision support system, or when a physician has failed to operate in accordance with the system's advice. Psychological factors have to do with the fear of working with computers, the loss of the professional
status of physicians and possible negative effects on employment. Organizational aspects involve changing information pathways in a treatment center, with the associated effects on the tasks of the staff members. Financial aspects have to do with the costs that may involve the use of a decision support system, for instance due to an increase in the number of surgical procedures, as well as with the cost of buying and the maintenance of hard- and software. For a cost-effective system these costs have to be balanced by benefits offered by the use of the system. As was already mentioned in Ch. 1, these benefits are often qualitative, such as improved diagnosis and improved patient care. For Plexus this is certainly the case. Financial aspects, to do with the costs of purchase and maintenance can be taken into account in system development by keeping the design simple. In developing medical decision support systems, however, there are often limits to the possibility of keeping a development process simple due to the unavailability of deep knowledge on the process. As mentioned earlier, the development of systems based on surface knowledge leads to a lengthy RUDGE process which makes development expensive. Even in the development of PLEXUS, however, where deep knowledge was available, the construction of a transparent and efficient system took several years. Whether this can be cost-effective depends on the number of systems that can eventually be sold. Organizational consequences and psychological factors can sometimes be dealt with by careful information planning and involving intended users of the system from the start of the project. However, if a system is to be developed for general use, this will often be impossible. Then these problems, as well as the other factors mentioned, can only be solved at the time of the introduction of the system. Since PLEXUS is still in the prototype stage these problems are not yet very urgent. In view of its proposed future use, they should be kept in mind, however. A more detailed overview of these aspects related to medical decision support system acceptance can be found in Van Daalen (1988).

prospects

As has been shown in Ch. 2, in the domain of management of brachial plexus injuries, there is a clear need for support. Knowledge of the diagnosis and treatment of these injuries seems to be limited in Dutch hospitals. Consequently, the results of treatment prove to be poor compared to those of
international experts (Tab. 2.4). Performance results of PLEXUS indicate that this medical decision support system may be a valuable aid in remedying this problem.

The database facility that has been incorporated allows the easy acquisition of patient data. Future retrospective research to assess the effect of different treatment schemes may greatly benefit from this feature.

The transparent and efficient design may facilitate acceptance if the system is to be introduced in Dutch hospitals. However, before a general introduction of the system can be achieved more research has to be conducted.

As to transparency, the ideas realized in the PLEXUS system can be made more explicit. Especially the diagnostic hierarchy, which is the backbone of surface strategic reasoning, should be made more explicit. Also the classification of evidence, which is implicitly present in the production rules and in the object definitions, can be more transparently represented in another representation formalism. To this end, the surface knowledge, i.e. the production rules, of the PLEXUS knowledge base has been converted to a representation based on objects and relations in the Delfi3 shell (Jonker, 1988). In this new implementation the second data abstraction task and the refinement task have remained unchanged. Part of some of the modules as implemented in this system are presented in appendix A. In this new implementation only the first data abstraction and the heuristic match tasks and the corresponding structural model these tasks reason about, i.e. the anatomy, have been converted. The external modules, i.e. the second data abstraction and the refinement tasks, have remained unchanged. It should be noticed that at the task level this new implementation is similar to the Delfi2+ implementation. It is felt, however, that at the implementational level the Delfi3 system is more transparent. Although a formal evaluation of this new implementation still has to be conducted, preliminary results indicate that the quality of advice and the efficiency of this system are comparable to that of the rule-based system. We plan to assess these aspects in relation to the rule-based implementation more thoroughly.

As far as transparency is concerned, it seems that this new implementation is to be preferred, which means that the Delfi3 shell might be a better choice for representing surface strategic knowledge for neurological localization than the Delfi2+ shell. However, a formal evaluation of efficiency is needed to enable a well-founded judgment concerning this choice to be made.
Chapter 7
Data based support: PLEXUS

7.1 INTRODUCTION

From previous chapters it will have become clear that knowledge based modeling may yield good results for problems in domains of which a sufficient amount of knowledge is available. However, a need for support may be present also in domains of which not enough knowledge is available to construct knowledge based models. In Ch. 2, it has been shown for instance, that there is a need for support in the prognosis and evaluation of treatment schemes of brachial plexus injuries where knowledge concerning these aspects of the domain is very limited. In such cases, data based modeling may be a good alternative in building support systems. Data based modeling of the prognosis of brachial plexus injuries is the subject of this chapter.

The domain model in data based decision support systems is derived indirectly from data, i.e. observations, of the process, instead of from theoretical domain knowledge or heuristics as in knowledge based decision support systems. The data based model, however, reflects knowledge about this domain which has been extracted from the data. Therefore, apart from yielding a framework for medical decision support, data based modeling may also be helpful in gaining new knowledge about the domain. Eventually, this new knowledge can be helpful in knowledge based modeling. A data based model may demonstrate new heuristic associations between evidence and hypotheses, or it may objectify such associations that were already felt to exist. If, for instance, the effect of different treatment schemes has been assessed by data based methods, knowledge about treatment planning of brachial plexus injuries becomes more complete, which allows a more structured, i.e. deep, representation in a knowledge based model.

On the other hand, data based models have their own characteristic function in decision support. Especially in complex domains with few a priori process knowledge, or where this knowledge is inadequate, and where there is a need for a dynamic description of the process, data based modeling, viz. system identification, may be the only viable possibility to derive an adequate process model.

The stages in data based modeling (Sect. 3.6):
**Figure 7.1 Sample form of the data acquisition system for brachial plexus injuries to be used by the rehabilitation physician.**

<table>
<thead>
<tr>
<th>Kontrakturen</th>
<th>Sterk</th>
<th>Matig</th>
<th>Geen</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fantoom</td>
<td>Fantoompijn</td>
<td>Fantoomgevoel</td>
<td>Geen</td>
</tr>
<tr>
<td>Zeer belemmerd voor</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Soort</td>
<td>Schietend</td>
<td>Krampend</td>
<td>Tintelend</td>
</tr>
<tr>
<td>Pijn</td>
<td>Ja</td>
<td>Nee</td>
<td></td>
</tr>
<tr>
<td>Zeer belemmerd voor</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Bewegingscoördinatie</td>
<td>Veranderd bew. patr.:</td>
<td>Compensaties:</td>
<td></td>
</tr>
<tr>
<td>Sensibiliteit</td>
<td>C1</td>
<td>C2</td>
<td>C3</td>
</tr>
<tr>
<td>Funktieonderzoek</td>
<td>Ja, zie FT4-5 zoek?</td>
<td>Nee</td>
<td></td>
</tr>
<tr>
<td>Houding T.A.V. Behandelingen</td>
<td>Zeer belemmerd voor behandeling</td>
<td>Zeer bevorderend voor behandeling</td>
<td></td>
</tr>
<tr>
<td>Ja, negatief:</td>
<td>Ja, positief:</td>
<td>Nee</td>
<td></td>
</tr>
</tbody>
</table>

*Note: The diagram includes a human figure with labeled nerves and skin conditions, indicating areas of sensitivity and pain distribution.*
Data based support: PLEXUS

- Data acquisition.
- Data analysis.
- Choice of model structure.
- Parametrization.

will be discussed in subsequent sections, for modeling the prognosis of brachial plexus injuries.

7.2 DATA ACQUISITION

To acquire the necessary data to assess the effects of treatment and to model the prognostics of brachial plexus injuries, a special-purpose database system has been incorporated in PLEXUS (Fig. 5.25). However, this is of no help for data acquisition for the present study, because this system is not yet in routine use in hospitals and rehabilitation centers where these patients have been treated. Therefore, in 1984 a data acquisition system was introduced in the rehabilitation center De Hoogstraat. Data collection was carried out by 6 treatment team members from the Orthotics and Prosthetics Team (OPT). A total of 265 variables were recorded by these team members. To allow for the files to serve as a medical record for each team member, some overlap occurred in the recording of the data. The rehabilitation physician recorded 117 variables, the physical therapist 111, the occupational therapist 60, the social worker 31, the prosthetist 30, and in their team meeting, the collective members recorded 30 variables. The data were classified in four categories:

1. Medical aspects: 51 variables describing the patient's initial condition, 18 treatment, 59 state-of-health and 37 variables describing boundary conditions, i.e. non-recurrent treatments applied during rehabilitation, such as neurosurgical repair or orthopedic reconstruction.
4. Assistive devices: 3 treatment and 7 state-of-health variables and 25 variables which describe boundary conditions.
This data acquisition system was implemented as a set of standardized forms to be stored in the paper medical record (Fig. 7.1). The results of this system were very disappointing. It never reached the status of a data recording system for routine use. However, the experiences of this work can illustrate some of the aspects discussed in Ch. 3.

7.2.1 Introduction of a data acquisition system

In introducing a standardized data acquisition system, it is of the utmost importance that the intended users of the system be involved in the earliest stages of design and implementation. In the case of the brachial plexus data acquisition system, this was assured by the participation of the designer in the OPT, and by extensive discussions with individual treatment team members (Jaspers, 1984). Although this is a necessary condition for the successful introduction of a data acquisition system, unfortunately, it is far from sufficient. As described in Ch. 3, the introduction of such systems inherently increases the workload of its users. This is due to the necessary completeness of the data to be recorded, to the sampling frequency necessary to describe the process dynamics and to the necessary changes in the organizational structure, formally as well as informally. The increase has to be balanced by direct benefits from the use of the system, in order to permit a successful introduction. Such benefits can either be in the marked improvement of patient care or in the simplification of tasks. The improvement of patient care, which for instance may be due to improved communication between team members, will usually go unnoticed or will not be attributed directly to the data acquisition system until retrospective studies have demonstrated this effect. Therefore, noticeable direct benefits will have to be in the form of additional features that simplify data processing tasks such as feedback of recorded data by means of graphical reviews of variables as a function of time, automated generation of team reports, letters of discharge etc. Such features require the introduction of a data processing system. The lack of such facilities, as in the introduction of the brachial plexus data acquisition system, withholds these benefits from the users and will result, in the long run, in a decreased motivation to use the system. In such a case, the long term objectives are not sufficient to stimulate user participation. This was the fate of the data acquisition system described above, but other
Data based support: PLEXUS

systems suffer from this phenomenon also. The structured data acquisition in the rehabilitation of quadriplegics, which originally lacked data processing facilities (Hoogendoorn, 1979; Stassen, 1989), was successful only because the system designer in person, each week encouraged the actual use of the system. Many problems arose, however, when this Rehabilitation Information System (RIS) was transferred to five other spinal cord injury units. At that stage, data acquisition and storage were automated and aimed at the development of a data based decision support system. However, at that point the encouragement of the designer was no longer available, which led to a situation in which it proved to be very hard to get the system in routine use. Had the introduction of the data acquisition system been accompanied with the introduction of simple data processing aids as described above, it might have diminished these problems considerably. Also, at this point the phenomenon of a seemingly uncontrollable increase in the size of the information system manifested. The original version of RIS required 227 variables to be recorded, which were reduced to 70 after data reduction. In the new system, this number has increased to 990 and take about 90 minutes to be recorded (Van Gijn, 1989).

7.2.2 Retrospective analysis of medical records

Due to the failure to introduce a structured data acquisition system for brachial plexus injuries another method of data acquisition was sought. A retrospective analysis of 116 medical records of brachial plexus injuries which had been treated in rehabilitation center De Hoogstraat, was conducted (Jaspers, 1983). Of these, only 49 proved to contain a reasonable amount of data. In order to ensure the best possible quality of data based modeling, only these 49 were used for modeling the prognosis of brachial plexus injuries (Happee, 1986). Due to this choice, the acquired data base does not contain data from a randomized selection of patients. The effect of this choice, which was born of sheer necessity, remains to be assessed. From these records, diagnostic data describing the patient's initial state-of-health, time series concerning muscle function and sensibility and data of applied treatments were recorded. For each patient, Jaspers (1983) recorded 121 variables, which were completed by 7 variables to do with diagnosis and state-of-health (Happee, 1986):
Table 7.1 Recorded variables of motor function for modeling the prognosis of brachial plexus injuries.

