Using artificial neural networks for the transformation of human body postures based on landmarks

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus prof. Dr.ir. J.T. Fokkema,
in het openbaar te verdedigen
op woensdag 15 Juni 2005 om 10:30 uur

door

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Ph.D. Thesis, Delft University of Technology.
ISBN 90-9019522-X

Keywords Computer-aided ergonomics design, 3D anthropometry, anthropometric digital human modeling, artificial neural networks, surface construction, posture prediction.

Propositions accompanying the dissertation

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1 Anthropometric landmarks lend themselves to an effective posture prediction and, at the same time, facilitate the reconstruction of a geometric model of the human body.

2 Back-propagation multi-layer perceptron artificial neural networks (BP-MLP-ANN) can process multi-dimensional variables (such as 3D coordinates of landmarks, demographic characteristics, and posture data) in an integral way.

3 There is an optimum number of layers, and an optimum number of neurons on the layers, for an optimum BP-MLP-ANN architecture, but it always depends on the application.

4 Even though there are general rules for finding an optimum architecture of a BP-MLP-ANN, it has to be found by a trial and error experimentation in each case.

5 Due to the phenomenon of over-training, a larger number of training epochs and a larger number of neurons will result in an over-fitted generalization in terms of the learned prediction rule.

6 Because certain groups of landmarks show similar behavior when the posture of the human body changes, a landmark cluster-oriented posture prediction method is more practical than a method handling all the body landmarks together.

7 The sensitivity of artificial neural networks is at least as difficult to measure as the sensitivity of human beings.

8 Our love of life should always be standing even when we have to take a seat.

9 Ph.D. students should be encouraged to do research in artificial neural networks that can predict the future of our life.

10 Looking backward is the best way of going forward.

These propositions are considered defendable and as such have been approved by the supervisors, prof. dr. I. Horváth, prof. dr. C.J. Snijders, and assoc. prof. dr. J.F.M. Molenbroek.

Stellingen behorende bij het proefschrift

Using artificial neural networks for the transformation of human body postures based on landmarks

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1 Antropocentrische markers zijn geschikt voor een effectieve houdingsvoorspelling en vergemakkelijken tegelijkertijd de reconstructie van geometrische modellen van het menselijk lichaam.

2 Back-propagation multi-layer perceptron artificial neural networks (BP-MLP-ANN) kunnen variabelen met meerdere dimensies (zoals 3D-coördinaten van markers, demografische eigenschappen en houdingskenmerken) integraal verwerken.

3 Er bestaat een optimaal aantal lagen en een optimaal aantal neuronen per laag voor een optimale architectuur voor de BP-MLP-ANN, maar dit is afhankelijk van de toepassing.

4 Hoewel er algemene regels bestaan, moet de optimale architectuur van een BP-MLP-ANN, per geval, en met behulp van trial and error, experimenteel worden gevonden.

5 Door het fenomeen van overtraining resulteren grotere aantallen trainingssessies en grotere aantallen neuronen in een overtrainde situatie bij toepassing van de geleerde voorspellingsregel.

6 Omdat bepaalde groepen markers gelijksoortig gedrag vertonen bij het veranderen van de lichaamshouding, is een methode van houdingsvoorspelling die gericht is op marker-clusters praktischer dan een methode die alle individuele markers tegelijk hanteert.

7 De gevoeligheid van Artificial Neural Networks is minstens zo moeilijk te meten als de gevoeligheid van mensen.

8 Onze liefde voor het leven moeten we staande houden, zelfs wanneer we moeten zitten.

9 AIO's moeten worden aangemoedigd om onderzoek te doen naar Artificial Neural Networks die het verloop van ons leven kunnen voorspellen.

10 Terugkijken is de beste methode om vooruitgang te boeken.

Deze stellingen worden verdedigbaar geacht en zijn als zodanig goedgekeurd door de promotoren prof. dr. I. Horváth, prof. dr. C.J. Snijders, en assoc. prof. dr. J.F.M. Molenbroek

Acknowledgements

The research presented in this thesis was carried out as doctoral research at Delft University of Technology. Firstly, I would like to heartily thank Professor I. Horváth who helped and strongly supported me to do my best to finish the research and write the thesis.

I would like to thank my daily supervisor, Dr. J. F. M. Molenbroek, for his continuous help and support of my research. I am also very grateful to my promotor, Prof. C. J. Snijders for his support which has encouraged me to go further in research.

I am thankful to all colleagues of Applied Ergonomics section, especially to H. Lok for his always effective technical support to my research. I want to thank Sander and Marco for their cooperation in the experiments and research. Furthermore, I am also thankful to all colleagues of the Industrial Design Department of Hunan University, especially to Prof. J. H. Zhao and Prof. R. K. He for their taking care of and helping me.

My appreciation also goes to my friends, Freija, Jing, Guanyi, John, Yanqing, Huisu, Xi, Yi, and particularly to Dr. B. Yu for his friendship, and for sharing the knowledge of artificial neural networks with me.

Finally, I appreciate indeed the opportunities provided for me by my family. My parents, Huimu Li and Jiaxing Zhang, provided me a warm and loving home and made me feel safe and happy. Their love and encouragement help me finish this thesis and go further. My husband, Jose, who is with me when I need somebody, and who helped me with his support and good suggestions to achieve the best in my research. My young brother, Jie, and my sisters, Xin, Ming, Fan, Lu, who always are of help for me to overcome the obstacles in my life.

Bing Zhang

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Chapter 1

Introduction

1.1 Background of the doctoral research

I used to be a product designer and also taught ergonomics before I started my doctoral research. As far as my design activities are concerned, I was involved in ergonomics design for the interior of trucks for a large Chinese automobile group. This involvement brought me to an understanding of human factors in designing and producing products for people. Soon after the product was manufactured, I could see the results of my interior design efforts, and I could also judge them based on the opinions and satisfaction of the customers. In the process of evaluating and analyzing the interior of trucks, I become more and more interested in considering the postures of the drivers, whose bodies always had different sizes and shapes. I was curious and interested to see if there would have been any effective way to predict the drivers' sitting posture based on anthropometric data, which would be measured only once in a standing posture (which would be the most natural). If so, I thought it would support the design for ergonomics and analysis of workspaces, and would save measuring time and costs. In fact, it was extremely difficult to achieve the objective with traditional anthropometric methods and manual mock-ups, because the human body is very complicated and dynamically changing. For example, in order to predict the postures using the conventional techniques, the human body needed to be divided into many different segments according to the anatomical construction. In addition, I also experienced a lack of proper computer support for the design activities. These factors, together with the growing expectations from the market, led me to the recognition that there is much to be done here that goes beyond the daily routine of interior designers. This recognition inspired me to deal with the abovementioned posture prediction problem with a scientific and technological intent. This dissertation summarizes what I have achieved during my doctoral research.

1.1.1 Ergonomics

My research is a combination of physical ergonomics and computer science. The term ergonomics comes from the Greek words *ergo* (meaning work) and *nomos* (meaning natural laws) (Wilson, 2000). Licht and Polzella (1989) analyzed 74 definitions of human factors, ergonomics, and human factors engineering by reviewing the different terminology used from 1949 to 1989. Pelsma (1987) gave the following definition to ergonomics: the application of knowledge about human characteristics and capabilities - physical, psychological, and cognitive - to the design of products, processes, and environments with the goal of improving well-being and optimizing productivity. In 2000, the International Ergonomics Association (IEA) Council adopted an official definition: ergonomics is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theories, principles, data, and methods to design in order to optimize human well-being and overall system performance. Ergonomists measure human characteristics and human function, and establish the way that the human body and the human mind work. The results of scientific work in the human sciences are applied by ergonomists in the solution of practical problems in the design and manufacture of products and systems (Galer, 1987). The domains of specialization within the discipline of ergonomics can broadly be distinguished as follows (Figure 1-1):

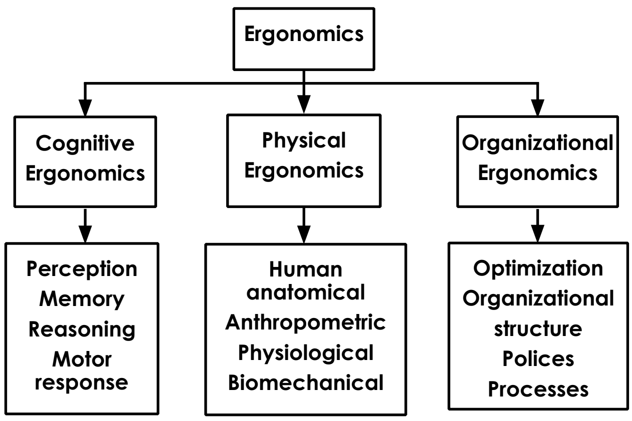


Figure 1-1 Classification of the sub-fields of ergonomics

1) Physical ergonomics is concerned with human anatomical, anthropometric, physiological, and biomechanical characteristics as they relate to physical activity. (Relevant topics include working postures, materials handling, repetitive movements, work-related musculoskeletal disorders, workplace layout, safety, and health.)

2) Cognitive ergonomics is concerned with mental processes, such as perception,

memory, reasoning, and motor response, as they affect interactions among humans and other elements of a system. (Relevant topics include mental workload, decision-making, skilled performance, human-computer interaction, human reliability, work stress, and training as these may relate to human-system design.)

3) Organizational ergonomics is concerned with the optimization of socio-technical systems, including their organizational structures, policies, and processes. (Relevant topics include communication, crew resource management, work design, design of working times, teamwork, participatory design, community ergonomics, cooperative work, new work paradigms, virtual organizations, telework and remote connectivity, and quality management.)

It has been established that ergonomics plays a prominent role in defining the dimensions and layouts of workspaces and products (Roebuck, 1975) (Roebuck, 1996). One of the most important subfields of physical ergonomics is anthropometry.

1.1.2 Anthropometry

Traditionally, anthropometric measurements have been oriented to landmarks which are anatomical points on the surface of human body, such as circumferences and breadths. In the measurements, simple instruments like tape measures and calipers were used; the most famous is the GPM anthropometer, produced by Siber Hegner Co., in Zurich (Martin et al., 1957). Methods that involve direct contact of anthropometric instruments with the surfaces of the body or the subjects' clothing (contact methods) or that use on-site readings of optical devices (optical methods) are called *direct* methods. Obtaining a complete outline of the body by the manual anthropometric techniques is time-consuming and awkward. Therefore, many *indirect* anthropometric methods have been proposed that are able to complement the traditional direct manual techniques, for example: (i) photography and video imaging; (ii) stereo-photogrammetry; (iii) stereo video recording; and (iv) 3D surface scanning. These techniques can support the capturing of the contour and provide the

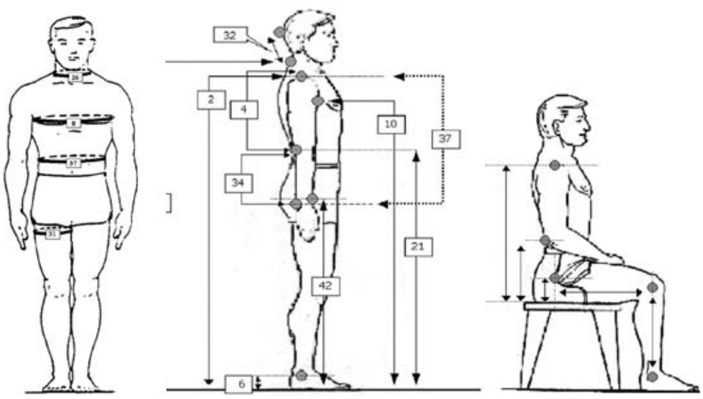


Figure 1-2 Traditional anthropometric measurements in one dimension (Roebuck, 1995)

opportunity to analyze the relationship between the user and the product (Robinette et al., 1997).

Traditional anthropometry involves measuring and recording the size, shape, and angles of human body with manual anthropological instruments. The measurements typically focus on different type of distances such as diameters, lengths, and circumferences. Though angles express special shape relationships, measurements of angles are rarely included in large-scale anthropometric surveys. It has been shown, however, that they are important for computer-based modeling of body postures and for the evaluation of mobility, reach, clearance, and vision (Roebuck, 1995). However, a disadvantage of the traditional anthropometry is that it can only provide designers and ergonomists with 1D or 2D data, which prevents them from understanding and studying the anatomical shapes of a human body in 3D space (Figure 1-2).

The trend in anthropometry has shifted from traditional manual anthropometry to modern 3D anthropometry by using laser or stereo-photogrammetry. It is no longer sufficient to define single-valued diameters, lengths, and circumferences in anthropometry. Dimensions need to be defined in terms of 3D coordinates (Roebuck, 1995). Also, the dimensions and postures selected should permit the designer to determine the locations of effective joint centers of rotation and help the designer to define body surface contours. On the other hand, there is a trend

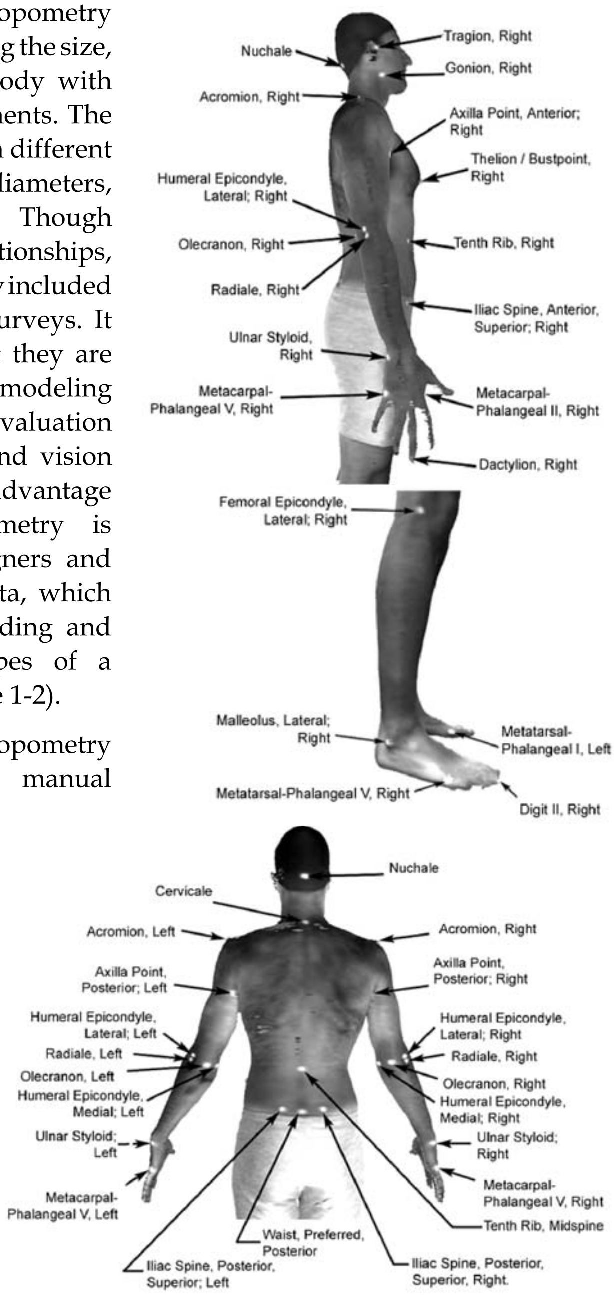
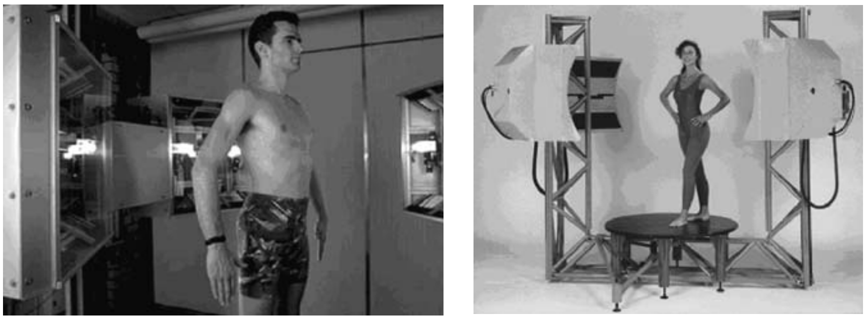


Figure 1-3 Landmarks location of whole body in 3D scanning procedure (Daanen et al., 2002)



(a) (b)

Figure 1-4 Measuring human body (a) Tecmath/Vitronic/Vitus Pro (the Netherlands), (b) Cyberware WB4 (North America/Italy)

away from the use of common-percentile mannequins for design criteria in favor of determination of true percentage accommodation (Roebuck et al., 1975). Some industries rely on multiple-subject mockup testing alone to develop these percentage accommodation statistics, whereas others are developing Monte Carlo and principal component analysis methods suitable for digital human modeling (Chaffin, 2001). The increased power of computer workstations has permitted more sophisticated statistical analysis than in the past and made it possible to complete such analyses in a timely manner.

In order to provide better support for the designers in measuring and modeling the human body, 3D anthropometry must be considered (Figure 1-3) (Daanen et al., 2001). Laser scanning, for example, is able not only to obtain information about the 3D surfaces of the subjects, but also to extract the landmark coordinates of the human body in 3D space.

However, there are just a few body-shape description methods based on 3D anthropometric dimensions (Mollard, 2003). Additionally, semantic descriptors such as esomorphic/dedomorphic are fuzzy and mathematically ill-defined. Incomplete human body description methods result in limitations and difficulties in generating a model of the 3D surface. On the other hand, in the area of anthropometric modeling, the concrete problem is how to relate large quantities of 3D coordinates to the proper morphological description of the human body (Figure 1-4). Although various anthropometric shape analysis techniques have been described to analyze the full range of body sizes and shapes in terms of curvatures, the methods typically used are based on one or two-dimensional quantities. In other words, they do not offer a proper method to apprehend the anatomical shapes and, in particular, their variation.

Traditional anthropometry predicts postures based on measurements of the distances and angles of anatomical landmarks, which overlooks the relationships between anatomical landmarks in space. Fortunately, some new techniques of modern 3D anthropometry, such as 3D surface scanning, make it possible to measure contours and to capture the spatial relationship between the scanning system and the person. Lasers, an acronym for "light amplification by stimulated emission of radiation," are the basis of some of the most promising indirect, high-technology measurement systems for modern anthropometry (Coblentz et al., 1991). Therefore, this dissertation works on the basis of this technology for providing human body data and in developing a posture prediction technology.

Technological innovations allow for a change from one-dimensional to three-dimensional anthropometry, resulting in data sets that are much more realistic for the world of the designer. Many recent studies have focused on the exploration of applications of the data of 3D scanned anthropometry (Lee, 2002) (Luximon et al., 2003). This research will partly contribute to this expanding field of 3D engineering anthropometry.

In the field of biology, landmarks extracted from 3D scanning data can be considered as a reduced 3D configuration of the human body (Bookstein, 1991). In other words, landmarks are a reduced descriptor of 3D data. In this sense, the landmark-based shape analysis methods will simplify the modeling procedure, because they deal with the landmarks instead of the large quantity of 3D coordinates.

In several industrial design cases, there is a need to take into consideration various postures of the human body when products are designed (Bridger, 1991). Generating human body models in various postures is a problem that is receiving distinguished attention in computer-aided ergonomics design in contemporary society. On the one hand, the major problem is how to obtain the information about the human body in various postures; on the other hand, the problem is how to produce the data for unknown postures, if the human body has been measured and modeled in a particular posture (Jung, 1996) (Leivseth, 1997). According to my understanding, it is necessary to move from the platform of a traditional anthropometry to the platform of a 3D anthropometry in generating the data for human body models. That is to say, this 3D anthropometric technique offers a 3D solution for working with the landmarks of human body directly.

1.1.3 Computer-aided ergonomics design

Computer-aided ergonomic design (CAED) is a multi-disciplinary sub-discipline currently emerging that combines the knowledge and resources of (i) physical and information ergonomics, (ii) customer-oriented product design, and (iii) advanced computational technologies in one. It is pushed by the proliferation of computer-based, advanced design support technologies, and pulled by the need for products better fitting the characteristics and expectations of customers (Wilson, 2000).

Meanwhile, fast, high-quality computer graphics now allow us to render very lifelike images of people performing a multitude of tasks within various computer-aided ergonomics design programs (Meunier, 1998). Furthermore, the statistical descriptions of various population attributes, such as the size, shape, strength, and range of motion of a specific group, have become quite sophisticated (Robinette et al, 1998). It is therefore possible to position and move computer-generated Digital

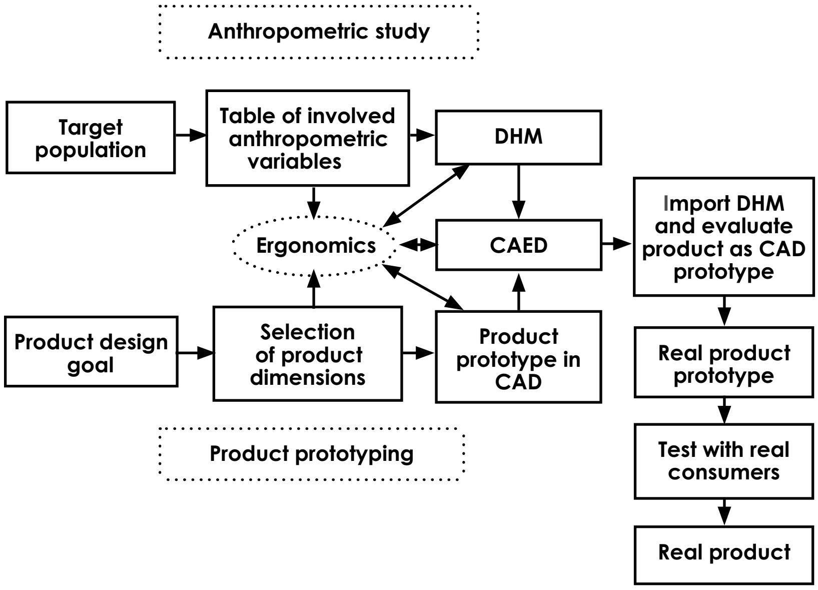


Figure 1-5 Flowchart of the rules for DHM of CAED in the product design and manufacturing procedure

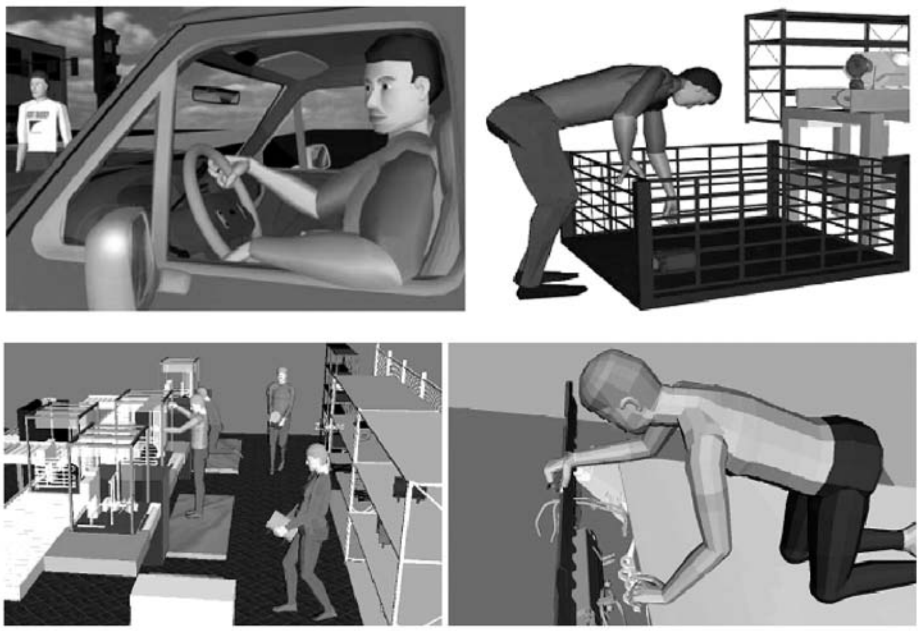


Figure 1-6 Popular DHMs from Jack and SAFEWORK: (a) test of vehicle accommodation with Jack; (b) Task analysis with Jack; (c) task analysis with SAFEWORK; (d) posture analysis with SAFEWORK.

Human Models (DHMs) to predict the performance capabilities of designated groups of people within a computer-rendered environment (Jones et al., 1995).

There are many aspects to the reason underlying the increasing importance of digital human modeling software in the design procedure (Molenbroek et al., 2000). It is believed by the designers and managers that using a digital human modeling system would decrease the design time and enhance the number and quality of design options that could be rapidly evaluated by the design team (Laurenceau, 2001). Figure 1-5 illustrates the important roles of DHMs and CAED in the product design procedure. When the product design goal and target population are decided, first of all, the product dimensions should be selected based on product functions. The ergonomics help the design locate the involved anthropometric variables in order to develop a product prototype (Adachi, 2001) (Chaffin, 2001). With the fast development of CAD, the progress of evaluating anthropometrics based on the product design can be achieved by employing DHMs of CAED. After evaluation of the CAED, the real product prototype can be produced. It will then be sent to real consumers for further evaluation. Finally, if the evaluation is acceptable, the real product will be manufactured and sent to market.