<table>
<thead>
<tr>
<th>shoulder_girdle</th>
<th>elbow</th>
<th>flexion</th>
</tr>
</thead>
<tbody>
<tr>
<td>shoulder</td>
<td>anteflexion</td>
<td>extension</td>
</tr>
<tr>
<td></td>
<td>retroflexion</td>
<td>pronation</td>
</tr>
<tr>
<td></td>
<td>abduction</td>
<td>supination</td>
</tr>
<tr>
<td></td>
<td>endorotation</td>
<td>dorsal_flexion</td>
</tr>
<tr>
<td></td>
<td>exorotation</td>
<td>palmar_flexion</td>
</tr>
<tr>
<td></td>
<td>hand</td>
<td></td>
</tr>
</tbody>
</table>

- 10 personal data and variables describing the initial condition.
- 73 + 7 medical diagnostic and state-of-health variables.
- 9 treatment variables concerning boundary conditions.
- 29 variables concerning dates of and time spent for treatments.

In the medical records, data of motoric function refer to global muscle function around joints, instead of individual muscle functions. These global muscle functions are scored similarly to the function of individual muscles, on a scale from 0 to 5. This reflects a step of data abstraction, carried out by the team members in the rehabilitation center. Data from the 53 shoulder and arm muscles is abstracted to 32 joint functions. Of these, the shoulder girdle functions fall somewhat outside the innervation by the brachial plexus. Therefore, in data acquisition these have been abstracted further to an average value for the shoulder girdle function. Also, data of the 14 joint functions of the hand was often lacking. To solve this, one average value for

![Diagram](image_url)

**Figure 7.2** The process of treating brachial plexus injuries in rehabilitation.
the hand has been recorded. This resulted in 13 motor function results (Tab. 7.1).

Due to imperfections in the medical records, the information content of the acquired data was far less than had been aimed for with the structured data acquisition system. Due to this inherent limitation of the data set, the goal for data based modeling of the prognosis of brachial plexus injuries had to be set lower. Therefore, in subsequent sections, sometimes results of the work on quadriplegics in RIS (Hoogendoorn et al., 1983), for which an informative data set was available, will be presented, in order to better illustrate the possibilities of data based modeling.

7.3 DATA ANALYSIS

The 128 recorded variables of brachial plexus injury treatment were divided into variables describing the patient's initial and boundary conditions (44), variables describing the treatments (38) and variables describing the patient's state-of-health (46). Treatment variables serve as the input to the process to be modeled, whereas the output is constituted by the state-of-health variables (Fig. 7.2). For modeling prognosis, variables describing a patient's initial condition serve to derive a classification of patients on theoretical grounds. For instance, patients with severe nerve injury, i.e. Sunderland degree 4 or 5 or root avulsions, have a bad prognosis, whereas for patients with degree 1 to 3 injury the prognosis will be better. This theoretical classification can then be tested by comparing the actual results of treatment for each class.

For this group of 41 patients the average treatment continued for 36 months after the trauma, varying from 4 to 81 months. Per patient an average of about 5 data samples was available, varying from 1 to 14. An analysis of their data revealed that data of the applied treatments, e.g. time spent on physical therapy, occupational therapy etc., were often absent or incomplete. Due to this lack of information of the input variables, it turned out to be impossible to analyze, not to mention model, the dynamic effect of the treatment on the prognosis. However, assuming that each patient within a certain category receives similar treatments after neurosurgical and orthopedic reconstruction, for each category the prognosis could be analyzed
### Table 7.2 Independent motor function variables, after data reduction.

<table>
<thead>
<tr>
<th>shoulder_girdle</th>
<th>=&gt;</th>
<th>shoulder_girdle</th>
</tr>
</thead>
<tbody>
<tr>
<td>shoulder</td>
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<td>anteflexion</td>
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<td>abduction</td>
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<td>endorotation</td>
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<td></td>
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<tr>
<td>elbow</td>
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<td></td>
<td></td>
<td>dorsal_flexion</td>
</tr>
<tr>
<td></td>
<td></td>
<td>palmar_flexion</td>
</tr>
</tbody>
</table>

and modeled (Happee, 1986). Owing to this assumption, the effect of the closed loop that is present in Fig. 7.2, is abolished (Fig. 7.3), which is very beneficial in modeling the process, especially because so few data are available. Theoretically, the state-of-health variables that best indicate the result of treatment are the motor function and sensibility variables. Of these, motor function seems to be the most important, since it greatly determines a patient’s functioning in vocational and ADL activities. Physicians most frequently present their treatment results as a function of this variable (Tab. 2.4). Therefore, it was decided to analyze and model the prognosis as the course and the end result of motor function.

![Figure 7.3](image-url)  
**Figure 7.3** The rehabilitation process with the assumption that each patient within a category receives similar treatments.
Data based support: PLEXUS

7.3.1 Data reduction

Data analysis and data reduction by means of factor analysis (Jaspers, 1983) and cluster analysis (Happée, 1986) on different groups of patients revealed that the 13 variables describing motor function could be reduced to 3 anatomically significant variables (Tab. 7.2). One variable describing the function around the shoulder joint, i.e. the function of muscles innervated by roots C5 to C7, one variable describing the function around the elbow and hand, i.e. the function of muscles innervated by roots C7 to T1, and another variable describing the function of the shoulder girdle, i.e. function of muscles innervated by roots C3 to C5. Of these variables, an average of five data samples per patient were available, varying from one to 14.

7.3.2 Patient categories

In classifying the patients, their initial condition, i.e. the diagnosis and treatment previous to the intake in the rehabilitation center, determine the category to which a patient belongs. Theoretically, patients with severe injury to or avulsion of roots C5 to C7 that have not been operated upon will not recover upper arm function. Also, unoperated patients with such severe injury to roots C7 to T1 will not recover lower arm or hand function. This knowledge serves as a basis for the classification of patients in either one of two categories for upper arm as well as for lower arm function:

1a. Recovery upper arm possible.  
1b. No recovery upper arm.

2a. Recovery lower arm possible.  
2b. No recovery lower arm.

This categorization which was based on theoretical knowledge was confirmed by an analysis of variance. This analysis revealed a high correlation of the condition of roots C6 and C7 with the function of the upper arm, where C8 and T1 are correlated to the function of the lower arm (Happée, 1986). Due to lack of information in their medical records in respect to upper arm functions, 18 patients could not be categorized. For the lower arm, this was the case for 10 patients. For each of the four groups described, the initial value of muscle function, the increase and the final value after treatment are presented in Tab. 7.3. Fig. 7.4 shows some typical output signals from
Figure 7.4 Output signals from category la: recovery upper arm possible.

Figure 7.5 Output signals from category lb: no recovery upper arm.
Table 7.3 Muscle function results of each category of brachial plexus injuries.

<table>
<thead>
<tr>
<th>Category</th>
<th>Mean</th>
<th>St.dv.</th>
<th>Category</th>
<th>Mean</th>
<th>St.dv.</th>
</tr>
</thead>
<tbody>
<tr>
<td>UPPER ARM, RECOVERY</td>
<td></td>
<td></td>
<td>UPPER ARM, NO REC.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no of cases</td>
<td>12</td>
<td></td>
<td>no of cases</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>initial value</td>
<td>2.0</td>
<td>0.67</td>
<td>initial value</td>
<td>0.5</td>
<td>0.36</td>
</tr>
<tr>
<td>increase</td>
<td>1.4</td>
<td>0.61</td>
<td>increase</td>
<td>0.1</td>
<td>0.38</td>
</tr>
<tr>
<td>post treatment</td>
<td>3.4</td>
<td>0.70</td>
<td>post treatment</td>
<td>0.6</td>
<td>0.61</td>
</tr>
<tr>
<td>LOWER ARM, RECOVERY</td>
<td>24</td>
<td>1.25</td>
<td>LOWER ARM, NO REC.</td>
<td>15</td>
<td>0.15</td>
</tr>
<tr>
<td>no of cases</td>
<td></td>
<td></td>
<td>no of cases</td>
<td></td>
<td></td>
</tr>
<tr>
<td>initial value</td>
<td>2.8</td>
<td>1.25</td>
<td>initial value</td>
<td>0.1</td>
<td>0.15</td>
</tr>
<tr>
<td>increase</td>
<td>1.0</td>
<td>0.92</td>
<td>increase</td>
<td>0.0</td>
<td>0.14</td>
</tr>
<tr>
<td>post treatment</td>
<td>3.7</td>
<td>0.83</td>
<td>post treatment</td>
<td>0.1</td>
<td>0.18</td>
</tr>
</tbody>
</table>

category 1a. In Fig. 7.5, some signals from group 1b are depicted. From these figures it becomes clear that in the recovery group the course of motor function looks like a (first-order) response to a step from the moment of intake in the rehabilitation center. In this response, owing to the reduction of the motor function variables to 3 independent variables, no time delay due to nerve growth to individual muscles can be distinguished. The responses show the combined reaction to treatment and nerve growth. Patients who started rehabilitation late show less recovery than patients who started treatment soon after the onset of the injury (Tab. 7.4). This can be explained by the fact that in these cases the effect due to nerve growth had already taken place prior to the start of the rehabilitation program. Then, only the learning effect of rehabilitation remains.

7.3.3 RIS

In RIS, where a complete database of quadriplegic patients was available for modeling, data reduction was carried out similarly. First, output variables
Table 7.4  Recovery of motor function of patients with early intake compared to patients with late intake in category la.

<table>
<thead>
<tr>
<th>Category</th>
<th>Mean</th>
<th>St. dv.</th>
<th>Category</th>
<th>Mean</th>
<th>St. dv.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intake</td>
<td></td>
<td></td>
<td>Intake</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Function</td>
<td></td>
<td></td>
<td>Function</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UPPER ARM, RECOVERY</td>
<td></td>
<td></td>
<td>UPPER ARM, RECOVERY</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EARLY INTAKE</td>
<td></td>
<td></td>
<td>LATE INTAKE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no of cases</td>
<td>10</td>
<td>0.74</td>
<td>no of cases</td>
<td>2</td>
<td>0.30</td>
</tr>
<tr>
<td>initial value</td>
<td>1.9</td>
<td>0.74</td>
<td>initial value</td>
<td>2.5</td>
<td>0.30</td>
</tr>
<tr>
<td>increase</td>
<td>1.6</td>
<td>0.70</td>
<td>increase</td>
<td>0.3</td>
<td>0.12</td>
</tr>
<tr>
<td>post treatment</td>
<td>3.6</td>
<td>0.75</td>
<td>post treatment</td>
<td>2.9</td>
<td>0.41</td>
</tr>
<tr>
<td>UPPER ARM, NO REC.</td>
<td></td>
<td></td>
<td>UPPER ARM, NO REC.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EARLY INTAKE</td>
<td></td>
<td></td>
<td>LATE INTAKE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no of cases</td>
<td>11</td>
<td>0.21</td>
<td>no of cases</td>
<td>8</td>
<td>0.57</td>
</tr>
<tr>
<td>initial value</td>
<td>0.2</td>
<td>0.21</td>
<td>initial value</td>
<td>0.7</td>
<td>0.57</td>
</tr>
<tr>
<td>increase</td>
<td>0.2</td>
<td>0.37</td>
<td>increase</td>
<td>0.0</td>
<td>0.39</td>
</tr>
<tr>
<td>post treatment</td>
<td>0.5</td>
<td>0.44</td>
<td>post treatment</td>
<td>0.8</td>
<td>0.83</td>
</tr>
<tr>
<td>LOWER ARM, RECOVERY</td>
<td></td>
<td></td>
<td>LOWER ARM, RECOVERY</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EARLY INTAKE</td>
<td></td>
<td></td>
<td>LATE INTAKE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no of cases</td>
<td>16</td>
<td>1.25</td>
<td>no of cases</td>
<td>8</td>
<td>1.26</td>
</tr>
<tr>
<td>initial value</td>
<td>2.7</td>
<td>1.25</td>
<td>initial value</td>
<td>2.9</td>
<td>1.26</td>
</tr>
<tr>
<td>increase</td>
<td>1.0</td>
<td>0.71</td>
<td>increase</td>
<td>0.8</td>
<td>1.34</td>
</tr>
<tr>
<td>post treatment</td>
<td>3.8</td>
<td>1.00</td>
<td>post treatment</td>
<td>3.7</td>
<td>0.50</td>
</tr>
<tr>
<td>LOWER ARM, NO REC.</td>
<td></td>
<td></td>
<td>LOWER ARM, NO REC.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EARLY INTAKE</td>
<td></td>
<td></td>
<td>LATE INTAKE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no of cases</td>
<td>8</td>
<td>0.12</td>
<td>no of cases</td>
<td>7</td>
<td>0.19</td>
</tr>
<tr>
<td>initial value</td>
<td>0.0</td>
<td>0.12</td>
<td>initial value</td>
<td>0.1</td>
<td>0.19</td>
</tr>
<tr>
<td>increase</td>
<td>0.1</td>
<td>0.12</td>
<td>increase</td>
<td>0.0</td>
<td>0.15</td>
</tr>
<tr>
<td>post treatment</td>
<td>0.1</td>
<td>0.15</td>
<td>post treatment</td>
<td>0.1</td>
<td>0.20</td>
</tr>
</tbody>
</table>
that did not contain dynamic information about the process, or that, according to the treatment team, were superfluous were not considered for modeling. In this way, 67 out of 148 output variables remained. Then, a covariance analysis further reduced this set to 12 variables. These were judged by 20 specialists by means of the Delphi ranking method (Stassen, 1989). This resulted in 12 output, i.e. state-of-health, variables and 4 input, i.e. treatment, variables which can describe the process of rehabilitation of quadriplegics in view of the prognosis (Hoogendoorn, 1979).

7.4 MODELING

In the previous section the course of the patients' state-of-health has been shown for different categories. With the model assumptions and limitations described before, to predict the prognosis of brachial plexus injuries means to predict the stationary state-of-health of each patient. In the recovery categories 1a and 2a, the prognosis of the state-of-health, \( x(t) \), can be modeled as a first-order function (Happee, 1986):

\[
x(t) = x(\infty) - (x(\infty) - x(0))e^{-t/r}
\]

7.1

In this model, it is assumed that the initial condition \( x(0) \) and the moment of intake in the rehabilitation center do not affect the prognosis of the stationary state-of-health, \( x(\infty) \). This does not agree with the observations in the previous section, where it was found (Tab. 7.4), that the time of intake as well as the initial physical condition affect the value of the stationary state. Therefore, it is more plausible that the process satisfies a model structure in which the stationary value \( x(\infty) \) is a function of the initial condition \( x(0) \):

\[
x(\infty) = x(0) + K(5 - x(0))
\]

7.2

This leads to a model in which the gain \( K \) will have different values for the group that started rehabilitation soon after the onset of injury and the group that started rehabilitation late. This may be the case for the parameter \( r \) also:
Table 7.5 Result of parameter estimation of model (7.3).

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameter</th>
<th>value</th>
<th>Category</th>
<th>Parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>UPPER ARM, RECOVERY</td>
<td>K</td>
<td>0.6</td>
<td>LATE INTAKE</td>
<td>K</td>
<td>0.2</td>
</tr>
<tr>
<td>EARLY INTAKE</td>
<td>r</td>
<td>98 [days]</td>
<td>LATE INTAKE</td>
<td>r</td>
<td>204 [days]</td>
</tr>
<tr>
<td>LOWER ARM, RECOVERY</td>
<td>K</td>
<td>0.7</td>
<td>LATE INTAKE</td>
<td>K</td>
<td>0.4</td>
</tr>
<tr>
<td>EARLY INTAKE</td>
<td>r</td>
<td>190 [days]</td>
<td>LATE INTAKE</td>
<td>r</td>
<td>460 [days]</td>
</tr>
</tbody>
</table>

Figure 7.6 Onset of muscle recovery in brachial plexus traction injuries, according to Bonney (1959).
Data based support: PLEXUS

\[ x(t) = x(0) + K(5 - x(0)) - K(5 - x(0))e^{-t/r} \]  

Since the closed-loop effect has been eliminated from this model, for parameter estimation, a simple Least-Squares estimator is sufficient.

7.4.1 Results

The models that result from the estimation of the parameters of model (7.3) are presented in Tab. 7.5. The line between early and late intake, \( T_{\text{intake}} \), was estimated to be at 300 days post-trauma (Happee, 1986). From the neurophysiological point of view, this seems to be reasonable. With a nerve growth rate of 1 to 2 mm per day, for a supraclavicular injury, muscle activity in the upper arm will return about 300 days post trauma. This is consistent also with the observations of Bonney (1959), which are presented in Fig. 7.6. For the lower arm, this should be later. However, recovery in the lower arm will mostly be of lower quality (Tab. 7.3), due to the large distances between the injured site and muscles and due to the problem of cross innervation of the small hand muscles. This makes estimation of the line between early and late intake more difficult for the lower arm.

For the categories in which no recovery is expected, the actual recovery indeed proves to be minimal (Tab. 7.3). In these cases, modeling the prognosis is not very interesting.

The model structure (7.3) obscures the effect of nerve growth. For each individual motion function this effect can be made explicit with a different structure:

\[ x(t) = x(\infty)_{\text{treat}}(1 - e^{-t/r_t}) + x(\infty)_{\text{nerve}}(1 - e^{-t/r_n})e^{-t/r_v} \]

In this model, \( x(\infty)_{\text{treat}} \) represents the stationary state due to treatment. \( x(\infty)_{\text{nerve}} \) is the stationary state due to nerve growth. Further, \( r_t \) and \( r_n \) are the time constants of recovery, due to treatment and to nerve growth, respectively and \( r_v \) is the time delay of nerve growth. It will be clear that the number of parameters in this model structure, i.e. 5, is much higher than in model (7.3). Results of parameter estimation proved that in view of the
limited data set, this number is too high to yield a useful model. Results in Tab. 7.5 indicate that model (7.3) leads to useful results for prognosis of the motor recovery of brachial plexus injuries. This is illustrated by some simulation results in Fig. 7.7. However, due to the poor information content of the data set, the estimated parameters $\tau$ and $T_{\text{intake}}$ are not very reliable.

validation

To objectively assess the quality of this simple model, it should be used to predict the motor recovery of a control group. Since so few patients were available, it was impossible to compose such a control group.

7.4.2 RIS

In the RIS project, research on the prognostics of quadriplegics by Hoogendoorn and his successors showed that a well-acquired data set allows a much more fundamental approach to modeling (Hoogendoorn, 1979; Vogel et al., 1988; Vogel, 1989; Stassen, 1989). If sufficient information about the process

![Graphs showing muscle function over time](image)

**Figure 7.7** Simulation results of some patients from category 2a: recovery upper arm possible.
is available, there is a large amount of freedom of choice of the model structure and the parameter estimation method.

prognosis model

To similarly get around the problem of identification in closed loop, as in modeling the prognosis of brachial plexus injuries, an ARMA model structure was selected. This model describes the course of the 12 variables constituting a patient's state-of-health as a function of the previous state (Fig. 7.8). In this prognosis model (Vogel et al, 1988), the effect of the applied treatments is only implicitly present in the model (Fig. 7.3). This simple structure allows the application of simple, robust parameter estimation methods as the Least-Squares estimator. Although the results of these models indicate that they can describe the behavior of the open loop process very well (Vogel, 1988a), they also present some disadvantages. If this model is put into daily use, the learning effect it is bound to have on the treatment team members, will alter the actual treatment process, which consequently will no longer be sufficiently described by the model. This calls for anew estimation of the model. Moreover, due to the implicit presence of the treatment effect in the model, the support function the model can fulfil is very limited. The likely course of a patient's state-of-health can be demonstrated by the model, but it is impossible to evaluate the effect of alternative treatment plans beforehand.

treatment model

To assess alternative treatment plans, a more complex model structure had to be selected. Based on the identified dynamics of the patient's rehabilitation process and the treatment team's decisions, it will be possible to support the team in the optimization of the treatment, since this treatment model shows the effect of different treatment schemes on the patient's state-of-health. This model restores the closed loop situation (Fig. 7.9). Because of this, parameter estimation calls for more sophisticated methods like Prediction Error Method (PEM) or Pseudo Linear Regression (PLR). Within the framework of the RIS project, both PEM and PLR estimation methods have been implemented for identification of the treatment model on IBM PC-AT computers in the participating rehabilitation centers. However, experiments with these methods
showed that memory limitations of these computers under MS-DOS make identification of these models impossible. Therefore, a test procedure was devised, based on the same identification methods, for use on PC 80386 computers (Vogel, 1989). Since prediction error methods only asymptotically yield unbiased estimates, the application of such methods require the availability of much more data, than simple LS estimators do. Since these data are not yet available from the participating rehabilitation centers, this test procedure could not yet be conducted.

7.5 DISCUSSION

Data based support, like database analysis systems and systems employing classification methods, has long been a major approach to medical decision support (Ch. 1). However, recently these methods have tended to be overshadowed by knowledge based methods. In previous sections, it has been shown that there may still be a place for data based methods. Especially for modeling the dynamical aspects of clinical processes, which is still a weak point in many knowledge based decision support systems, system identification, in combination with control theory, is a potentially powerful method. The effects of treatments on a patient's prognosis, for instance, can easily be described by data based models. The dynamic models that can be achieved are

---

**Figure 7.8** The prognosis model.

**Figure 7.9** The treatment model.
especially suitable to support treatment planning and prognosis. This makes data based decision support a useful complement to knowledge based methods which usually aim at, and are best suited to, diagnostic support. Moreover, data based methods may be used for the acquisition of judgmental knowledge that can be used to construct knowledge based decision support systems. Data based modeling actually means uncovering the empirical relations that are present in the database. These relations are no different from the experiential heuristic knowledge an expert acquires throughout years of professional work. The work on data based modeling presented in the previous sections, however, is merely a good illustration of the problems system designers face when using this methodology in medical domains, instead of a clear demonstration of its assets. Whereas system identification and control theory provide a large variety of methods for modeling (medical) processes and designing optimal controllers, the major impediment causing these problems seems to be the lack of large, reliable databases containing dynamic patient information. In system identification in medicine, a large amount of data is especially important, since the process to be modeled is operating in closed loop (Fig. 7.2). This requires the application of PEM identification methods. These yield estimates that are only asymptotically unbiased which poses the need for much data. Moreover, the information content of medical databases tends to be less than optimal, since experimentation by the application of test signals to the process is often impossible. Therefore, construction of medical databases should be the main goal of system designers relying on data based methods. Many researchers in the field of medical decision support have been occupied with this subject. They either needed data for database analysis systems (Feinstein et al, 1972; Fries, 1972; Starmer et al, 1979; Feigenson et al, 1979), or for systems based on classification methods (Warner et al, 1961; Gorry and Barnett, 1968; De Dombal et al, 1972; Schwartz et al, 1973), or for systems based on system identification (Beneken et al, 1974; Blom, 1975; Hoogendoorn et al, 1983). As a result, in some domains large databases and associated analysis systems have been created. The RIS system described in previous sections should eventually become such a large time-oriented database system. However, data acquisition in medical domains still remains a major problem for a number of reasons:

1. Data acquisition systems tend to increase a physician's workload.
2. Computerized record-keeping is felt to threaten the confidentiality of medical data.