There is a demand for the rapid development of computer-aided digital modeling of humans in current design applications. Human body models as an aid in the design procedure exist in many forms, including two-dimensional drawing board templates and mannequins, three-dimensional physical dummies for bio-dynamic tests, and 3D digital human models. Most computer models were developed with a particular purpose in mind, such as biodynamic testing, strength assessment, or geometric evaluations. Whatever their differences, models share a basic need for an accurate representation of body size, shape, and proportion in all of their possible permutations. The three-dimensional anthropometric methods, such as laser scanning and stereo-photogrammetry developed especially for CAD, are the current research focus (Robinette et al., 1998).

Body dimensions are of the utmost importance for the design and evaluation of workspace as well as personal protection equipment. Unfortunately, few up–to-date databases of the civilian population are currently available. This is partly due

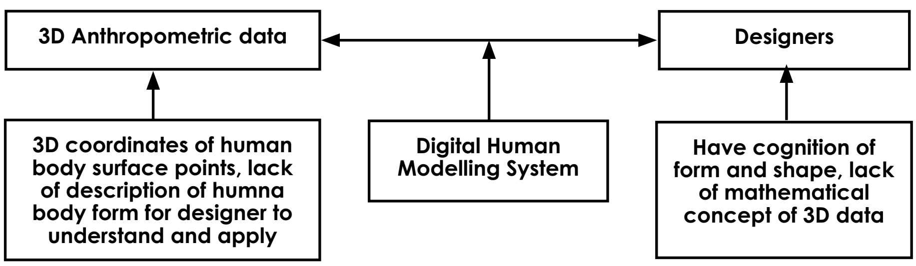


Figure 1-7 Gap between 3D anthropometric data and designers

to the labor costs of manual measurements. 3D surface anthropometry offers a cheaper alternative for a large-scale anthropometric survey. In a few seconds, the outside of the body is digitized and labor costs are drastically reduced. A large-scale anthropometric survey in the USA, the Netherlands and Italy, called CAESAR, was carried out using 3D scanning. The scan data has a wide range of applications such as optimized clothing fit, improved workspace design, and a variety of medical applications (Daanen et al, 2001). Figure 1-6 is a composite of pictures showing two current popular DHM systems in use, known as Jack and SAFEWORK (Chaffin, 2001). Figure 1-6.a shows a result of the application of Jack's vehicle accommodation toolkits. Figure 1-6.b illustrates the application of Jack's task analysis toolkits. Figure 1-6.c presents the assessment of the risk of injury based on posture, muscle use, load weight, task duration, and frequency, as well as the degree of intervention in order to reduce risk, all evaluated by SAFEWORK's task analysis toolkit. Finally, Figure 1-6.d shows an example of SAFEWORK's posture analysis function.

It is clear that a new method of digital modeling is necessary. Models frame data into meaningful interrelationships and define new data requirements (De Greene, 1980). A major drawback is that there is no clear bridge between 3D data and the design process (Roebuck, 1990). This is why designers are always confused about using anthropometric theory to guide their design (Kouchi et al., 1996).

Figure 1-7 illustrates the understanding of barriers between designers and 3D anthropometric data. The potential bridge between 3D anthropometric data and design parameters for the designer is a DHM which is constructed using 3D anthropometrics data.

The aim of this dissertation is to develop the core methodology and technology for a computer-aided ergonomics design (CAED) system, which is intended to provide posture prediction for designers.

1.1.4 Digital human modeling

The digital human modeling (DHM) technologies are advancing at the speed of light. In the past couple of decades, digital human modeling has become increasingly versatile and convenient to use in ergonomics and in design procedures. DHM offers very powerful tools when coupled with a knowledge of anthropometrics, ergonomics, and human factors. Chaffin (2001) concludes by describing the most popular applications for DHM: (1) replacement of 2D and 3D physical mannequins in order to solve problems in a more efficient, cost-effective, and timely manner; (2) solving problems related to the strength of people performing manual exercises; (3) assessing comfort or endurance, and (4) providing models which look and behave like real people for analysis purposes. The afore-mentioned human simulation methods enhance designing for people. This technology has the potential to drastically change the process by which most designers decide on the appropriate features needed to improve the interaction of people with the products, tools, and workstation they design.

Perhaps the first attempt to develop a computer simulation of a person performing a reach task was done by Ryan and Springer for the Boeing Aircraft Company in the late ’60s. During the early ’80s, COMBIMAN was reconfigured to stand, stoop, kneel, and bend not only while reaching about the immediate environment, but also while lifting, pulling, and pushing on various tools and objects placed in the hands. During the same general period, SAMMIE, developed by Case, Porter, and Bonney at Nottingham and Loughborough Universities in the UK, was conceived as a very general model for assessing various reach, interference, and sight-line issues posed by a designer. For vehicle interior package designs, the German model RAMSIS (Realistic Anthropological Mathematical System for Interior Comfort Simulation) is an important system. The recent hominoid form in RAMSIS uses a fully enfleshed deformable graphic with hidden lines and shadowing to create a very realistic-looking person. Another more general-purpose model, which is known as SAFEWORK, was being developed at Ecole Politechnique in Montreal, Canada during the ‘80s. One well-known human simulation model is Jack. Jack started out as a NASA-supported effort within the Department of Computer and Information Science at the University of Pennsylvania during the mid-1980s. In addition, the Boeing Human Modeling System (BHMs), first released in 1990, is a tool specifically designed for engineering applications in the aircraft industry (Chaffin, 2001).

The most prevalent use of digital human modeling is to simulate people of extreme sizes (i.e., to perform 3D anthropometric analyses) for the purpose of providing designs in which a large variety of people can reach, see, and/or manipulate objects. The most important feature of DHM is that the simulations and associated graphics allowed designers to gain a better understanding of the potential problems that might face a particular population subgroup when they operate or service a proposed design. It is believed that the use of a digital human model can save many months and thousands of dollars in design and prototype testing, compared to traditional methods.

Digital human modeling system, as a new technology in computer-aided ergonomics design, is beginning to be applied in various applications. The benefits and limitations of digital human modeling were discussed by Chaffin (2001) through case studies. The surveys of past users have listed many different desirable features to have in any future digital human modeling and analysis system which are the main issues in this field. Some of the most desirable features of a digital human modeling system are listed below. This list is actually compiled from 40 responses obtained in a survey of users (Nelson, 1996):

- Selection of several different population anthropometric databases
- Inclusion of different clothing and personal protection equipment
- Prediction of population strength and endurance in manual tasks
- Accurate representation of normal human motions in dynamic tasks
- Prediction of line of sight and projecting mirror view capabilities

- Prediction of normal task performance times
- Assessments of maximum reach and obstacle interference
- Seamless integration with other CAD systems and databases

One of the most frequently discussed limitations in the use of digital human modeling is in the difficulty in obtaining the necessary input data for a complete analysis, or in embedding the digital human model into an existing CAD model, which could provide much of the needed input data (Chaffin, 2001). The geometric data describing a vehicle interior or work environment is only part of the data necessary for a complete ergonomics analysis. The future digital human models must allow the user to quickly and easily access a great deal of geometric and human performance data, for example, the data about the repetition or length of time a particular task is to be performed, or what manual force must be applied to move an object, or whether the floor or handle is slippery, or if the temperature or lighting is sufficient.

Positioning the digital human model correctly is also a major issue. Many DHM users believed that having valid posture and motion prediction capability would greatly improve the ease of use of their particular digital human modeling (Chaffin, 2001). However, they are concerned that many future users of DHMs won't have the training or experience necessary to be able to accurately move and position the model correctly within a particular physical environment being studied. This limitation is most important in those situations when a proposed design must accommodate a large variety of people, those that are large or small, men or women, and young or old. In other words, the average designers of a new system could hardly be expected to know how their proposed designs could accommodate the motions and postures of an "average" person, not to mention extreme populations. Therefore, the future DHMs must provide all such knowledge.

To perform a shape analysis, a biologist traditionally selects ratios of distances between landmarks or angles, and then submits these to a multivariate analysis (Kendall et al., 1987) (Lele et al., 1991) (Lele et al., 1992). This approach is called "multivariate morphometrics" in biology. Similarly, traditional anthropometry extracts 1D or 2D measurements from samples and sends them to statistical analysis, then providing this statistical data for product design or workspace design in percentile or in multi-variable results. In the studies of multivariate morphometrics, one deals exclusively with positive variables (length, angles, and ratios of lengths) (Robinette et al., 1997). However, to consider only distances and angles can be inferior to using the actual coordinates of the landmarks, because the geometry is often discarded when using the former. Distance ratios can easily be calculated from coordinates, whereas the converse is not generally true. A considerable amount of work was carried out in multivariate morphometrics using distances, ratios, angles, etc. and it is still very commonly used in both biology and anthropometry (Roebuck, 1995).

However, there are few digital human modeling systems built based on 3D anthropometric data. Therefore, how to explore the large amounts of 3D coordinates scanned by 3D anthropometry is the current general issue that is open to discussion. By introducing an artificial neural network into the analysis and exploration of 3D scanned data, a promising posture prediction technology for building advanced digital human modeling system is expected to be developed in this doctoral research.

1.2 The content of the doctoral research

1.2.1 Definition of the problem

In the preceding part of this introductory chapter, I tried to point out the fact that a great deal of research has been done in the field of digital human modeling in order to support computer-aided ergonomics design (CAED). As has been discussed, the functionality of digital human modeling systems varies widely. One of the most interesting functions is posture prediction. Posture prediction is a very challenging task, since there are no conventional technologies to support the generation of postures for (i) large populations, and (ii) all postures in multiple actions. As it was hypothesized, a solution could only be expected from a combination of advanced anthropometric methods and high-end computer technologies. It is clear that conventional digital human modeling, which is based on 1D/2D anthropometric data (dimensions and angles), cannot lend itself to effective posture transformation. It does not involve and process a sufficient amount of the information needed to reconstruct the complete geometric model of the human body in a three-dimensional Euclidian space. In addition to a lack of sufficient information, the conventional methods are cumbersome, error-prone, time-consuming, and less than cost effective. Adaptive computational methods, which are based on learning algorithms rather than on rigid numerical algorithms, would seem to be the appropriate tools.

3D anthropometry based on direct body scanning and utilization of landmarks can provide a sufficient amount of information even for the reconstruction of the geometric model of the human body. It should therefore be taken into consideration in direct posture prediction. 3D anthropometry goes beyond the scope of the analysis methods currently used in DHM in the commercialized CAED systems. The first, seemingly trivial, but very important difference is that the data generated by 3D anthropometry is in the 3D space *ab ovo*, while the data produced by 1D/2D measurements based on manual instruments needs geometric transformation, extension and reinterpretation. The second issue is that the traditional statistical method presents barriers in exploring 3D anthropometric data, since it prevents the designer from understanding the true spatial aspects of the human body. Nevertheless, there are also some problems with 3D anthropometric data-based posture prediction. One of them is connecting 3D anthropometric data with a processing algorithm, which provides optimal efficiency even in the case of an extremely large set of descriptive geometric data. This efficiency is indispensable when one considers quasi-real time transformation of the data sets of various postures of the human body. This efficiency problem requires an effective computational method which is also able to reduce the procedural and computational complexities.

In order to rationalize the processing of bulky 3D anthropometric data, many researchers proposed to use landmarks. Actually, the landmark-based approaches proved to be extremely useful in various anthropometric and morphological manipulations of the shape of the human body. Landmarks not only rationalize how anthropometric information is processed, but also facilitate the application of non-conventional geometric transformation methods. In other words, landmarks can be considered natural ways of reducing the representational complexity of the human body, without destroying the interpretability of the data. Relying on landmarks in posture transformation can also contribute to the reduction of the computational efforts and time.

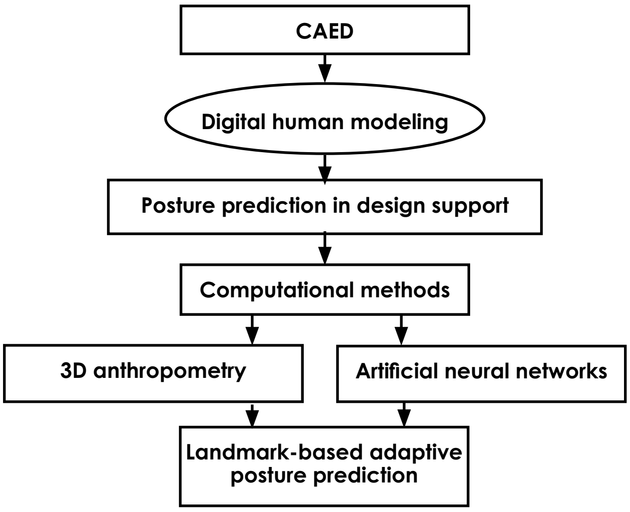


Figure 1-8 The scheme of knowledge contribution to enhance the power of CAED

As it will be underpinned by the literature study presented in the following chapters, artificial neural networks (ANN) can be trained to perform complex functions in various fields of application, including pattern recognition, identification, and classification. The knowledge available in this context indicates that, based on the analogies of previous applications, neural networks have learning capabilities and, similarly, for adaptation to various situations and conditions. The idea of ANNs emerged in 1987 as a result of the research in artificial intelligence technologies (Engelbrecht, 2002). Significant progress has been achieved in the last 20 years, both in the mathematical underpinning of the ANN technologies and in tailoring of the technologies to the particular needs of practical applications (Murakami, 1991) (Spelt, 1991) (Spelt, 1992). ANNs have been proposed as an alternative to statistical methods, in particular to modeling non-linear functional relationships. The differences between ANNs and statistics are that an ANN is based on determining and adjusting weights in the computational mechanisms. There are no assumptions in an ANN about the interrelationships among the descriptive parameters, and it maintains the independence of the descriptive parameters. The advantages of an ANN are that it automatically searches for all possible interrelationships among the key parameters (factors), and that it is able to extract solutions for a series of application cases much faster than many other tools. Additionally, it can handle noisy data and work with a large number of parameters or variables (Simpson, 1990) (Engelbrecht, 2002).