3. Computerized record-keeping is felt to depersonalize medical care.

As has been made clear earlier, these aspects can be dealt with in system design. In order to balance the increase in the physician’s workload, the data acquisition system should be extended with useful additional features, such as easy data retrieval and statistical analysis, and report generation. In decentralized computing facilities, privacy protection can easily be assured by taking sufficient security measures, like password-protected access to facilities. In centralized computing facilities more extensive measures are called for. To eliminate fear of the depersonalization of care, it is important that potential users are involved in system development from the start of the project. Possible solutions either involve the avoidance of direct physician-computer interaction, which requires data recorded on paper forms to be transferred to the database later, or to develop flexible, user friendly interfaces.

One more factor limiting the acceptance of data based decision support systems should be mentioned here. Since these systems only employ empirical associations derived from the database, they have no demonstrable direct physi(ological)cal significance and do not bear resemblance to the way physicians approach patient management problems. Therefore, unlike knowledge based systems, they will generally be unable to provide a convincing explanation or justification of their advice. They are merely black boxes that demonstrate similarities between a new patient and patients treated before, without being capable of justifying these.
Chapter 8
Discussion

From the previous chapters two prevailing methodologies for building medical decision support systems have become clear:

1. Knowledge based modeling
2. Data based modeling

Each of these methods has brought about a wide variety of techniques for modeling specific processes, many of which have been applied to and have been shown to work for a large number of applications in medical decision making. In this thesis, it has been shown that knowledge based decision support systems, as well as data based systems, rely on models of the problem domain. Therefore, the suitability of the resulting system is determined by the quality of the model. Hence, the knowledge (or data) on which the model is based, and the simplifying modeling assumptions that have been made, determine system performance more than the actual representation that is chosen. For instance, in knowledge based modeling, which knowledge is incorporated in the model is more important than how it is represented, e.g. in frames or production rules. Similarly, in data based modeling, model structure and parameter values should reflect relevant process properties. Whether an Input-Output structure or a State-Space structure is chosen is less important.

In this chapter, an attempt will be made to summarize, in a general sense, the pros and cons of these two methodologies. Clearly, there is no one best method, but each has its merits and limitations which make it suited to solve specific kinds of problems. In Ch. 6, three important issues regarding the usefulness of medical decision support systems have been distinguished:

1. Performance
2. Transparency
3. Efficiency

In Sect. 8.1, these issues will be dealt with in respect to knowledge based systems. Data based systems will similarly receive attention in Sect. 8.2. Based on these results, in Sect. 8.3 a synthesis of these methods for constructing medical decision support systems will be discussed. Sect. 8.4
will deal with the significance of this research in regard to the treatment of brachial plexus injuries.

8.1 KNOWLEDGE BASED MODELING

The most important condition for a successful knowledge based approach to constructing medical decision support systems is that knowledge about the problem domain has to be available somewhere and in some accessible form. This observation restricts the class of problems to which a knowledge based approach is applicable to those where sufficient knowledge is available either in the form of heuristics or of well understood physi(olog)ical laws, or a combination of these forms of knowledge. The purpose of such a decision support system would be to propagate this knowledge in places where it is not readily available.

Apart from the availability of knowledge, which is most decisive for the applicability of knowledge based decision support systems to a certain problem, at present there are other factors that determine whether the performance of a knowledge based model is suitable. In Ch. 3 it has been postulated that data based methods for constructing non-linear models are still limited in system identification. Knowledge based models present a suitable alternative in this respect. Representation of knowledge in surface heuristics makes it easy to incorporate non-linear relations. It should be realized, however, that these relations are non-numerical. Knowledge based systems based on AI techniques are qualitative models, as opposed to the quantitative models in data based systems (Clancey, 1989). This makes knowledge based systems less suited for application to problems that require numerical calculations, as is the case in prognosis for instance.

Compared to data based methods, knowledge based methods for constructing dynamic models of a process are still limited. Therefore, medical problems that require inferences about the dynamics of a process can not be modeled conveniently by knowledge based methods. Thus knowledge based decision support systems seem to be best applicable to static problems where a sufficient amount of knowledge is available. Often, these characteristics apply to
diagnosis and treatment planning. Prognosis, however, requires chiefly a
dynamic model of the reaction to therapy.
However, medical decision support systems that supply dynamic advice do seem
to exist. ONCOCIN (Shortliffe, 1986) aids in the management of patients with
cancer, receiving chemotherapy. Its advice is based on a temporal record of
a patient's ongoing treatment. The reason this system succeeds in dynamically
modeling the process is that cancer therapy is protocol-directed. The
incorporation of these protocols in the ONCOCIN model actually makes this
model quasi-static instead of dynamic. It is exactly the dynamic part in the
planning process, i.e. simulation of a patient's response to suggested
treatment plans, that is lacking in ONCOCIN. In ONYX (Langlotz et al, 1985,
1987), this dynamic part is being incorporated by means of what is called a
symbolic simulation model. This model contains symbolic knowledge of
physiological structure and three rule bases describing the behavior of each
component in the structure. The authors indicate that simulation results are
not yet at expert level, that the model can not represent the variability in
patient population, and that it is not viable to adapt its parameters or
structure to particular patient characteristics.

**qualitative vs quantitative modeling**

Langlotz et al (1985) discuss the unacceptability of deterministic
mathematical models for ONYX. A well-established stochastic quantitative
modeling approach as presented in Ch. 3, however, may be very suitable to
solve the problems described above.

In this domain, where there is a need for the predictive power of numerical
simulation results with associated confidence intervals (Langlotz, 1987), a
numerical instead of a symbolic modeling approach seems to be the obvious
choice. Considering their present investigation of quantitative techniques,
the authors seem to have realized this too. This example reflects what, due
to the rise of interest in knowledge based modeling, may become a common error
in constructing knowledge based systems, i.e. the failure to seriously
determine whether a knowledge based approach is most suitable to solve a
specific problem. Often, in a knowledge based environment, the choice of
modeling technique is restricted to the kind of knowledge based model that is
best for a given problem, whereas data based approaches that might be more
suitable, are not considered. Constructing a knowledge based model for a
problem the technique is not really suited to, may be extremely difficult and will probably lead to disappointing results.

transparency

The transparency of a medical decision support system is of utmost importance. It determines the extent to which a system will be able to explain and justify its advice, which has been shown to be a predominant factor in acceptance (Teach and Shortliffe, 1981). Also, transparency determines system maintainability, which may also become an important factor in acceptance. A system that is not regularly updated will become awkward to use. Updating will be costly, i.e. time consuming as well as financially expensive if its maintainability is poor. Unlike other acceptance issues, explanation, justification and maintainability can not be solved by an appropriate interface.

From previous chapters, it has become clear that knowledge based modeling allows the construction of very transparent models. For instance, these may closely mimic physician reasoning, which benefits interpretability, or reasoning may be based on transparent deep medical knowledge of the process and its components. In real problem domains this will generally not be sufficient. Complex problems usually lead to complex knowledge based systems, which require well structured, modular knowledge bases to stay transparent. Therefore, the utmost attention should be paid to knowledge organization in medical knowledge based systems.

A very important issue to do with transparency is the representation and calculation of uncertainty. It has been shown in Ch. 4, that ad-hoc numerical methods that accumulate evidence by some analytical function are unsuitable. These methods fail to represent how evidence confirms or excludes hypotheses. They make a system's line of reasoning unpredictable to a certain extent. Therefore, it is necessary to represent uncertainty in a non-numerical, explicit way.

efficiency

Efficiency is another important issue in building decision support systems. First of all, if potential users are required to work with the system in a
direct fashion, it is important that it reacts at once to the user’s input. However, even if the system is designed to run in the background, so as not to interfere with the normal routine, it is still of the utmost importance that the software makes economical use of computing resources. These systems can not be imagined to come into routinely clinical use if they are required to run on large, expensive computers.

Efficiency, as well as transparency, require the knowledge to be organized hierarchically. What may sometimes be in contrast to transparency, however, is that apart from a hierarchical structure, efficiency requires additional knowledge structures to focus the reasoning process. Often, these can be surface structures that mimic physician reasoning, which will keep the system transparent. Otherwise, a tradeoff has to be made between transparency and efficiency.

**constructing a medical knowledge based system**

In this section, issues in the knowledge acquisition and knowledge representation stages, which have been presented in Ch.4, will be discussed. The purpose of the medical knowledge based system is determined in the Identification stage. This leads to a global identification of the task the system will have to perform.

As was made clear in the previous section, in Conceptualization it is of vital importance to determine whether the process to be modeled is suitable for a knowledge based approach:

1. Is a static or dynamic model needed?
2. Should the model be linear or non-linear?
3. What process knowledge is available?
4. Is this sufficient for a completely knowledge based approach?
5. Identify areas of completeness and incompleteness of knowledge.
6. What knowledge is relevant to the specified tasks?

Furthermore, in Conceptualization, it is important to:

7. Uncover the hierarchical domain structure that is relevant to system task.
This determines which parts of the process can possibly be modeled at a deep level, and which parts, necessarily, have to be modeled at surface level (5). It guides the choice for the type of model (6), for structuring the knowledge base (7) and it indicates possibilities to improve efficiency by domain-specific strategies (8).

In the Formalization stage, together with efficiency requirements identified in Identification, the actual choice is made concerning:

9. The hierarchical structuring of the knowledge.
10. The level of knowledge that is best for each part of the system.
12. Choice of representation language.

These choices are realized during Implementation.

Finally, in the last stage, the choices are evaluated and system performance, transparency and efficiency are assessed.

In this scheme, the choice of a knowledge representation language is made only when all other design decisions have been made. It is felt that design considerations presented here, either unambiguously lead to a certain choice, or are independent of the representation method. Therefore, emphasis should be on the tasks the system has to perform and on the associated task characteristics that lead to choices regarding knowledge structuring and strategies to use, rather than on implementational details. Postponing computational choices to a stage in which sufficient domain insight has been gained will lead to more structured system architecture. When implementational aspects are considered too early, the chances are that system design will be tailored towards the representational possibilities of a certain language, instead of an appropriate language for a specific design being chosen. It should be realized, however, that the applicability of the sequential development process presented here depends to a large extent on the choice of knowledge level. If deep knowledge is to be the main knowledge source in the system, a sequential development scheme is suitable which leads to a rapid and efficient design. However, due to efficiency requirements for the run-time system or to the unavailability of deep knowledge, it may be
necessary to incorporate a substantial amount of surface knowledge, which calls for an iterative development process, which will take considerably longer. Here again a system designer faces a tradeoff, i.e. that of an efficient sequential development process and an inefficient run-time system, or an inefficient development process, but an efficient run-time system. The best choice in this tradeoff will depend on the specific problem the system is designed for.

8.2 DATA BASED MODELING

Although data based models seem to have somewhat dropped out of sight, due to the rise of interest in knowledge based techniques, they have been shown to perform well for problems requiring static (Warner, 1961; Gorry and Barnett, 1968; De Dombal et al, 1972; Schwartz et al, 1973) as well as dynamic (Beneken, 1974; Blom, 1975; Hoogendoorn et al, 1983; Stassen et al, 1989) models.

performance

A prerequisite for the applicability of the data based approach in a certain domain is that data of the process are already available, or can be acquired through the introduction of a data acquisition system. For the former, data based modeling is a natural choice that will be relatively straightforward. Where data are not yet available, data based modeling may be far more complicated, since data acquisition in medical domains remains a major problem (Chs. 3,7).