These are the fundamental facts that provided the stimulus for combining the concepts and means of 3D anthropometry and neural networks in this research in what was referred to as landmark-based posture prediction technology. This novel posture prediction technology fills in the existing gap between 3D anthropometric data and digital human modeling systems. The characteristic relationship of this posture prediction technology to CAED can be seen in Figure 1-8.

Driven by the understanding and reasoning discussed above, the following problems were identified as relevant general problems for this doctoral research project:

1) Adopting artificial neural networks, which are widely used in data mining in many applications in the field of ergonomics, in posture prediction transformation based on landmarks;
2) Converting bulky 3D data clouds efficiently, with a view to quasi-real time processing and spatial reconstructability of the human body;
3) Avoiding losing the relationships between anatomical landmarks of the body, which typically occurs with a purely geometric treatment;
4) Overcoming the difficulties in relating the implementation of the 3D human body data and artificial neural network-based technology in a conveniently usable ergonomic design support system;
5) Finding a solution for the creative use of this technology in industrial design applications.

1.2.2 Research questions

I was interested in how different knowledge, anthropometric technologies and computer technology can be combined to provide a support tool for industrial design engineering. My focus has been on digital posture prediction, so my major research questions center on the issues related to it. In fact, the research questions I have formulated have their roots in the previously formulated specific research problems. Obviously, in my doctoral research I could address only a limited set of questions and had to leave much more for further research, though the other issues are equally important and influential. I concentrated only on those questions which are directly related to the idea of using ANNs and landmark-based 3D anthropometric data for posture prediction. I formulated these specific questions as follows:

1) How should one manage the reduction of the amount of human body surface data obtained by the 3D scanning technique?

2) What type of ANN would be the most appropriate for posture transformation and prediction?
3) How should one utilize the landmarks concept to simplify the transformation of posture data by ANN?
4) What are the methods for training the ANN for posture prediction?
5) What is the best-fitting ANN structure (algorithm) for this specific implementation?
6) How should one verify the proper functioning of an ANN?
7) How should one validate the usefulness of 3D anthropometry and ANN-based posture prediction with application case studies?

From a research methodological point of view, the principle of how I derived these questions was induction. Based on my preliminary exploratory research, I aggregated a reasonably large set of knowledge related to anthropometry, digital human modeling, artificial neural network technologies and ergonomics-driven product design. Since my goal was to solve a practical problem by using the existing knowledge and the new knowledge that I explored/constructed during my research, I hypothesized various methods to arrive at a testable solution. Based on rational analyses and empirical tests, I abandoned several hypotheses and arrived at a interrelated set of sub-hypotheses which lead to the results documented in this dissertation. I discuss my main and component hypotheses below.

1.2.3 Resolution of the main research hypothesis

In simple words, I assumed that the conventional method of human posture recognition can be substituted by a new methodology that starts out from 3D anatomical data and predicts the changes in postures automatically, by learning the rules of transformation and regeneration. Having recognized the opportunities offered by a landmark based approach to shape transformation as well as the potentials of artificial neural networks (ANNs), my conjecture is that efficient posture prediction can be achieved by integrating of these two concepts. The difference between this new concept and the conventional posture prediction is graphically illustrated in Figure 1-9. The conventional methods include extra 1D/2D measurements in the posture generation process. The proposed new posture prediction approach predicts posture directly from the landmarks' positional data and relationships).

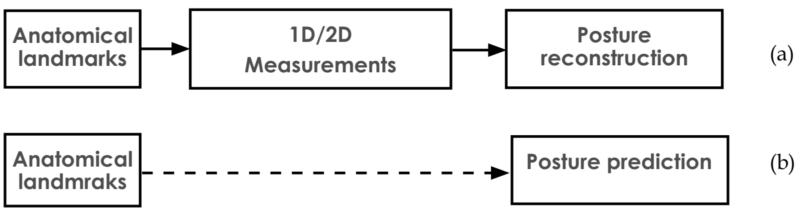


Figure 1-9 Comparing the conventional and the proposed concepts of posture prediction

Based on the specific research questions above-mentioned, I assumed that:

1) By using a set of landmarks belonging to a validated set of scanned 3D body data, the posture prediction problem can be simplified.

I believe that posture prediction could be simplified this way since more calculation work will be done by the computer and less manual measurements and processing will be needed. From the practice it is known that conventional posture prediction is very time consuming and error prone due to the manual measurement of 1D/2D anthropometric data and manual identification of anatomical landmarks.

2) Combination of geometric data and selective demography data will give sufficient bases for teaching the appropriately chosen artificial neural network system for posture prediction.

Because different gender, different race, different age and different occupation have impact on the body shape and the postures, including demography data to makes it possible to make the relationship between postures explicit. This way it is possible to create a correlation between the descriptive anthropometric data and the posture data, as relationships between the input and output of the ANN. The properly conditioned ANN can learn the rules of the posture transformation.

3) Based on experience with ANNs, my other sub-hypothesis is that back-propagation ANN (BP-ANN) will work better with small training samples and provide efficiency in posture prediction.

According to the experiences with various ANNs, they work correctly only if the input data is sufficient and if the learning mechanism is sufficiently efficient. Radial basis function-based ANN (RB-ANN) and back-propagation based ANN (BP-ANN) were two competing candidates based on the preliminary literature study. From the development and application reports I concluded that BP-ANN is more suitable for small samples, because it learns all of the input data. RB-ANN learns better in case of large samples. It has to be seen that the ease and simplicity of input data preparation is a cardinal issue in using an ANN-based system for posture prediction for product design.

4) It can be hypothesized that a method orientated to a limited set (a cluster) of landmarks can achieve better efficiency in posture prediction than a method that is oriented to the simultaneous processing of all landmarks of the whole human body.

It is well known from the past experiences with ANNs that they behave differently with large set of input data. For each neural network architecture and learning method there are optimal data sets which will provide the optimal results in application. If the input data are close to each other and homologous, learning is faster and more accurate than that with strongly dissimilar discrete input data. Therefore, the input data need to be clustered optimally.

5) Since there is no universal method for constructing an optimal ANN architecture

with different training mechanisms, it is assumed that the optimal ANN architecture can only be developed by repeated computer experiments.

All applications are case dependent. In other words, the relationship between the input and output data is different in each application case, as well as the data themselves. The only way to find the optimal architecture for the considered ANN is to experiment with changing the learning parameters, for example, the number of neurons on the layers of it, and also the number of hidden layers.

6) The operation, efficiency and reliability of the ANN can be verified by various training experiments.

ANNs actually implement an approximation method. It means that it has no determined learning results, and the performance depends heavily on a large set of interacting factors. In other words, the operation, efficiency and reliability of ANN are influenced not only by the input and output data sets, but also by the learning rules and learning epochs. Due to the non-explicit nature of the interactions and influences, the performance characteristics have to be verified by making computer experiments.

7) The utility of the ANN and landmark-based posture prediction technology can be validated by indexing the utility in appropriate application cases.

For designers the most important issue related to a design support tool is how helpful (useful, dexterous, and obvious) it is. However, the helpfulness may vary from application to application. The designers want to know in advance what they can expect from a given tool in various design processes and application. It is very difficult to believe that there might be a universal principle that is relevant for all applications. In other words, it is not possible to tell if an ANN will behave exactly the same way in all design applications. However, general utility indicators can be constructed for designers that show them how a particular set-up performed in various past applications. The applications must be characterized with indices as the validation of utility has been calculated or estimated.

Based on the above main hypothesis and the sub-hypotheses a supporting theory and an implementation methodology were developed for posture prediction. These will be presented in Chapter 5 and Chapter 6, respectively. It will also be shown that that the landmark and ANN-based PPT can effectively support solving of design problems involving changing postures.

1.2.4 Research methodology

In the various phases of my research I used various research and information/knowledge processing methods. In the knowledge aggregation part of the process explorative methods were given bigger emphasis, while in the multi-disciplinary knowledge synthesis part mainly constructive (rational) methods were used. The explorative methods included three comprehensive literature studies, whose results will be presented in Chapters 2, 3, and 4. It also included methods for obtaining new skills such as learning the latest version of the SAFEWORK, CAED software, the advanced programming language of Matlab for technical computing. It included experimental studies related to the theory, operation, and applicability of ANNs, mastering the user-friendly interface of Neurosolutions, as well as of the Delphi software package for programming. This knowledge was integrated with a wide range of existing knowledge, and adapted in the development of the theoretical foundations of landmark and ANN-based posture prediction.

As a logical implication of the sub-hypotheses, the knowledge synthesis part of the work had been decomposed to four major activities with different purposes and were completed in the subsequent phases:

1) Development of research concept based on further explorative and constructive methods. For instance, I conducted experiments with body shape measurement by Microscribe 3D and with reconstruction of the human body by a 3D data recording software. In the measurement experiment, samples were selected (from students of our Faculty), and the anatomical landmarks on the pelvis and belly area of the body of the subjects were located and marked. Using a 3D scriber and 3D software, the data were recorded and reconstructed in the computer for further statistic analyses. Another experiments included comparative studies with various ANNs. In the forerunning experiments with ANNs, I first sampled various sets of input data, and trained and tested RB-ANNs and BP-ANNs.

2) Implementation of an ANN for posture prediction. This work involved architecture building and testing, and presenting 3D coordinates of landmarks in a specified posture, together with demographic information and 1D/2D anthropometric variables. I mainly concentrated on back-propagation multi-layer perceptron (BP-MLP) type of ANN (two hidden layers one output layer). For the performance analysis I used a simplified case, that is, the 3D coordinates of the landmarks of head as input and target data set in training and testing of ANN. For the actual posture transformation and prediction, the anthropometric data were received from TNO. The coordinates of data points and landmarks were obtained by laser scanning. The total number of scans that were considered in the doctoral research project is 32, from which 28 scans were used to train the neural network, and 4 scans were used to test the performance of the neural network.

3) Verification of the posture prediction technology. BP-MLP-ANN were used to transform input data. I have considered both the common algorithm and the genetic algorithm of BP-MLP-ANN. In the research the scanned human body was substituted by a proper set of landmarks, which was used as a basis of transforming the data, as they were needed to describe specific body postures. The testing concentrated not only on the proper transfer, but also on the comparison of the performance of the ANN in two cases, when it was used to transform the landmarks coordinates of the whole body, and when it was used to transform clustered landmarks. In the extensive verification process, a large number of teaching experiments and comparative tests were conducted.

4) Validation of the posture prediction technology by application case studies. The goal was to validate the usefulness of ANN-based posture prediction technology in design processes from an information provision and processing point of view. Because the intention was to apply the ANN-based posture prediction technology in ergonomics-inclusive conceptual design of consumer products, three related criteria were defined, with measures and indices. Three design cases were selected that represent three different levels of requirements from an application point of view.

1.2.5 Relation of the doctoral research to the research portfolio and research programs of the Faculty of Industrial Design Engineering

The mission of Industrial Design Engineering (IDE) is to contribute to the knowledge, skills, methods, and professional attitudes in the field of integrated product development. The core of our mission statement and the major concern is designing successful products that the people like to use. The research in Industrial Design Engineering intends to study, innovate and improve the development process of products on the basis of the balanced interests of users, industry, society, and environment. IDE is predominantly concerned with durable, mass- or series-produced products for use in daily life, for example, at work, home, school, or for transportation, communication of leisure. These products are characterized by a significant interaction between user and the artifacts. All research activities focus on design by a multi-disciplinary approach. This means that ergonomics, marketing, organization, and aesthetics are integrated with engineering, industrial production and sustainability.