Data based modeling is especially attractive in domains where knowledge is still incomplete, which limits the applicability of knowledge based techniques. The data based model represents new knowledge about the process that is extracted from the data. Since the physi(ologi)cal interpretability of most data based models is low, this new knowledge will be surface level, comparable to expert judgmental knowledge, with no reference to underlying deep models.

In general, the data based approach is applicable to problems requiring dynamic models, such as treatment and prognosis, or to diagnostic problems
that require a case to be classified within a limited number of categories. If the number of diagnostic categories becomes large, or when the diagnosis has to be constructed from primitive solution components, as in diagnosing brachial plexus injuries, data based classification systems (Ch. 1) are generally less suitable. In such cases the discriminant function becomes very complicated and the required size of the training set to estimate the parameters of this function becomes very large. Also, the possibilities for constructing non-linear data based models are limited.

Finally, concerning performance, it is important to note that many data based techniques make assumptions about conditional independence of symptoms and mutual exclusiveness of disease categories (or treatment categories). Violation of these assumptions, can lead to poor system performance.

transparency

The importance of the transparency of a medical decision support system in relation to acceptance, has been stressed in the previous section. Besides the data acquisition problem, this is a major weakness of data based systems. As far as maintainability is concerned, the problem is not very hard. If it is ensured that data acquisition continues while the data based system is in use, it can easily be assured that the model is updated whenever new data become available. This can either be done by human intervention, or, in system identification models, updating may be taken care of automatically by recursive identification methods (Ljung and Söderström, 1983).

As far as the explanation and justification of the system's advice is concerned, data based models will mostly yield very poor results. Medical processes to be modeled are usually far too complex to allow the choice of a model structure that is physiologically interpretable. Therefore, simple model structures are often selected (Ch. 3) the output of which is fitted to the data by adjusting the parameters. These black-box models are not easily interpretable. They provide only a description of process input-output behavior. This phenomenon will seriously affect acceptance by physician users, who need to be convinced that the system provides the right advice. In data based systems this will be even more necessary than in knowledge based systems based on expert heuristics. The fact that the latter are based on expert knowledge that can be examined by the user may serve as a convincing argument, whereas the fact that a data based model was abstracted out of a dataset will
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be less convincing.

efficiency

Concerning efficiency, the same observations apply to data based systems as to knowledge based systems. To avoid direct physician interaction the system can run in the background. However, data based classification models, consisting of a discriminant function, or simulation models, consisting of a number of differential equations, are often rather simple. No specific efficiency measures are required for such models.

constructing a medical data based system

In constructing medical data based systems similar stages can be identified as those described in Sect. 8.1.
The purpose of the decision support system is determined in the Identification stage.
In Conceptualization, it is decided whether the problem is suitable for a data based approach:

1a. Is a static or dynamic model needed?
1b. Can a possible classification problem be solved by simple classification within a limited number of categories?
2. Should the model be linear or non-linear?
3. Is sufficient process data available, or can it be acquired?
4. Identify relevant input and output signals of the process.

In Formalization, it is possible to:

5. Choose a model structure.

In Implementation, a suitable method is employed to:

6. Estimate the parameters of the model.

Finally, the resulting data based system is validated and tested to evaluate choices regarding model structure and parametrization.
8.3 SYNTHESIS

From the foregoing, an interesting perspective arises in respect to medical decision support. Knowledge based methods and data based methods prove to have a number of complementary characteristics regarding suitable problem domains and transparency that make it worthwhile to examine the possibility of combining these approaches in a generalized method for constructing medical decision support systems.

First of all, knowledge based modeling and data based modeling each serve a different purpose. Knowledge based techniques yield models that describe existing knowledge about a process which may be used to propagate this knowledge in areas where it is not readily available. For instance, the knowledge of diagnosing brachial plexus injuries and the protocol-based knowledge of treating these injuries are presently available only to domain experts in a few specialized hospitals. A knowledge based decision support system like PLEXUS can serve to make this knowledge available to neurologists in other hospitals and to guarantee that their patients will receive optimal treatment.

On the other hand, data based techniques yield models that extracted their knowledge from data about the process. Because of this, these models are very suitable to acquire new knowledge about processes when there is an overall lack of sufficient insight in the domain. For instance, the knowledge of prognosis of brachial plexus injuries is very limited, and the effect of different types of treatment still needs to be assessed. Data based methods may be used in such a case to assess treatment effects and to model the prognosis of brachial plexus injuries as a consequence of diagnosis and treatment.

8.3.1 Combining knowledge based and data based modeling

A combination of knowledge based and data based modeling, as suggested above, would combine the advantages of each method:

data based models
- extract new knowledge from data
- are well suited for modeling dynamic processes
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knowledge based models - propagate knowledge
- their transparency allows explanation

Combining different methods, however, may in the worst case lead to adding their disadvantages also. In this case, it seems that the disadvantages of the knowledge based approach, to a large extent, are remedied by the combination with data based methods. The problem of the fact that knowledge based modeling can be used only in domains with sufficient knowledge, and that it can only model static or quasi-static processes if no deterministic models are available, is solved by the combination with data based techniques. A remaining impediment that requires a lot of effort in order to solve it is the problem of knowledge acquisition.

Concerning the limitations of data based methods, the fact that some complex classification problems are not well suited to be approached by data based techniques can be remedied by their combination with knowledge based methods. The solving of other disadvantages of data based modeling is less straightforward.

Of course, the need to acquire a large amount of process data remains. Although this may seem similar to the knowledge acquisition problem, up to now it has proven to be much more awkward. Data acquisition requires physicians to record patient data, either directly interacting with the computer, or via standardized paper forms. This data acquisition process is bound to interfere continuously with physicians' daily routine. Knowledge acquisition may be less disagreeable. Speaking exaggeratedly, first of all, it leaves the physician the status of the omniscient doctor instead of degrading him to some sort of clerical employee. Then, the knowledge furnished by physicians has been compiled out of patient data from years of experience. Therefore, the amount of knowledge to be supplied will be inherently less than the amount of data necessary to yield the same information.

To date, it can not be seen how the integration with knowledge based techniques in these domains with incomplete knowledge could guarantee the regular routine use of these information systems. The only viable solution to the data acquisition problem seems to be to construct medical information systems that interfere as little as possible, and which supply useful information such as automatically generated reports etc. (Chs. 3 and 7).

Another impediment to the data based approach that will continue to exist for
Figure 8.1 Stages of constructing a medical decision support system.
some time is the intransparency of data based models, due to their black-box structure. It can easily be foreseen that physicians will hesitate to rely upon advice the underlying reasoning process of which can not be justified. Therefore, initially, physicians' acceptance of these models will be hampered. However, when experience shows the model's advice is correct in a good number of cases, hopefully, it will be accepted as a useful tool, the advice of which will be considered similarly as that of a human expert.

Future experiences with the RIS project (Ch. 7), will show whether such a situation can be attained. If it succeeds, then the data based model may serve to pass on its new knowledge about the process to the physician who may internalize this knowledge in his own internal process model. Subsequently, this knowledge can be made explicit in the form of expert heuristics, which can be represented in a knowledge based model. These heuristics may prove to be more acceptable to physician users than the numerical knowledge represented in the model structure and parameter values of the data based model. In this way the data based model can serve as a tool to speed up the physician's process of compiling experiential knowledge out of data.

8.3.2 Concluding remarks

A general scheme for constructing medical decision support systems, consisting of the right combination of data based and knowledge based models, can easily be derived from the schemes presented in Sects. 8.1 and 8.2 (Fig. 8.1). The major deviation from these schemes is that the Conceptualization stage is extended. Once the problem has been identified, it is important to determine which parts are most suitably modeled by knowledge based and which by data based techniques. Several data based models, relying on different model structures and implemented with different parameter estimation methods, may have to be combined with various knowledge based models, each with different knowledge levels and specific inference strategies. In this view the notion of hybrid systems is not limited to knowledge based systems that incorporate different knowledge representation languages, but it is extended to encompass systems that consist of combinations of data based and knowledge based models, each implemented in the most suitable knowledge representation language. In this view the notion of hybrid systems is not limited to knowledge based
systems that incorporate different knowledge representation languages, but it is extended to a higher level of abstraction to encompass systems that consist of combinations of data based and knowledge based models, each implemented in the most suitable 'knowledge representation language'.

In previous chapters, many of the development stages have been described regarding the PLEXUS system. Processes to be modeled knowledge based, i.e. diagnosis and treatment, and data based, i.e. prognosis and evaluation of treatments, have been identified. As far as the knowledge based approach is concerned, results indicate the merits of transparent design, efficient reasoning and explicit modeling of uncertainty (Ch. 6). The results concerning the data based approach are preliminary only. A great deal of effort still has to be put in solving the data acquisition problem, which proved unsurmountable up to now. Whereas this requires many research endeavors, future results of the introduction of RIS in Dutch treatment centers may help to elucidate the potential of data based modeling. Especially the process of sped up compilation of judgmental knowledge derived from data, which was envisioned in the previous paragraph, deserves close attention in this work. Once RIS has become an accepted information system, it should be extended to other categories of injury. Introducing the brachial plexus injury data acquisition system (Jaspers, 1984) in RIS will then allow structured modeling of prognosis and evaluation of treatments.

In this chapter it has been postulated that a very important stage in the design and realization of (medical) decision support systems is the choice of modeling technique, based on a thorough problem and domain analysis. Important factors influencing this choice are the availability of process data and process knowledge. The scheme for constructing medical decision support systems as presented here is still very global. A lot of work remains to be done in order to develop design tools based on such a scheme that aid in constructing transparent, efficient systems. To date, tools are restricted to knowledge based modeling and cover only a few of the stages described.

8.4 SIGNIFICANCE IN RESPECT TO THE TREATMENT OF BRACHIAL PLEXUS INJURIES.

In Ch. 2 it has been shown that there is a clear need for support in regard to the diagnosis, treatment planning and prognosis of brachial plexus
injuries. Is PLEXUS able to alleviate this need? To do so, it would have to have a good performance regarding its advice, be accepted by neurologists and preferably be sufficiently transparent to allow propagation of its knowledge to its users. Results as to its performance derived from the first laboratory test and from the Turing Test (Ch. 6) indicate that it may have a positive impact on the diagnosis and treatment planning of brachial plexus injuries. Moreover, the knowledge based modules that check the diagnostic procedure and that send diagnostic and treatment messages to the user will help propagate knowledge to do with the management of these injuries. To actually cash in on this potential would require the overcoming of the acceptance threats described in Ch. 6, which have partly been confirmed by the inquiry among Dutch neurologists (Ch. 6). A number of consequent system requirements have been presented:

1. Flexibility of the dialogue, possibly by means of I/O facilities.
2. Efficient dialogue that is not very time consuming.
3. Possibility for the user to generate his own solutions.
4. Good explanation facilities on several levels of detail.

The first two of these have been solved: A prototype graphical I/O interface has been developed (Grolman, 1989), that has achieved positive reception by physicians. The efficiency of the dialogue has been shown to be good, first of all since the consultation system requires no direct physician interaction due to the database facility, but also because consultation itself is efficient.

The last three requirements call for more research to be conducted. Thus far, explanation and critiquing have not received much attention. These aspects are dealt with in another research project, however (Van Daalen and Jaspers, 1989). It is felt that the new implementation in Delft3 (Ter Haar, 1989) is a good starting point at which to incorporate these facilities. Cost-effectiveness has been dealt with in Ch. 6. There it was shown that this requirement is hard to assess due to the fact that the system's benefits are of qualitative nature which can not easily be quantified.

A number of issues requiring research remain:
- A comparative efficiency evaluation of the Delfi2+ and Delfi3 implementation of PLEXUS should be conducted.

- Before the PLEXUS system comes into routinely use by physicians, a performance evaluation on patients other than those treated by the cooperating experts should be conducted.