This doctoral research project was initiated in the Ambition research program in 2000. This program targeted multidisciplinary research within the faculty of Industrial Design Engineering at the Delft University of Technology. The Ambition program comprised of three research themes, Product Conceptualization, Intelligent Products, and Product Sustainability. The work in the program aims at a direct support of the mission of the Faculty: design products for people. In 2003, Ambition was included in the new research program that is titled Human Centered Product Design. This research program includes two parts: Design Theory and Support; Design of Future Products. The subprogram of Design of Future Product consists of Product Intelligence and Design for All projects. The *Design for All* program has a focus on understanding human-product interaction during product use. In the past, effort was put in describing human characteristics in static situations (static anthropometrics, static force exertion in product use). In the current program, dynamic aspects of product use play an important role. This topic is approached from a biomechanical point of view as well as from an anthropometric point of view. The anthropometric approach focuses on product-dimensions in relation to dynamic user dimensions. The goal of this program is twofold: (i) a scientific analysis of the dynamic aspects during use, and (ii) develop ways of providing these data to the designer of everyday products.

1.2.6 *The scope of the dissertation*

This dissertation reports on the results of the research in the development of a posture prediction technology. The research work involved five phases, which are shown in Figure 1-10. The posture prediction technology developed in this context is the proprietary work and contribution of the author. This proposal offers new opportunities for updating the posture-generating technologies of the current DHM of CAED system.

Chapter 2 reviews anthropometric and mathematical fundamentals and instruments to represent the geometry of human body. The reported studies include analysis of the knowledge of traditional anthropometry and the state of the art of 3D anthropometry. Four mathematical methods to reconstruct the human body surface were analyzed, namely: point clouds and meshes, radial basic function, B-spline surfaces, and the active contour method. Landmark-based shape analysis methods and theory are also covered at the end of this chapter.

Chapter 3 surveys the knowledge of posture prediction technology in current digital human modeling systems. Both the commercialized software packages and the academic research development have been taken into consideration. Chapter 4 studies computational methods for processing scanned surface data of the human body, including the study of the theory and application of artificial neural networks.

Chapter 5 describes the concept and development of the pilot system for the ANN-based and landmark-based posture prediction technology (PPT). It deals with the implementation of ANN-based and anatomical landmark-based posture prediction technology, including the developmental and experimental work. The point of the latter is to show that back-propagation artificial neural networks (BP-ANN) are capable of memorizing and predicting the landmarks of the surface of the human body with considerable accuracy, though the learning of ANN

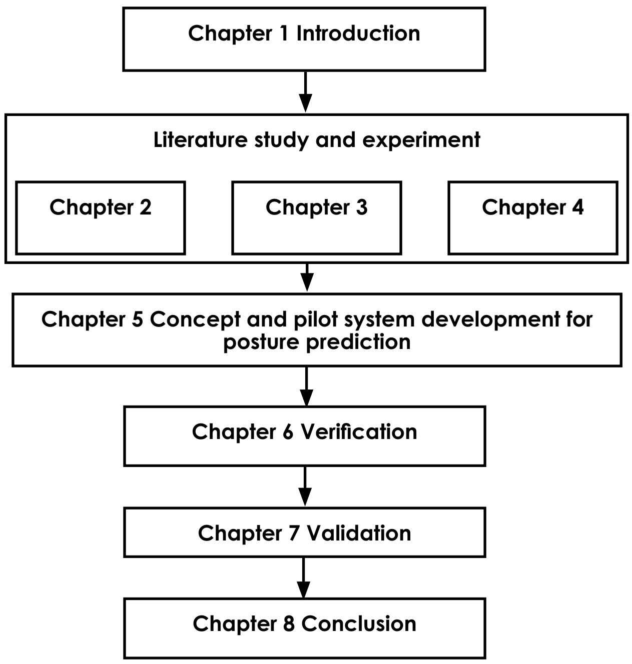


Figure 1-10 Consturct and scope of the dissertation

is not stable with different numbers of neurons in the hidden layer. Additionally, one preliminary study related to landmarks on the human head is presented in this chapter. A radial basis artificial neural network (RB-ANN) was employed in the experiment. In this chapter, one experiment with 3D anthropometry in the pelvic region is discussed, which was conducted in the Applied Ergonomic Lab of IDE at the Delft University of Technology. This experiment employed a 3D scriber and the built-in functions of the 3D CAD software Rhinoceros 1.1.

Chapter 6 describes the verification of PPT. This chapter presents two research activities: (a) transforming scanned body data between various postures, and (b) comparing algorithms of multiple layers of BP-ANN. In this verification, the scanned human body is substituted by a proper set of landmarks, which is used as a basis for transforming the data by ML-BP-ANN. The results of transforming the landmarks of the whole body and transforming clustered landmarks are compared and evaluated. The message here is that the genetic algorithm can help the network automatically search for optimal design at a low cost, but it needs a great deal of time for computing posture prediction compared to the common algorithm.

Chapter 7 describes the validation and assessments of PPT. This chapter investigates the validity and usefulness of the proposed posture transformation and prediction technology from an application point of view. Three application cases were investigated in the experiments. The results show that the proposed posture prediction technology is computationally effective, and it enables the designers to use arbitrary posture data in designing consumer products, such as furniture design, workspace design, and automobile interior design. However, it needs to be developed further in order to properly consider the specialties of different user groups. The neural network-based technology developed here is generally applicable and makes it possible to continue the research in human motion and hand postures prediction.

Chapter 8 discusses the main findings of this research and draws the conclusions. It points out the limitations of current PPT, and gives recommendations for further research.

1.2.7 Related publications

1) Zhang B., Molenbroek J.F.M. *Structuring interactive three-dimensional human body scanning database for product designers*. In: Actes des conferences human modeling - 3D com, Numerisation 3D scanning 2000, Paris, France, May 24-25, 2000.

2) Zhang B., Molenbroek J.F.M. 3D anthropometric data to support human centered industrial design. In: *Occupational ergonomics*, Tianjin Science and Technology Press, 2001, pp. 142-144.

3) Zhang B., Molenbroek J.F.M., Snijders C. J., Horvath I. *Fundamental research of mathematical model of human head form*. In: Proceedings of DHMC 2002, Germany.

4) Zhang B., Molenbroek J.F.M. Representation of a human head with B-splines techniques based on the laser scanning technique in 3D surface anthropometry.

Applied Ergonomics, **35**, 2004, pp. 459-465.

5) Zhang B., Molenbroek J.F.M., Horváth I., Snijders C. J. *Automatic landmarks prediction using the artificial neural-network-based technique on 3D anthropometric Data*. In: Proceedings of 8th International Design Conference, May 17-20, 2004, Cavtat-Dubrovnik-Croatia, pp. 817-826.

6) Zhang B., Molenbroek J.F.M., Horváth I., Snijders C. J. *Research of 3D anthropometry regarding to posture changing with artificial neural networks. Comparison of genetic optimization algorithm and general algorithm in posture prediction based on 3D scanned landmarks*. In: Proceedings of conference of Europe Chapter of the Human Factors and Ergonomics Society, Oct. 27-29, 2004, Delft.

7) Zhang B., Molenbroek J.F.M., Horváth I., Snijders C. J. Research of posture prediction by using artificial neural networks with 3D scanned landmarks of human body. Accepted by: *Journal Industrial Ergonomics*, 2005.

8) Zhang B., Molenbroek J.F.M., Horváth I., Snijders C. J. Assessment of a posture prediction technology based on application case studies. Submitted to: *Journal Industrial Ergonomics*, 2005.

Chapter 2

Measuring and representing anthropometric data

2.1 General introduction to the literature study

As explained in the introduction, the author's general hypothesis has been that the computational posture transformation and prediction problem can be effectively solved by the application of landmark-oriented anthropometric data representation and properly teachable artificial neural networks. As a first step in the knowledge aggregation process, I surveyed the related literature. In harmony with the definition of the problem and the research hypothesis, I placed the focus of the literature study on three major fields of interest: (i) measurement and representation of anthropometric data, (ii) advances in digital human modeling, and (iii) developments and applications of artificial neural network technology.

My idea has been that integration of landmark-based handling of anthropometric data with neural network-based information processing can provide a flexible solution for the posture prediction problem. This relationship is graphically represented in Figure 2-1. Consequently, by studying the literature in the above-mentioned fields I wanted to have an overview on (i) the current state of the art, (ii) the approaches that other researchers applied to similar and analogous problems, and (iii) the concept and sub-solutions that can possibly be integrated in a pilot system.

I used the above reasoning to structure the chapters reporting on the literature study. In the following part of this chapter, I will present (i) a survey of traditional anthropometry and statistical analysis approaches and methods, (ii) an analysis of three-dimensional surface anthropometry, (iii) the limitations of 3D anthropometry

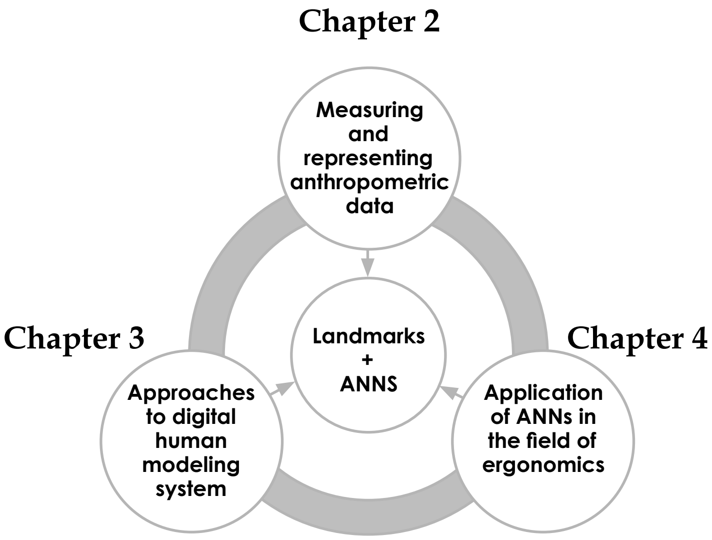


Figure 2-1 Argument structure of literature survey and study

and traditional analysis of 3D anthropometric data, (iv) an investigation of landmark-based shape analysis methods, and (v) the mathematical instruments for representing the morphology of human body.

2.2 Survey of traditional anthropometry and statistical analysis

2.2.1 Traditional anthropometry

Anthropometry is an outgrowth of physical anthropology. Anthropometry became an important branch of physical ergonomics at the beginning of the twentieth century. From 1940 to 1970, the need for collecting and processing data on human body dimensions significantly increased in many industrial application fields. It has been recognized that ergonomic analysis can enhance user satisfaction and efficiency of use for various artifacts. For instance, it was found that cockpits were often actually too small for many pilots, thus hampering or even preventing certain movements of the pilots. The study of body dimensions and their incorporation into the design of artifacts helped the designers to solve many human accommodation and human-artifact interaction problems. Roebuck et al. (1975) traced the development history of human body measurement methods. It started with the application of a limited set of specific anthropometric techniques, and developed over the years into a cohesive discipline which is known today as engineering anthropometry (or applied anthropometry).

The various sub-fields of anthropometry have been described as: (i) static anthropometry, concerning human body dimensions in static postures such as standing upright or sitting; and (ii) dynamic anthropometry, in which the distances are measured when the body is in motion, or engaged in a physical activity (Cuergo, 2002). Dynamic anthropometry is also concerned with functional postures. On the one hand, it is relatively easy to obtain data on static dimensions, when the body of the human subjects is in a fixed, standard position, and the techniques of static anthropometry can readily be applied to equipment design. On the other hand, it is much more complex and difficult to measure dynamic dimensions, which need to be taken on the human body at work or in motion, or those which are influenced by some mechanical factors (Damon et al., 1966).

In the context of applied ergonomics, anthropometry mostly appears in the form of ”static anthropometry”. Many anthropometric studies have been completed, because the results provided further information and even helpful instruction for workplace and product design. For objective reasons, many investigations and surveys concerned pilots (Bolton et al., 1973), flight personnel (Pheasant, 1986), or military personnel (Kelly et al., 1990). Far fewer studies have been done concerning civilians (Al-Haboubi, 1990), (Lin et al., 1999). Nevertheless, more attention has been given in anthropometry to the study of special populations such as disabled people (Yazici et al., 1986), or elderly people and children (Molenbroek et al., 1994). In addition, some special anthropometric surveys related to the face, nose, and foot have also been conducted and anthropometric data have been generated to support various design problems (Farkas et al., 1987), (Farkas et al., 1989), (Farkas et al., 1992).

Baker (1998) studied not only the principles and methods of static anthropometry, but also the issues of reach, clearance, and postures. He presented useful tables containing the results of actual measurements. His conclusion was that gender, ethnicity, age, and occupation affect anthropometric measurements. Other researchers dealt with the issue that the shape of any stable population changes from generation to generation. This phenomenon has been termed secular trend (Pheasant, 1986). In general, the population has been becoming taller. Most researchers have tried to be cautious about how to explain this phenomenon. One sensible theory is that secular trend is due to changes in the living environment, such as improved diet and the reduction of infectious disease. Pheasant, however, could not explain in his paper how much it depends on gender, ethnicity, and age.

The precision and reliability of anthropometric measurements play a very important role in product design. Therefore, these issues have been studied from many aspects in publications such as Mueller et al. (1988), Gordon et al. (1992), and Jamison et al. (1993). Kouchi (1996) studied the magnitude and variance of random errors in anthropometry. In order to quantify the magnitude and variance of this type of anthropometric errors, he conducted 219 measurements on 12 subjects. What he found was that the measurement of larger dimensions tended to have larger random errors. However, random errors were relatively smaller in the size range of 1-10 cm, and the reliability was higher. Imprecision is an inherent feature of anthropometric measurements because of the fact that human body is not rigid. There can be many reasons for relatively large mean differences and low reliability coefficients. For instance, these can be due to (i) the size of the body, (ii) the difficulty of locating the landmarks precisely, (iii) deformation of the soft tissues, and (iv) inconsistency in the posture of the subject.

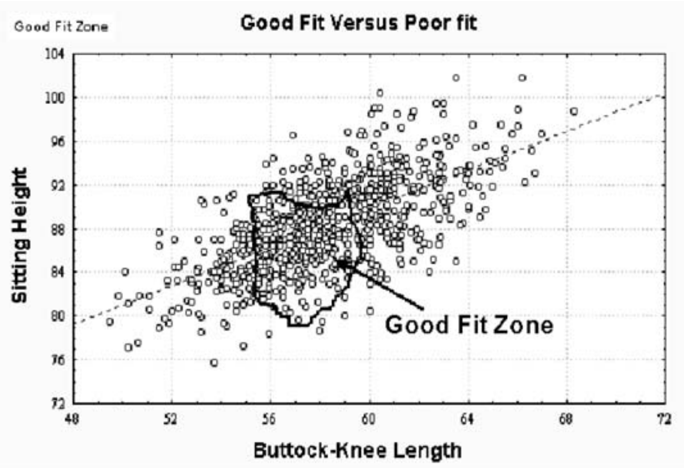


Figure 2-2 The relationship between the measured sitting height and the buttock-knee length (Lee, 2002)

One of the objectives of anthropometry and ergonomics is to solve the so-called ”fit” problem. In simple terms, it means fitting the product to human body dimensions (Case et al., 1989). In the past decades, traditional anthropometry studied the principles of how to achieve the best fit in design (Damon et al., 1966). As a result, a large number of rules have been defined and offered to designers. Before the emergence of the principle of mass customization, designers usually tried to accommodate the widest range of sizes from small to large. However, with the advent of 3D anthropometry, designers have the opportunity to measure various clusters of people, and to customize the product according to a given target group. Statistical data processing and the application of probabilistic methods further extend the possibilities. The process of translating the ergonomic concept of fit to a proper selection of critical design dimensions is already supported by formal (computational) means and has become less dependent on the intuitions of designers. For instance, the so-called fit survey sorts a population of subjects into the categories of good fit and poor fit. Based on graphical diagramming, as shown in Figure 2.2, the designer can determine and analyze the most important anthropometric variables (Lee, 2002).

The challenge for designers is to achieve a satisfactory fit while accommodating individual variability. Just to give an example: in principle, it is possible to attain specific designs and specifications of workstation components and arrangements by combining the “envelope” of the ergonomically constrained postures and the set of task constraints with a set of specific physical constraints for individuals. It is important to allow for anthropometric variability, and to consider the body characteristics according to the needs of the task and environment under consideration (Dainoff et al., 2003).

2.2.2 *Statistical issues in anthropometry*

The basic statistical definitions and concepts for anthropometry can be found in Roebuck (1975), but also in other literature sources. From the point of view of anthropometry, the main issues related to statistical processing are (i) determination of sample size, (ii) analyses of continuous characters and testing of normality, (iii) testing for curvilinearity, (iv) the application of regression, and (v) use of statistics for prediction. There are two methods of analyzing anthropometric data on various design applications, namely: (i) uni-variate analyses, and (ii) multi-variate analyses. The following section offers a short overview of these methods.

Univariate statistical analyses

This approach considers the relationship between single, independent variables (Molenbroek, 1994). It has become common practice to specify anthropometric limits (constraints) and to select standards for designing in terms of statistical numbers called percentiles. In simple terms, percentiles indicate the percentage of persons within the population who have a body dimension of a certain size (or smaller) (Damon et al., 1966). Structured percentile tables and graphs have been developed, which are helpful for the reverse process: given a specification of design limits (constraints) in terms of percentiles, it is possible to find the permissible limits for the dimensions of individuals. Workspace can be evaluated in terms of population percentiles, that is, from the point of view of accommodating of the largest body size for that will work efficiently within a workspace (Churchill et al., 1977). Similarly, clothing sizes can be sorted according to the percentiles. Moreover, in the field of predicting human postures, percentiles do have a role to play in terms of expressing body dimensions as posture patterns in percentiles (Roebuck, 1975) (Roebuck, 1995).

To predict population percentiles from other statistical information, or from sample data, requires additional statistical concepts and mathematical tools. More specifically, information is needed about the distribution of the aggregated data that can be expressed in terms of frequency of occurrence versus magnitude (Pheasant, 1996). These data are the basis for predicting design criteria. Distributions are expressed or approximated mathematically by standard distribution functions such as normal or Gaussian distribution. This bell-shaped, symmetrical distribution curve describes the common anthropometric data sufficiently well, for instance, as a plot of frequency of occurrence versus size. Other applicable statistical theories, such as cumulative distribution graphs, normal probability graphs, and measures of central tendency, dispersion, symmetry, and peakedness, can also be purposefully applied in anthropometric data analysis.

Kreifeldt et al. (1996) explored the concept that the accelerating ratio of physical size to percentile, as one approaches the upper extreme end of the Gaussian distribution, often limits the maximum percentile or minimum percentile that can be realistically accommodated. The reason is that it generally implies concomitant costs and/or spatial impacts on the physical system considered. However, what is not generally realized is the significance of the relative sizes of the physical dimensions involved. This might be a consequence of the fact that so much work is done with percentiles which are dimensionless quantities.

However, when improperly applied, percentiles can also cause misleading results. Some characteristics of percentile values have been identified which should be taken into consideration in order to reduce the frequency of errors which can occur when applying a percentiles-based technique (Robinette et al., 2001). These are as follows:

- A percentile is a point on a cumulative percentage scale for a specified population. Misleading results can be expected if percentile values are selected from a less representative population.
- A percentile scale is an ordinal scale. With respect to some body dimensions, the interval between the 70th and 75th percentiles may be only 0.2 inches, while that between the 95th and 99th may be 2 inches.
- Anthropometric percentiles on actual individuals refer to one, and only one body dimension. In all cases, it must be indicated which dimensions the rating refers to.
- The magnitude of percentile ratings should not be used to infer exact percentile ratings of other dimensions (Hertzberg et al., 1954). 90th-percentile knee height plus 90th-percentile knee-to-crotch length does not equal 90th percentile inseam. In other words, percentage cannot be accumulated.

Multivariate statistical analyses

In the past, designers and engineers typically designed and constructed product for the "average man". However, they quickly learned that designing for the anthropometric average does not fulfill each individual need. Daniels (1952) demonstrated that in a sample of 4000 men there was no one left in the center after just introducing 15 variables. It can therefore be stated that nothing like the average man exists in the real world. Therefore, it is necessary to consider multivariate (n-dimensional) statistics in most of the anthropometric problems. Methods of multivariate statistics are based on making estimates that take into account the interrelationships between the variables. The estimates are calculated by using all of the variables together, rather than by making estimates based on a percentage accommodating for each variable separately. This usually means forming a small number of composite variables. Multivariate methods such as principal component analysis (PCA) and discriminate analysis can be best used for anything that has more than one important dimension (Bittner, 1975). However, the more dimensions there are, the greater the need for a multivariate approach (Bittner et al., 1987). Lin and Lee (1999) developed an effective anthropometric basis-grouping technique by combining factor analysis, cluster analysis, and multivariate analysis of variance. This work shows that an appropriate grouping of subjects can result in higher statistically significant differences between subject groups in experimental results, than without grouping in advance.

However, there are some side effects of multivariate statistic methods due to the data reduction on anthropometric accommodation. Hendy (1990) examined the effects of interactions between individual anthropometry and workspace geometry with a view to establishing the consequences of these interactions in developing selection strategies and guidelines for design. The non-linear multi-variate nature of defining physical compatibility in the workspace is demonstrated through computer simulations fitting trials of subjects in a number of cockpit-like geometries. The computations make use of a simple sagittal plane manikin to represent the human skeletal form. Pierre (1998) compared a set of eight design mannequins which were located on the periphery of a circle encompassing 90%, 95%, and 99% of the population on two principal components with the true multivariate 90%, 95%, and 99% of the population. The PCA mannequins were found to include less of the population than originally intended. It was found that the degree to which the mannequins included the true percentage of the population was dependent mainly on the size of the initial envelope; larger envelopes were closer to the true accommodation limits. It was proven that there are many limitations on using limited numbers of test cases to predict population accommodation (Lin et al., 1999).

Anthropometric data estimation and prediction

Anthropometric data can be calculated approximately if measurements cannot be made or are insufficient (Roozbazar et al., 1979) (Resnick, 1995). There is a standard work by Hennie (1977), who estimated female dimensions of populations for which only male dimensions were available. In this study, 20 regions representing the populations of the world were involved, and the ratios between male and female measurements were calculated. It was found that female dimensions (especially erect stature height) could generally be estimated as 93% of the male dimensions, and that the greatest variability in the ratio between males and females were in the regions including the legs.

When anthropometric surveys are conducted involving specific populations, and it is necessary to know the distribution of these body measurements as a group rather than as separate populations, a composite population must be synthesized (Roebuck et al., 1975) (Roozbazar, 1979) (Schoor et al., 1996). Muhammad (1997) demonstrated a technique to pool the available anthropometric information and use this for designs for the composite population. Given the density functions of a certain random variable X for two populations A and B as $f_A(X)$ and $f_B(X)$, which may or may not follow the same distribution, it is necessary to combine both functions into a composite density function $f_C(X)$ and find the mean, standard deviation, and some percentiles for the combined population C (Muhammad, 1999). Resnick (1995) measured twenty key dimensions of the Colombian population to establish preliminary anthropometric measures in anticipation of a wider study, and evaluated the ability of the Scaling Ratio method to predict these data from anthropometric data of other populations. He found that prediction errors were generally small when the reference population was similar in age, size, and ethnicity to the target population.

Even if the exact size and shape of the representative samples of the target population is acquired, there are other important factors which should be taken into consideration during designing. Let's take an example from the clothing industry. In this professional field, the term ″ease″ means the amount of offset of the mask from the body (Lee, 2002). In other words, the mask will not properly fit if it is exactly the same shape as the face. Conversely, it needs to be smaller at some places and larger in other regions. How, then, should the fit be determined? The answer is dependent not only on general fit requirements, but also on the particular fit requirements of a given type of mask and a given design. Once the prototype is built, there is an opportunity to test the fit. This test checks if a proper proportioning of the piece was achieved, a range of fit per size was established, the impact of design trade-offs have been considered correctly, the number of sizes has been minimized, and, ultimately, the design has been optimized.

2.3 Three-dimensional surface anthropometry

2.3.1 Methods of three-dimensional surface anthropometry

Obtaining a complete outline of the body is time-consuming and awkward using the traditional (direct and manual) anthropometric methods. However, there are many *indirect* methods of anthropometry that can either complement or substitute the traditional manual techniques. Among these are, for example, (i) photography and video imaging; (ii) stereo photography; (iii) stereo video recording; and (iv) lasers and other optical surface scanning methods. Roebuck et al. (1975) reviewed the evolution and application of photogrammetric methods for static anthropometry from 1925 to 1972. They investigated the equipment, the subject matters, and the main observations. Stereo-photogrammetry was already used in the early 1920s in the medical and dental fields (Ghosh, 1968). The principle of stereoscopic vision was applied to determine the depth of body parts as well as their length and breadth (Hertzberg, 1957).

Modern anthropometry provides a very broad scope for various applications, for instance in industrial design. 3D surface anthropometry was brought to existence in order to meet the needs for increased precision and automation of measurement. It also favored data reduction, thus making it possible to fully define human body size and functional mechanics for workspace, clothing, and equipment design. Jones and Rioux (1997) provided an overview of the literature prior to 1997, with a view to the applications of 3D anthropometry. This survey describes a multitude

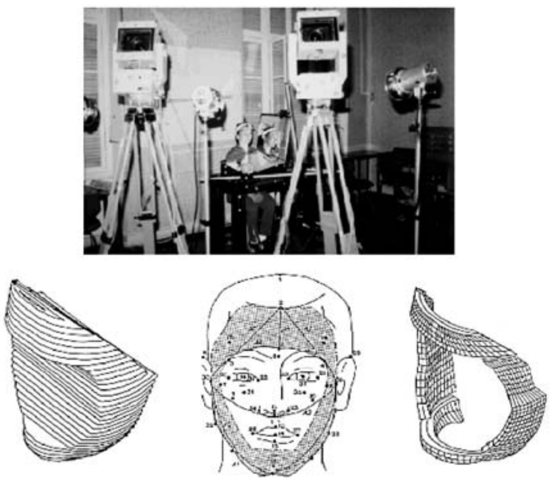


Figure 2-3 3D Simplified model of the face by photogrammetry(Mollard, 2002) of applications, for example medical, product design, human engineering, anthropometry, and ergonomics, and explains how the methods were applied.