- A formal acceptance test of the system has to be conducted.

- A lot of work still is to be done on data based modeling for the formal assessment of treatment results and the modeling of prognosis of brachial plexus injuries. The PLEXUS database facility may be helpful in this respect in acquiring the necessary data of the treatment process.

- A formal evaluation of the system's cost-effectiveness still has to be conducted. This requirement will determine the suitability of routine use of the system.
References


Akasaka Y. (1987). Intercostal nerves reinnervating free transfers of muscle into the arm. Presentation at the brachial plexus meeting, Lausanne.


References


References


Dolenc V.V. (1985). Role of reconstructive surgery in peripheral nerve injuries and results. Presentation at symposium Diagnosis and treatment of traumatic brachial plexus lesions, Rotterdam.


Flaubert A.C. (1927). Mémoire sur plusieurs cas de luxation dans lesquels les efforts pour la réduction ont été suivis d'accidents graves.


References


References


References

Leiden, pp. 147-151.


References


Murphy F., Hartung W., Kirklin J.W. (1947). Myelographic demonstration of


Narakas A.O. (1987c). Neurotization of the suprascapular nerve with the spinal accessory nerve. Presentation at the brachial plexus meeting, Lausanne.


Rauch Hindin W.B. (1986). Artificial Intelligence in business, science and


Seddon H.J. (1972). Surgical disorders of the peripheral nerves. Baltimore, Williams & Wilkins.


References


Slooff A.C.J. (1986). Personal communication.


Smellie W. (1764). Collection of prenatal cases and observations in midwifery compleating the design of illustrating his first volume on that subject. vol. 3, London.


References


Appendix A

The DELFI3 implementation of PLEXUS

In DELFI3, knowledge can be represented in 'objects' and 'relations' among objects. On the 'definitional' level these objects and relations describe the structure of the domain. Generalization and specialization of objects and relations are provided for with the 'SUPERS' connection. Instantiations of these Definitional Objects (DOBJ) and Definitional Relations (DREL) can be made in Individual Objects (IOBJ) and Individual Relations (IREL). Attributes describe properties of an object. Values of shared attributes are shared for all instantiations of that definition object. Values of private attributes may differ for each instantiation of the definition object. Facets describe certain aspects of attributes. Existing facets are the TYPE, LEGAL, i.e. legal values, VALUE, DEFAULT, IF_NEEDED and IF_ADDED facets. More detailed information on DELFI3 can be found in Jonker (1988).

In the DELFI3 implementation of PLEXUS, knowledge has been represented explicitly, in so-called 'modules'. Modules constitute a hierarchy, in which module A supersedes module B, if B imports objects or relations from A. Objects and relations that are exportable from a module are marked *. The top-module of this hierarchy is 'patient'. It contains the object Patient, in which patient findings, hypotheses about the location of the injury etc. are stored. The other modules of the knowledge based have been classified into 6 categories:

1. A total of six modules, that contain patient-independent information.
2. Two 'data abstraction' modules that contain patient data.
3. Three modules for the second data-abstraction task 'Checkerboard'.
4. Three 'interface' modules that take care of interfacing the knowledge base with the database and the deep refinement task.
5. Fifteen 'hypothesis' modules that constitute the diagnostic hierarchy. In each of these modules the classification of evidence for each of its hypotheses is represented as attributes of the hypothesis.
6. A module that contains knowledge to infer the diagnosis from the asserted hypotheses.

The inference is started by the relation 'go' from the module 'patient'. This relation infers the diagnosis for a specific patient that is identified by its
attribute 'name'. The value of this attribute is asked from the user via the IFN-facet (IF Needed) ASK. When the name is known, the value of the attribute 'db_record' can be traced via the relation 'read_db_record'. As a result, the database is read, with the patient name as a key. Subsequently, other attributes are traced and the inference proceeds, via the tasks data abstraction in the data abstraction modules and heuristic match in the hypothesis modules. Each object 'Hypothesis' has attributes 'triggers', 'necessary', 'exclusive' and 'corresponding' to classify its evidence. Also, a Boolean attribute 'asserted' has been defined, that says whether a hypothesis is asserted or not. The value of this attribute can be traced via the relation 'deduce_hypothesis'. Subsequently, the external refinement task is accessed via an external RELation (XREL) 'akt_locs' in the interface module 'aktlocation'. Finally, in the 'diagnosis' module the three diagnosis-attributes are traced, and the diagnosis is printed by the relation 'go'. More detailed information on the Delfi3 implementation of PLEXUS can be found in Ter Haar (1989). In this appendix, part of some of the modules described is presented in the original Delfi3-syntax.
THE DELFI3 IMPLEMENTATION OF PLEXUS

MODULE patient

USE dbase

| exam_results TAKING Exam_results, get_exam_results, muscle_status, muscle_status_text
| anatomy TAKING Muscle
| anamnese TAKING Anamnese, Cause_trauma, Addit_trauma, new_anamnese
| type TAKING LOCATION, FUZZYBOOL, STATUS
| aktlocation TAKING Akt_locations, akt_locs
| hyps_location TAKING Hyps_location, hyps_location, print_hypslocation
| hyps_root_av TAKING Hyps_root_av, hyps_root_av, print_hyps_root_av
| hyps_truncus TAKING Hyps_truncus, hyps_truncus

DOBJ **Patient
PRIVATE name

IFN [ASK("What is the name of the patient ? ",

'name)]
| db_record : <DB_record>
  IFN [read_db_record(name,'db_record)]
| exam_results : <Exam_results>
  IFN [get_exam_results(db_record,'exam_results)]
| root_av_hyps : <Hyps_root_av>
  IFN [hyps_root_av(exam_results,anamnese,
                      cl_stat,proc_av_hyps,
                      loc_hyps,pregangl_hyps,
                      postgangl_hyps,
                      'root_av_hyps') AND !
                      AND print_hyps_root_av(de.mo,root_av_hyps)]
  (IFA [print_hyps_root_av(de.mo,root_av_hyps)])

DREL go
VAR p:<Patient>
[p = Patient(),?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?] AND
WRITE( "name : ", p.name ) AND WRITELN(1) AND
write_diagn_sup(p.sup_diagn) AND
write_diagn_per(p.per_diagn) AND
write_diagn_inf(p.inf_diagn)
]
ERELE

IOBJ pat : Patient(),?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?,?
EOBJ

END
MODULE type

DOBJ **FUZZYBOOL
EOBJ

IOBJ *True,
    *False,
    *Unknown : FUZZYBOOL()
EOBJ

DREL *fuzzy_bool
RANGE fb : <FUZZYBOOL>
    | b : <BOOL>
        [[ fb = True AND b = TRUE
        OR fb = False AND b = FALSE
        OR fb = Unknown AND b = FALSE
        ] AND !
    ]
EREAL

DOBJ **LOCATION
EOBJ

IOBJ *Supraclavicular,
    *Infraclavicular,
    *Retroclavicular,
    *Two_level,
    *Unknown_location : LOCATION()
EOBJ

DOBJ **STATUS
EOBJ

IOBJ *Intact,
    *Partially_damaged,
    *Damaged,
    *Unknown_status : STATUS()
EOBJ

DOBJ **SIDE
EOBJ

IOBJ *Lateral_side,
    *Medial_side,
    *Two_sides,
    *No_side,
    *Unknown_side : SIDE()
EOBJ

DOBJ **STATUSTEXT
EOBJ

IOBJ *Loc_status : STATUSTEXT()
    | *Mus_status : STATUSTEXT()
The DELFI3 implementation of PLEXUS

MODULE anatomy

USE lib TAKING intersection, join, subset, walk
   | type TAKING LOCATION, Supraclavicular, Infraclavicular,
   | SIDE, Medial_side, Lateral_side

DOBJ Anat_unit
PRIVATE location : <LOCATION>
EOBJ

DOBJ **Gen_Nerve
SUPERS Anat_unit
EOBJ

DOBJ **Root
SUPERS Gen_Nerve
CHANGES OF location MAKE SHARED
   | VAL Supraclavicular
PRIVATE trunci : <LIST <Truncus>>
   | nerves : <LIST <Per_Nerve>>
   | neighbours : <LIST <Root>>
EOBJ

DOBJ **Truncus
SUPERS Gen_Nerve
CHANGES OF location MAKE SHARED
   | VAL Supraclavicular
PRIVATE roots : <LIST <Root>>
   | divis : <LIST <Division>>
   | nerves : <LIST <Per_Nerve>>
EOBJ

DOBJ **Division
SUPERS Gen_Nerve
CHANGES OF location MAKE SHARED
   | VAL Supraclavicular
PRIVATE trunci : <Truncus>
   | fasci : <Fasciculus>
EOBJ

DOBJ **Fasciculus
SUPERS Gen_Nerve
CHANGES OF location MAKE SHARED
   | VAL Infraclavicular
PRIVATE divis : <LIST <Division>>
   | nerves : <LIST <Per_Nerve>>
EOBJ

DOBJ **Per_Nerve
SUPERS Gen_Nerve
CHANGES OF location MAKE SHARED
   | VAL Infraclavicular
PRIVATE offspring : <LIST <Gen_Nerve>>
| muscle : <LIST <Muscle>>
| EOBJ

DOBJ **Muscle
SUPERS Anat_unit
CHANGES OF location MAKE SHARED
  VAL Infraclavicular
PRIVATE roots : <LIST <Root>>
  | halfrfs : <LIST <Root>> (roots marked with a small x by Kendall & K)
  | nerves : <LIST <Per_Nerve>>
| EOBJ

IOBJ

  ( ROOTS )

  *C5 : Root (  
    (trunci) [T_superior],
    (nerves) [N_dorsalis_scapulae, N_thoracicus_longus],
    (neighbours) [C4, C6] )

  ...

  ( TRUNCI )

| *T_superior : Truncus (  
  (roots) [C5, C6],
  (divisi) [D_trunc_sup_anterior, D_trunc_sup_posterior],
  (nerves) [N_suprascapularis] )

  ...

  ( FASCICULI )

| *F_dorsalis : Fasciculus (  
  (divisi) [D_trunc_sup_posterior, 
    D_trunc_med_posterior, 
    D_trunc_inf_posterior],
  (nerves) [N_radialis, N_axillaris, N_subscapularis, 
    N_thoracodorsalis] )

  ...