By using a plaster model of the face, the accuracy of the early stereo-photogrammetric methods was investigated by Burke and Beard (1967). Measurements of various spot heights on the plaster model were made. Upon comparing these measurements with micrometer measurements of the same points, differences of less than 1 mm were found. Mollard (2002) presented a method based on 3D measurements of the head to develop a model of the face for the purpose of mask design. A bio-stereometric method of data processing was used which included (i) identification of the key information for designing the product (dimensions, angles, curvatures), (ii) finding the 3D locations of landmarks and/or reference points, and (iii) defining the constraints and creating geometrical models according to the defined constraints. The problem with this method is that it is limited to simple models. In the case of a complex model, it is very time-consuming and costly (Figure 2-3).

In contemporary society, laser-based 3D surface scanning is becoming the promising technological basis of indirect measurement systems for modern anthropometry. This high-technology equipment can provide a sufficient amount of information and can equip us with the ability to capture the relationship between the user and the product being used (Roebuck, 1996). There are three kinds of laser scanning methods which can scan the entire shape of the subject. The first one rotates the scanning device to be able to scan the entire shape. The second one rotates the subject and keeps the scanner fixed in space. In the case of the third one, both the scanning device and the subject are fixed, but the laser beam is moved vertically.

There are many benefits of using 3D data to support product design. 3D anthropometric data make it possible to ergonomically improve designs – practically everything from better clothes, through protective gear, to better seats and workstations (Robinette et al, 1997). Ferrino et al. (1996) defined the morphometric characteristics of the body-seat interface by digital photogrammetry and geometric reasoning techniques. The resulting geometric models of the human back surface have been analyzed by a geometric reasoning technique with the goal of automatically recognizing and extracting morphological characteristics from the surface. The research has mainly been oriented to the geometrical analysis of the lumbar region and to contributing to the definition of the zone where a possible lumbar backstop may occur. The automatic technique of shape analysis has been applied to compare the back surfaces of a subject in standing and sitting postures in the early phase of design.

The capabilities of such equipment are continually improving. For instance, the Dutch TNO owns a whole-body scanner, 'Vitronic', which was made in Germany (Daanen, 2002). This scanner has 16 "depth" cameras and 4 color cameras. A scan is made within about 20 seconds. The resolution of the scanner is about 3 mm. There is another high-quality scanner on the market, the Cyberware WB4 Whole Body Color 3D Scanner, which captures the shape and color of the entire human body in

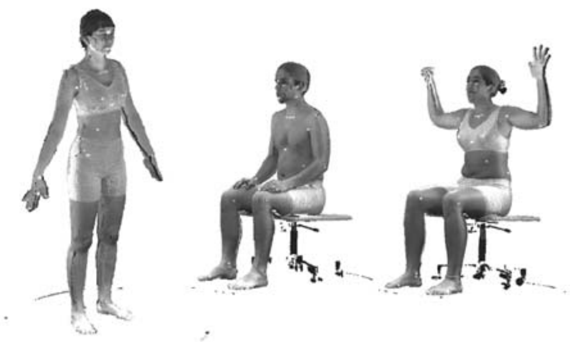


Figure 2-4 Three postures scanned in CAESAR project

as little as 17 seconds (Robinette et al, 1997). The scanner's rapid data acquisition speed "freezes motion" and makes it easy to scan many subjects, or to capture different poses in the application at hand. To capture the intricacies of the human body in one pass, the Cyberware Whole Body Colour 3D Scanner uses four scanning instruments mounted on two vertical towers. With a person standing on the scanner's platform, the scanning instruments start at the person's head, and move down to scan the entire body.

The data from a color Cyberware scan is stored in two files: one of these contains the range information, and the other contains the surface color information. The range data file, usually about 600kb in size, has an ASCII header that ends with DATA=. The values are given in order by contour or profile, from top to bottom, clockwise around a top view of the object. The range data can be converted into a number of different formats, including ASCII, AutoCad (.dxf), Wavefront, Dig. Arts, Byu, and IGES. This allows the data to be imported into a number of commercially available computer-aided design (CAD) and solid modeling programs. The WB4 scans a cylindrical volume 2 meters (79") high with a diameter of 1.2 meters (47"). These dimensions accommodate the vast majority of the human population. For even larger subjects, software enables the user to combine two or more scans quickly into a complete 3D color model.

The first effort with the goal to generate truly 3D anthropometric human models was made in the CAESAR project. Researchers employed both 3D scanning and traditional tools (Robinette, 2002). This project was a multi-million dollar collaboration of more than 35 companies, several government agencies, and the representatives of 6 countries. More than 13,000 3D scans were made and 4,431 subjects were measured. The three scanning postures that were used are shown in Figure 2-4. The full 3D data sets were used to calculate volumes, surface areas, segmental shapes, body contours, and other measurements which are not attainable with traditional tools. The data sets could also be used to enflesh models, and to build physical forms such as the dress forms used in the

Figure 2-5 Locating and marking of landmarks on subject's body surface before scanning (CAESAR project)

Table 2-1 Anatomical Landmarks

Name	Number	Name	Number
Tenth Rib	1	Calcaneous, Post.	20
Clavicale	2	Dactylion	21
Iliac Spines, Post. Sup.	3	Digit II	22
Thelion / Bustpoint	4	Femoral Epicondyle, Lat.	23
Substernale	5	Femoral Epicondyle, Med.	24
Gonion	6	Humeral Epicondyle, Lat.	25
Tragion	7	Humeral Epicondyle, Med.	26
Suprasternale	8	Knee Crease	27
Tenth Rib Midspine	9	Malleolus, Lat.	28
Iliac Spines, Ant. Sup.	10	Malleolus, Med.	29
Axilla Point, Ant.	11	Metacarpal-Phalangeal II	30
Axilla Point, Post.	12	Metacarpal-Phalangeal V	31
Iliocristale	13	Metarsal-Phalangeal V	32
Waist Preferred, Post.	14	Metatarsal-Phalangeal I	33
Acromion	15	Radial Styloid	34
SupraMenton	16	Radiale	35
Cervicale	17	Sphyrion	36
Sellion	18	Trochanterion	37
Nuchale	19	Ulnar Styloid	38

apparel industry. The reusable products of the project include: (i) 3D scan models for 3 postures for each subject in the .ply format; (ii) demographic information such as age, gender, fitness level, place of birth, etc.; (iii) 99 traditional style measurements such as chest circumference, sitting height, etc., forty of which were taken with traditional tools; (iv) 73 3D landmark locations in the standing pose and most of the 73 landmark locations in the comfortable working pose. These were marked with a sticker prior to scanning by a member of the measuring team. Landmarks were used in the project to identify the underlying bony structure, to sufficiently segment the body, and to produce anatomical reference axis systems for the key body segments and joints (Figure 2-5). The landmarks which were pre-marked are listed in Table 2-1 (CAESAR project).

It is also possible to make basic measurements based on surface models (Robinette et al., 1997). These include cylindrical and/or Cartesian coordinates of discrete points, which can be stored in a data file and exported into a spreadsheet for further analysis and comparison with normative values. Other common scalar measurements include distances between points, the angle subtended by three points, and surface distance between two points. Furthermore, quantities such as surface areas and volumes within user-defined boundaries can be computed. Further information can also be extracted about the surface contour. Measurement of the curvature and the rate of curvature are also possible. Basic approaches to measuring curvature usually involve Gaussian and mean curvature (Roebuck, 1995).

2.3.2 Processing 3D anthropometric data based on surface landmarks

A better capture of shape details by 3D measurements lends itself to a more detailed description of variations of the human body compared to manually obtained 1D or 2D data. However, there are not many body shape description methods, which are based on key anthropometric dimensions (such as circumference or height). Another recognized problem is that qualitative descriptions, such as esomorphic/ dedomorphic, are fuzzy and mathematically ill-defined and therefore difficult to include in a computer-based system (Lee et al., 1987).

Incomplete human body description methods result in limitations

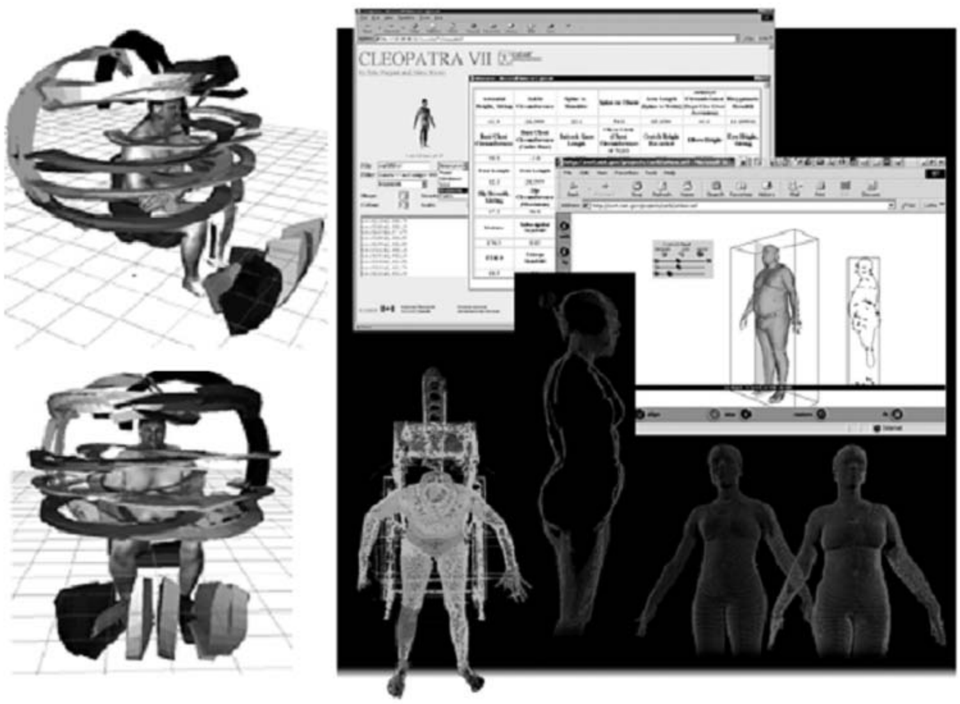


Figure 2-6 3D anthropometry in action. (a) 3-D visualization of reach envelope; (b) Web-based, comprehensive, international, 3-D shape data (Robinette, 2002).

and difficulties in terms of applications of 3D surface scanning. In the field of anthropometric modeling, a challenging problem is how to relate a large pool of 3D coordinate data to the body morphology (Robinette, 2002). The typical techniques for extracting morphological information include curvature map generation, feature recognition and extraction, and computational shape analysis (Jones et al., 1993) (Ras et al., 1996) (Martino et al., 1997). Although anthropometric shape analysis techniques were reported to be able to analyze the full range of body sizes and shapes in terms of curvatures, they are still relying on non-spatial methods. In other words, they are still not the ultimate methods for apprehending anatomical shapes and their variations in a three-dimensional space.

Youngsuk Lee (2002) described the application of scanned 3D body data of a certain Korean population. The method of processing the 3D data was actually based on slicing the body, and simplifying the 3D data into 1D or 2D data. In this case, the overwhelming majority of the 3D information acquired by scanning is partly wasted. Having 3D anthropometric data provides the opportunity not only to represent the differences and changes of human bodies in visualization, but also to identify where the differences are, as well as their magnitude. Standardization is also a challenging issue related to processing scanned 3D data. Some specific problems are to provide standardized file formats for the measured data, to provide criteria for the errors and incompleteness in data, and characterizing and indexing huge sets of 3D human body data in a way that supports effective searches, data mining and visualization (Robinette et al., 1997).