  ( PERIPHERAL NERVES )

| *N_radialis : Per_Nerve (  
  (offspring) [F_dorsalis],
  (muscles) [M_triceps, 
    M_brachioradialis, 
    M_extensor_carpi_radialis, 
    M_supinator, 
    M_extensor_digitorum, 
    M_extensor_digitii_minimi, 
    M_extensor_carpi_ulnaris, 
    M_abductor_pollucis_longus, 
    M_extensor_pollucis_brevis,
( MUSCLES )

| *M_triceps : Muscle ( 
|    (roots) [C7, C8],
|    (halffrts) [C6, T1],
|    (nerves) [N_radialis] )

"

EOBJ

DREL anat_units_roots
( a root r is in lr iff an element e in l exists and l is innervated by r )
DOMAIN 1 : <LIST <Anat_unit>>
RANGE lr : <LIST <Root>>
VAR lr1, lr2 : <LIST <Root>>
| h : <Anat_unit>
| t : <LIST <Anat_unit>>

[[ l - [] AND ! AND lr = []]
OR LISTER(h,t,1) AND
anat_unit_roots(h,lr1) AND
anat_units_roots(t,lr2) AND
join(lr1,lr2,lr)
]
}
EREL

DREL anat_unit_roots
( lr is the list of roots by which au is innervated )
DOMAIN au : <Anat_unit>
RANGE lr : <LIST <Root>>
VAR t : <TEXT>
| rt : <Root>
| tr : <Truncus>
| di : <Division>
| fa : <Fasciculus>
| pn : <Per_Nerve>
| mu : <Muscle>

[GETDEF(au,t) AND
[ t = "Root" AND rt = au AND lr - [rt]
OR t = "Truncus" AND tr = au AND truncus_roots(tr,lr)
OR t = "Division" AND di = au AND division_roots(di,lr)
OR t = "Fasciculus" AND fa = au AND fasci_roots(fa,lr)
OR t = "Per_Nerve" AND pn = au AND nerve_roots(pn,lr)
OR t = "Muscle" AND mu = au AND muscle_roots(mu,lr)
OR lr = []
] AND !
]
}
EREL

DREL *truncus_roots
( lr is the list of roots which innervate tr )
DOMAIN tr : <Truncus>
RANGE lr : <LIST <Root>>
[lr = tr.roots]
EREL

DREL *fasci Roots
( lr is the list of roots which innervate fa )
DOMAIN fa : <Fasciculus>
RANGE lr : <LIST <Root>>
[anat_units_roots(fa.divisi,lr)]
EREL

DREL *nerve_roots
( lr is the list of roots which innervate pn )
DOMAIN pn : <Per_Nerve>
RANGE lr : <LIST <Root>>
[anat_units_roots(pn.offspring,lr)]
EREL

DREL *muscle_roots
( lr is the list of roots which innervate mu )
DOMAIN mu : <Muscle>
RANGE lr : <LIST <Root>>
[lr = mu.roots]
EREL

END

MODULE hypothesis

DOBJ *Hypothesis
PRIVATE triggers : <Evidence> DEF No_evidence
| necessary : <Evidence> DEF No_evidence
| exclusive : <Evidence> DEF No_evidence
| corresponding : <Evidence> DEF No_evidence
| asserted : <BOOL> IFN [deduce_hypothesis(triggers,necessary,
| exclusive,
| corresponding,
| 'asserted)]

EOBJ

DOBJ *Evidence
PRIVATE present : <BOOL> DEF FALSE
EOBJ

IOBJ *No_evidence: Evidence(FALSE)
EOBJ

DREL *hypothesis
DOMAIN h : <Hypothesis>
RANGE b : <BOOL>
[b = h.asserted]
EREL
The DELFI3 implementation of PLEXUS

DREL deduce_hypothesis
DOMAIN trig, nec, excl, corr : <Evidence>
RANGE asserted : <BOOL>
[[ [ trig.present
  OR nec.present AND NOT excl.present
 ] AND ! AND asserted = TRUE
 OR asserted = FALSE
 ] ]
EREL

DREL *hyp_excl_ev_present
DOMAIN h : <Hypothesis>
RANGE b : <BOOL>
[b = h.exclusive.present]
EREL
END

MODULE hyps_root_av

USE type
| anatomy TAKING Supraclavicular, Two_level
| hypothesis TAKING Root, C4, C5, C6, C7, C8, T1
| anamnese TAKING Hypothesis, Evidence, hypothesis
| exam_results TAKING Anamnese, ana_xfr_present
| radio_root_not_visible, radio_root_meningocele, sap_root_not_present, hr_root_negative,
| sen_root_an, sen_root_dys, contr_root_sap_hr_sen, tinel_location, tinel_root_radiating,
| horner_present
| cluster_status TAKING Cluster_status, main_cluster_root_damaged
| hyps_location TAKING Hyps_location, hyp_loc_le
| hyps_proc_av TAKING Hyps_proc_av, hyp_proc_avulsion
| hyps_pregangl TAKING Hyps_pregangl, hyp_pregangl
| hyps_postgangl TAKING Hyps_postgangl, hyp_postgangl

DOBJ **Hyps_root_av
PRIVATE avulsion_c5,
  avulsion_c6,
  avulsion_c7,
  avulsion_c8,
  avulsion_tl : <Hyp_root_avulsion>
EOBJ

DREL *hyps_root_av
DOMAIN exs : <Exam_results>
| ana : <Anamnese>
| cs : <Cluster_status>
| hpa : <Hyps_proc_av>
| hloc : <Hyps_location>
| hprg : <Hyps_pregangl>
| hpog : <Hyps_postgangl>
RANGE hyps : <Hyps_root_av>
[hyps = Hyps_root_av(? ,? ,? ,? ,? ) AND
root_av_hyp(C5,exs,ana,cs,hpa,hloc,hprg,hpog,hyps.'avulsion_c5) AND
root_av_hyp(C6,exs,ana,cs,hpa,hloc,hprg,hpog,hyps.'avulsion_c6) AND
root_av_hyp(C7,exs,ana,cs,hpa,hloc,hprg,hpog,hyps.'avulsion_c7) AND
root_av_hyp(C8,exs,ana,cs,hpa,hloc,hprg,hpog,hyps.'avulsion_c8) AND
root_av_hyp(T1,exs,ana,cs,hpa,hloc,hprg,hpog,hyps.'avulsion_t1)
]
EREEL

DREL *hyp_root_avulsion
DOMAIN root : <Root>
  | hyps : <Hyps_root_av>
RANGE b : <BOOL>
  [[ root = C4 AND b = FALSE
    OR root = C5 AND hypothesis(hyps.avulsion_c5,b)
    OR root = C6 AND hypothesis(hyps.avulsion_c6,b)
    OR root = C7 AND hypothesis(hyps.avulsion_c7,b)
    OR root = C8 AND hypothesis(hyps.avulsion_c8,b)
    OR root = T1 AND hypothesis(hyps.avulsion_t1,b)
    ] AND !
  ]
EREEL
;
{ HYPOTHESES ROOT AVULSIONS }

DOBJ Hyp_root_avulsion
SUPERS Hypothesis
CHANGES OF necessary TYPE <Root_av_nec_evidence>
  DEF No_root_av_nec_evidence
 OF exclusive TYPE <Root_av_excl_evidence>
  DEF No_root_av_excl_evidence
 OF corresponding TYPE <Root_av_corr_evidence>
  DEF No_root_av_corr_evidence

EOBJ

DREL root_av_hyp
DOMAIN root : <Root>
  | exr : <Exam_results>
  | ana : <Anamnese>
  | cs : <Cluster_status>
  | hpa : <Hyps_proc_av>
  | hloc : <Hyps_location>
  | hprg : <Hyps_pregangl>
  | hpog : <Hyps_postgangl>
RANGE hyp : <Hyp_root_avulsion>
  [hyp = Hyp_root_avulsion(?,?,?,?,?,?) AND
    root_av_nec_ev(root,ana,exr,hpa,hyp.'necessary) AND
    root_av_excl_ev(root,ana,exr,cs,hloc,hpog,hyp.'exclusive) AND
    root_av_corr_ev(root,ana,exr,cs,hprg,hyp.'corresponding)
  ]
EREEL

DOBJ Root_av_nec_evidence
SUPERS Evidence
CHANGES OF present IFN {root_av_nec_ev_present(not_visible,
  proc_avulsion,
  'present)}
The DELFI3 implementation of PLEXUS

PRIVATE not_visible : <BOOL>
    | proc_avulsion : <BOOL>
EOBJ

IOBJ No_root_av_nec_evidence : Root_av_nec_evidence(FALSE,?,?)
EOBJ

DREL root_av_nec_ev
DOMAIN root : <Root>
    | ana : <Anamnese>
    | exs : <Exam_results>
    | hpa : <Hyps_proc_av>
RANGE ev : <Root_av_nec_evidence>
    [ev = Root_av_nec_evidence(?,...) AND
     radio_root_not_visible(root,exs,ev,'not_visible) AND
     hyp_proc_avulsion(root,hpa,ev,'proc_avulsion)
    ]
EREL

DREL root_av_nec_ev_present
DOMAIN not_visible, proc_avulsion : <BOOL>
RANGE present : <BOOL>
    [[ not_visible OR proc_avulsion] AND present = TRUE
     OR present = FALSE
    ] AND
EREL

DOBJ Root_av_excl_evidence
SUPERS Evidence
CHANGES OF present IFN [root_av_excl_ev_present(sap_not_present,
hist_resp_negative,
sen_an,
sen_dys,
contr_sap_hist_resp,
tinel_suprACL,
tinel_radiating,
main_cluster_damaged,
extraforaminar,
two_level_lesion,
postgangl_lesion,
'present)]

PRIVATE sap_not_present,
hist_resp_negative,
sen_an,
sen_dys,
contr_sap_hist_resp,
tinel_suprACL,
tinel_radiating,
main_cluster_damaged,
extraforaminar,
two_level_lesion,
postgangl_lesion : <BOOL>
EOBJ

IOBJ No_root_av_excl_evidence: Root_av_excl_evidence(FALSE,?,?,...)
DREL root_av_excl_ev
DOMAIN root : <Root>
  | ana : <Anamnese>
  | exs : <Exam_results>
  | cs : <Cluster_status>
  | hloc : <Hyps_location>
  | hpog : <Hyps_postgangl>
RANGE ev : <Root_av_excl_evidence>
[ev = Root_av_excl_evidence(\(?,\ldots,?,\ldots,?,\ldots,?,\ldots,?,\ldots,?,\ldots?)\) AND
  sap_root_not_present(root, exs, ev, 'sap_not_present) AND
  hr_root_negative(root, exs, ev, 'hist_resp_negative) AND
  sen_root_an(root, exs, ev, 'sen_an) AND
  sen_root_dys(root, exs, ev, 'sen_dys) AND
  contr_root_sap_hr_sen(root, exs, ev, 'contr_sap_hist_resp) AND
  tinel_location(exs, Supraclavicular, ev, 'tinel_supracl) AND
  tinel_root_radiating(root, exs, ev, 'tinel_radiating) AND
  main_cluster_root_damaged(root, cs, ev, 'main_cluster_damaged) AND
  ana_xft_present(ana, ev, 'extraforaminar) AND
  hyp_loc_les(Two_level, hloc, ev, 'two_level_lesion) AND
  hyp_postgangl(root, hpog, ev, 'postgangl_lesion)
]
ERELE

DREL root_av_excl_ev_present
DOMAIN sap_not_present,
  hist_resp_negative,
  sens_an_dermatome,
  sens_dys_dermatome,
  contr_sap_hist_resp,
  tinel_supracl,
  tinel_radiating,
  main_cluster_damaged,
  extraforaminar,
  two_level_lesion,
  postgangl_lesion : <BOOL>
RANGE present : <BOOL>

[ [[ extraforaminar
   OR [tinel_supracl AND tinel_radiating]
   OR [NOT main_cluster_damaged AND NOT sens_dys_dermatome]
   (RULE 2215, 2216, 2217, 2218, 2219)
   ]
   OR [postgangl_lesion AND NOT two_level_lesion]
   (RULE 2200, 2204)
   ]
   OR [[sap_not_present OR hist_resp_negative] AND
       sens_an_dermatome AND NOT contr_sap_hist_resp AND NOT
       two_level_lesion]
   AND ! AND present = TRUE
   OR present = FALSE
   ]
ERELE

DOBJ Root_av_corr_evidence
SUPERS Evidence
CHANGES OF present IFN [root_av_corr_ev_present(radio_men,
  sen_dys,
  main_cl_dam,
  pregangl_lesion,
  horner,
  'present)]

PRIVATE radio_men : <BOOL>
  | sen_dys : <BOOL>
  | main_cl_dam : <BOOL>
  | pregangl_lesion : <BOOL>
  | horner : <BOOL>
EOBJ

IOBJ No_root_av_corr_evidence: Root_av_corr_evidence(FALSE,?,?,?,?,?)
EOBJ

DREL root_av_corr_ev
DOMAIN root : <Root>
  | ana : <Anamnese>
  | exs : <Exam_results>
  | cs : <Cluster_status>
  | hprg : <Hyps_pregangl>
RANGE ev : <Root_av_corr_evidence>
  [ev = Root_av_corr_evidence(?,?,?,?,?,?,?) AND
    radio_root_meningocele(root,exs,ev.'radio_men) AND
    sen_root_dys(root,exs,ev.'sen_dys) AND
    main_cluster_root_damaged(root,cs,ev.'main_cl_dam) AND
    horner_present(exs,ev.'horner) AND
    hyp_pregangl(root,hprg,ev.'pregangl_lesion)
  ]
ERELE

DREL root_av_corr_ev_present
DOMAIN radio_men : <BOOL>
  | sen_dys : <BOOL>
  | main_cl_dam : <BOOL>
  | pregangl_lesion : <BOOL>
  | horner : <BOOL>
RANGE present : <BOOL>
  [[radio_men OR sen_dys OR pregangl_lesion OR main_cl_dam OR horner] AND
    present = TRUE AND
  ]
ERELE
END
Summary

Medical decision support relies on models of the problem domain. The suitability of the decision support system is determined by the quality of these models, which primarily depends on the ‘knowledge’ present in the model and not on the way it has been represented. To construct models, two approaches can be distinguished, i.e. a data based approach and a knowledge based approach. Each of these has its own merits and demerits. Data based methods are especially suited to construct dynamical models in domains where little a-priori knowledge is available. In these domains data based models may be used to compile new, judgmental knowledge derived from data. Knowledge based methods are more suitable to model and propagate available knowledge, especially of static or quasi-static processes. Knowledge based methods mostly yield non-numerical models and are thus less suitable if numerical advice is needed, as may be the case in dynamically prognosing a patient’s state of health.

Concerning acceptance, data based and knowledge based systems also have very distinct characteristics. Medical processes to be modeled are generally very complex. Therefore, in data based modeling it is mostly impossible to choose a physi(ologically) interpretable model structure. Simple black-box model structures then have to be selected that yield very intransparent models. Knowledge based methods, on the contrary, can yield very transparent models if sufficient effort is devoted to this aspect in the design stage.

Because of their complementary characteristics, a combination of data based and knowledge based models may be necessary for many complex medical decision support problems. A general scheme for constructing such hybrid systems has been presented in Ch. 8.

These ideas have been tried out in the domain of brachial plexus injuries. A need for support in diagnosis, treatment planning and prognosis in this domain has been demonstrated in Ch. 2. There it was also shown that knowledge concerning treatment planning is largely judgmental, thus posing a need for the formal assessment of treatment schemes. Processes to be modeled either knowledge based or data based have been identified: Knowledge based models for diagnosis and treatment planning and data based models for the evaluation of treatment schemes and for prognosis. With respect to the knowledge based approach, the research has shown the importance of revealing the domain
structure which can guide the organization of knowledge. The explicit representation of uncertainty, instead of the use of ad-hoc numerical methods and the use of deep knowledge have been shown to are important to keep the development process manageable and to achieve transparent models. For efficiency in the resulting run-time system, however, it is necessary to apply surface strategic knowledge.

A knowledge based system has been developed which consists of two models: One for localization of brachial plexus injuries and one for determining the severity of the injury and establishing a treatment plan. Each model consists of at least three task modules which constitute the strategy of heuristic classification, i.e. data abstraction, heuristic match and refinement. In the localization system, this domain independent diagnostic strategy has been based on the classification of evidence that provides a high level control structure for the heuristic match task. The heuristic match task yields a small set of plausible hypotheses that in the successive refinement task is searched by a hypothesize and test method, based on the A*-algorithm, for the minimal set of hypotheses that best explains the evidence. The heuristic match task is constituted of surface knowledge that is used to focus reasoning and the refinement task is based on deep knowledge. It was shown that the resulting task specific strategy bears high resemblance to expert physicians' diagnostic strategy in this domain.

In Ch. 6 it was shown that the incorporation of both deep and surface knowledge in one system yields good transparency and efficiency results. The quality of advice of the resulting system proved to be at expert level. Although it was felt that knowledge representation only is of secondary importance in modeling, the rule based formalism of the Delfi2+ shell that was used for modeling the surface strategic knowledge proved to yield sub-optimal models with respect to transparency. Because of this, the same surface knowledge has been implemented in a semantic net of objects and relations, in Delfi3. At the task level, this Delfi3 system is similar to the Delfi2+ system. It employs the same tasks of heuristic match, based on the classification of evidence, and refinement based on deep knowledge. However, in regard to the transparency of representation and system modularity, on the implementational level, this implementation is to be preferred over the rule based implementation. A formal assessment of efficiency has not yet been conducted for this implementation.

The results of the data based approach to support in the evaluation of
treatment schemes and prognosis have been rather disappointing thus far (Ch. 7). A major impediment to the applicability of data based methods in medical domains is the data acquisition problem. This problem may be alleviated through the introduction of medical information systems. In this research, a special-purpose database facility has been developed for data acquisition of the treatment process of brachial plexus injuries.
Samenvatting

Modellen vormen de basis van medische beslissings-ondersteunende systemen. De toepasbaarheid van een systeem wordt bepaald door de kwaliteit van het model waarop het is gebaseerd. Dit is in de eerste plaats afhankelijk van de ‘kennis’ in het model, en niet van de manier waarop deze kennis is geregistreerd. Voor het ontwikkelen van deze modellen zijn twee methoden beschikbaar: Een kennis gebaseerde methode, en een gegevens gebaseerde methode. Elk van deze methoden heeft zijn voor- en nadelen. Gegevens gebaseerde methoden zijn vooral geschikt voor het ontwikkelen van dynamische procesmodellen in domeinen waar slechts weinig a-priori kennis beschikbaar is. Gegevens gebaseerde modellen kunnen dan worden gebruikt voor het extraheren van nieuwe domeinkennis uit gegevens van het proces. Kennis gebaseerde methoden zijn daarentegen meer geschikt voor het modelleren en verbreiden van reeds bestaande kennis van statische of quasi-statische processen. Deze methoden leiden dikwijls tot niet-numerische modellen. Dit maakt ze minder geschikt voor problemen waarvoor numeriek advies noodzakelijk is, zoals bijvoorbeeld in het beschrijven van de dynamica van de toestand van een patiënt. Ook voor wat betreft akceptatie door gebruikers zijn kennis gebaseerde en gegevens gebaseerde systemen verschillend. De te modelleren medische processen zijn doorgaans zeer complex. Dit maakt het noodzakelijk te kiezen voor een black-box modelstructuur voor gegevens gebaseerde systemen, hetgeen leidt tot ondoorzichtige modellen. Kennis gebaseerde methoden kunnen daarentegen tot zeer doorzichtige modellen leiden.

Ten gevolge van deze complementaire eigenschappen, ligt voor complexe problemen betreffende medische beslissings-ondersteuning het combineren van gegevens gebaseerde en kennis gebaseerde modellen voor de hand. In hoofdstuk 8 is een globale methodiek gepresenteerd voor het ontwikkelen van dergelijke hybride systemen.

In dit onderzoek is gepoogd een dergelijk systeem te ontwikkelen in het domein van plexus brachialis Letsels. In hoofdstuk 2 is de noodzaak van beslissings ondersteuning in dit domein aangetoond. Daarnaast is gewezen op het belang van een formele evaluatie van behandelmethoden van deze Letsels, vanwege het gebrek aan objectieve kennis op dit gebied. Voor advisering omtrent diagnose en behandeling is gekozen voor kennis gebaseerde systemen. Voor prognose van deze Letsels is gekozen voor een gegevens gebaseerd systeem. Het onderzoek met
betrekking tot de kennis-gebaseerde systemen heeft het belang aangetoond van
een grondige studie teneinde de structuur van het domein bloot te leggen. Deze
domein structuur biedt een goede richtlijn voor het structureren van de kennis
in het systeem. Tevens bleek het voor het verkrijgen van inzichtelijke
modellen van belang te kiezen voor het expliciet representeren van
onzekerheid, in plaats van het gebruik van ‘ad-hoc’ numerieke methoden als de
certainty-factor methode of de Dempster-Shafer theorie en dergelijke. Teneinde
het ontwikkeltraject beheersbaar te houden is het van belang het model te
baseren op diepe kennis. Teneinde een voldoende efficient systeem te
verkrijgen is het echter noodzakelijk om voldoende oppervlakkige kennis toe
te voegen.
Er is een kennisysteem ontwikkeld dat uit twee modellen bestaat: Een model
voor het localiseren van plexus brachialis letssels, en een model voor het
bepalen van de ernst van het letsel en het vaststellen van een behandelpplan.
Ieder model bestaat uit ten minste drie taak-modules, die tezamen de strategie
van heuristische classificatie vormen: ‘data abstraction’, ‘heuristic match’
en ‘refinement’. In het localisatie-model is deze strategie gebaseerd op de
'classification of evidence', die een taak-specifieke inferentiestruktuur
vormt voor de 'heuristic match' taak. Na de 'heuristic match' blijft een
beperkte verzameling hypothesen over. In de 'refinement' taak wordt hieruit
met behulp van een heuristische hypothese-test methode gebaseerd op het A*-algoritme de minimale oplossing gezocht.
De 'heuristic match' taak is gebaseerd op oppervlakkige kennis die wordt
gebruikt om de zoekruimte in te perken. Daarentegen is de 'refinement' taak
gebaseerd op diepe kennis. De resulterende taak-specifieke strategie vertoont
veel overeenkomst met die van een menselijke expert.
De resultaten met betrekking tot inzichtelijkheid en efficiency van het
systeem tonen aan dat de combinatie van oppervlakkige en diepe kennis een
goodere methode is. De kwaliteit van het advies van het systeem blijkt op het
nivo van een menselijke expert te zijn. Hoewel werd verwacht dat
kennisrepresentatie slechts van secundair belang is, bleek de rule-based shell
Delfi2+ toch te leiden tot sub-optimale modellen voor wat betreft de
inzichtelijkheid. Dientengevolge is dezelfde oppervlakkige kennis
gerepresenteerd in een semantisch net van objecten en relaties in Delfi3. Op
taak-nivo leverde dit dezelfde modellen op als de implementatie in Delfi2+. Op
implementatienivo kon het systeem echter meer modulair en meer inzichtelijk
worden opgebouwd. De efficiency van deze implementatie is niet onderzocht.
Samenvatting

De gegevens-gebaseerde methode voor het modelleren van de prognose van plexus brachialis letsels heeft teleurstellende resultaten opgeleverd (hoofdstuk 7). De noodzaak grote hoeveelheden gegevens te verzamelen vormt een grote barrière voor de toepasbaarheid van deze methode in medische domeinen. Mogelijk kan dit probleem worden opgelost door de introductie van medische informatiesystemen. Ten behoeve van gegevensacquisitie van de behandeling van plexus brachialis letsels, is in het kennisysteem een database-faciliteit ingebouwd.
Curriculum vitae

The author was born on November the 23rd 1957 in Amsterdam. He was educated at the St. Nicolaas Lyceum, Amsterdam (1970-1976), and afterwards studied mechanical engineering at Delft University of Technology (1976-1983). During this period he was employed as a teaching assistant at the same university (1979-1981). He graduated in 1983 at the Laboratory for Measurement and Control under supervision of Prof. dr. ir. H.G. Stassen. From 1983-1989 the author was employed at Delft University of Technology, Laboratory for Measurement and Control as a PhD-student on the subject of medical assessment and clinical decision support systems. The research was conducted with grants from the Delft University Fund and the Prevention Fund under supervision of Prof. dr. ir. H.G. Stassen and Prof. dr. ir. E. Backer. The results of this research are the subject of this thesis.

Presently the author is employed at the Institute of Applied Computer Science of the Netherlands Organization for Applied Scientific Research, ITI-TNO.