The techniques used to describe human body shapes include (i) super-quadrics, which are deformable solid modeling primitives, (ii) mesh-based surface models, where an energy function is employed for physical-based modeling and deformation of shapes, and (iii) meta-balls, which are adaptively parameterizable spheres, with distribution intervals (Robinette et al., 2004). The first two techniques have been applied to Cyberware-based data processing and support the development

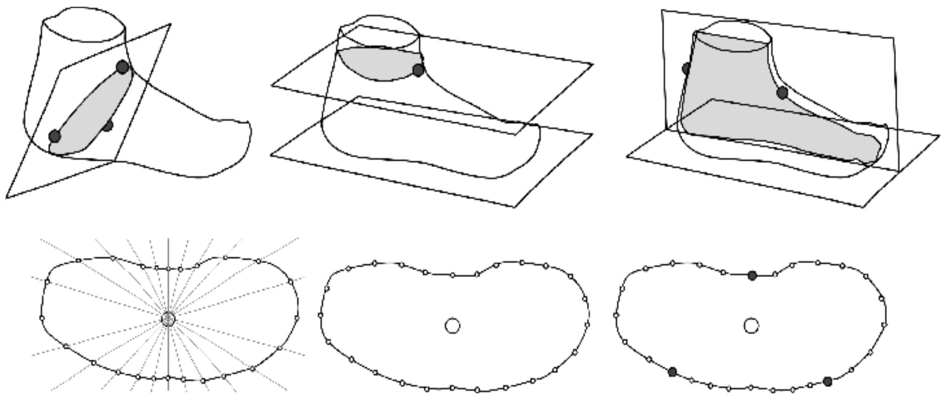


Figure 2-7 Generation of a cross-section through landmarks and generation of divided points on a cross-section (Mochimaru and Kouchi, 2002)

of parameterized body models for analysis, comparison, and recognition. The measurements can be in the form of simple scalar metrics such as distances, angles, proportions, surface area, or volumes, or they can even involve more complex relationships of morphological parameters such as contour and form.

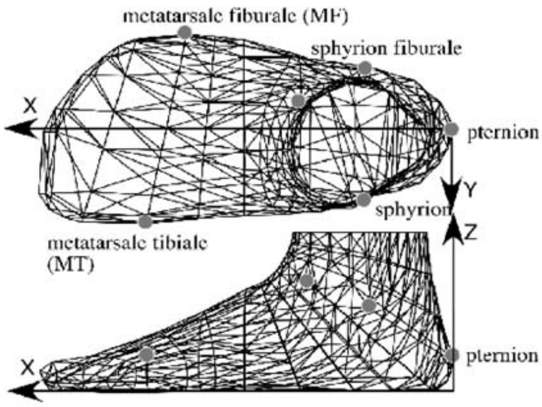


Figure 2-8 Foot model for shoe lasts: 295 data points (586 polygons) based on 9 landmarks (Mochimaru and Kouchi, 2002).

Mochimaru and Kouchi (2002) presented a method to automatically model foot shape and build a database of foot shapes (Figure 2-7). The methodology includes (i) statistical analyses of the 3D shapes of feet based on shape distance matrix, (ii) using the free-form deformation technique, (iii) representation of the distortion of a reference grid, (iv) calculating the optimal grid distortion from the average shape to the individual shape, and (v) calculating the shape distance with the grid distortion (Figure 2-8) (Mochimaru and Kouchi, 2004).

For presentation and analysis systems, compact descriptions of the human body shape are required in order to save storage space and achieve reasonable response time in uploading 3D human body data for the background database. Azouz et al. (2002) described a method based on a set of coefficients matrix representing the correlation with each eigen-person. The preliminary results of the abovementioned authors show that the Karhunen-Loève expansion method is a beneficial approach to develop compact description of the human body. The descriptive power of the database could be maintained by 185 eigen-persons on the level which is equivalent to a database of 300 persons. It means that 25,000 polygons included in the model could be reduced to hundreds of coefficients (Figure 2-9). However, this analysis and classification method is advantageous only for simplifying the management of the 3D database, but does

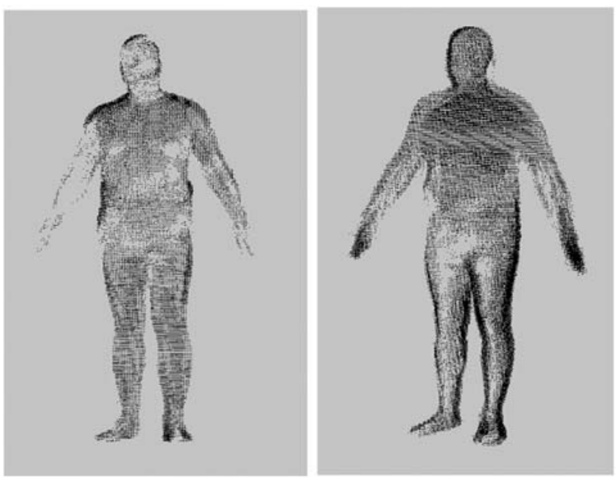


Figure 2-9 Two eigen-persons (Azouz et al., 2002)

not specifically support product design.

In a survey of applications related to the measurement of the human body, the results showed that at least three levels of resolution are needed: (i) high resolution (10-100um) for shapes in the size range of teeth, (ii) medium resolution (100um-1mm) for the face, hand and foot, and (iii) low resolution (1-5 mm) for the trunk and limbs (Robinette et al, 1998). Moreover, it has become clear that no current surface imaging system will be able to digitize 100% of the body's surface. This is a particularly important issue in the cases where there is a need to make recordings with the subject in different postures. The human shape is too complex and possesses too many degrees of freedom, which hinders the development of an all-embracing surface digitizing system with 100% practical fidelity. These issues will be further investigated in the next section.

2.4 Limitations of 3D anthropometry and traditional analysis of 3D anthropometric data

The advantages of 3D surface anthropometry are: (i) accuracy is generally much better than that of the methods using manual nodes or anthropometers, (ii) measurement errors can be reduced and controlled by the standards for the devices, and (iii) the data set is truly three-dimensional, which makes it easy to build a 3D digital product prototype in a CAD environment (Robinette, 1997). However, even 3D anthropometry is not free from some limitations. The first limitation appears in the fidelity of measurement and data acquisition. The reason is that the human body is a living organism, typically in constant micro- and macro-motion. The build-up and interconnection of elements of the human body result in a structural complexity, which is further increased by the whole-body topology and the large number of degrees of freedom of its segments. Skin pigmentation and scattering properties also influence the achievable accuracy of measurements. Because the human skin is quite transparent, most optical sensing techniques will underestimate skin elevation.

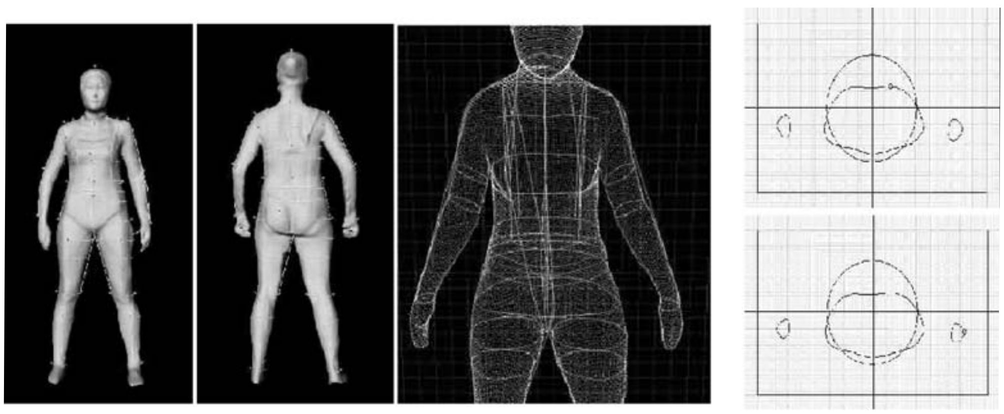


Figure 2-10 Acquiring 1D or 2D anthropometric data from 3D scanned data (LEE, 2002)

The 3D laser scanning methods have limitations, as do the camera-based ones: (i) they can not see obscured armpits or spaces between the legs or fingers or behind ears; (ii) the scanning speed of scanners is lower than the image capturing speed of cameras, though much faster than manual methods; (iii) the costs in terms of equipment, software, computers are high compared with traditional methods; (iv) applications involving 3D data are much more complex than the applications based on traditional anthropometric data; and (v) the subjects are not supposed to move during recordings.

In addition, 3D scanning technology is still in its maturing stage; therefore, it has not yet been fully integrated with computer-aided ergonomics design systems (Robinette et al., 1998). Translation of 3D data points and surfaces into a correct model is another challenge. The common difficulties are: (i) processes of obtaining anthropometric data are not tailored to and have not been conceived with the aim of developing digital human models; (ii) with few exceptions, the largest relative changes in the shape of human body take place in the soft tissues, rather than in the skeletal parts, and they can not straightforwardly measured; (iii) people of different age should be measured and their models should be built separately. The second issue is important, because it has an influence on the landmark-based anthropometric processing. That is, landmarks placed on softer regions such as the region of the abdomen need much more attention in measurement and assessment than those placed on bone-supported skin surfaces (Jones et al., 1997).

Traditional approaches to anthropometric measurement are constrained in their ability to comprehensively describe the three-dimensional features of the human body (Dryden et al., 1998) (Remondino, 2003). Although many important relationships can be derived between anatomic points, these distances or angular measures only provide a minuscule description of the three-dimensional morphology (form and structure). For example, if one were provided with all of the conventional anthropometric facial measurements from a subject and then were to attempt to backtrack and reconstruct the spatial position (x, y, z coordinates) of each of the anatomic landmarks in space, this task would probably not be accomplished. The main disadvantage of this "backtrack" method of coordinate acquisition is the large number of measurements needed if there are more than a few landmarks. For n landmarks there are $(n^2 - n)/2$ distances, so for ten landmarks there are 45 distances to be measured per subject, and for 73 landmarks there are 2628 distances to be measured per subject (Hammer, 2002).

Although it has become feasible to accurately and efficiently sample three-dimensional spatial relationships of anatomic tissues with minimal distortion, many new scientific and technological questions have been raised (Ressler et al., 2002) (Yuan et al., 2003). Only to the most important ones are summarized here. How might it be possible to accurately describe the intricate contours and structural forms of human bodies? What is the most tangible, but statistically robust and easy-to-use way of describing this for product design? What would be the best way to integrate the large database of two-dimensional relationships with these new three-dimensional data formats? Answering these questions will of course require further research, and new approaches must be developed for the analysis of 3D anthropometric data.

2.5 Methods of landmark-based shape analysis

It is now appropriate to clarify what landmarks are. Landmarks are cognitively interpretable and physically detectable elements (points, spots, regions) of the human body that have significance for the processing of body-related information (Bookstein, 1986). In anthropometry, landmarks are anatomical points on the surface of the human body. There are three basic types of landmarks: (i) anatomical, (ii) mathematical, and (iii) pseudo-landmarks. In the literature there have been various synonyms for landmarks, including vertices, anchor points, control points, sites, profile points, sampling points, design points, key points, facets, nodes, model points, markers, fiducial markers, and markers (Dryden, 1998). Assigned by an expert, an anatomical landmark is a point that corresponds to organisms in some biologically meaningful way, e.g. the corner of eye or the meeting of two sutures on a skull.

Anatomical landmarks designate parts of an organism that correspond in terms of biological derivation; these parts are called homologous (Jardine, 1969). Mathematical landmarks are points located on an object according to some mathematical or geometrical property of the figure. For instance, they can be identified at a point of high curvature, or at an extreme point. The use of mathematical landmarks is particularly advantageous in automatic recognition and analysis. Pseudo-landmarks are constructed points on an organism, located around the outline or in between anatomical or mathematical landmarks. Lohmann (1983) took equally spaced points on the outlines of micro-fossils. Pseudo-landmarks were used to mark the outline of a second thoracic mouse vertebra. From a geometric point of view, landmark data are the coordinates of those biological loci (Bookstein, 1986).

Given a set of medical objects, a statistical shape model can be obtained by Principal Component Analysis (PCA) (Lele, 1991). This technique requires that a set of complex shaped objects be represented as a set of vectors that uniquely determine the shapes of the objects and, at the same time, are suitable for statistical analysis (Lele et al., 1991). The correspondence between the vector components and the respective shape features has to be identical in order for all shape parameter vectors to be considered. This method has been successfully applied to obtain a statistical shape model for the lumbar vertebrae (Lorenz et al., 1996).

In biometrics, many statistical theories relating to the shape of human body have been studied. Kendall (1989) reviewed these statistical theories of organic shapes. One of these methods, morphometrics, is the statistical study of biological shape and shape changes. It is based on semantic data that are offered by landmarks (that is, by points such as "the bridge of the nose" that have both a biological name and a specific geometric location). Among the first researchers to do so, Bookstein (1991) conducted a systematic survey of morphometric methods for processing landmark data. The methods presented combine conventional multivariate statistical analysis with themes from plane and solid geometry, and from bio-mathematics, that provide biological insight into the features of various organs and organisms.

In spite of the many advantages, landmark-based shape analysis methods also suffer some limitations. For instance, landmark data alone do not provide a sufficient amount of information about the observable form of the object. Though the curvature distribution of the surfaces between landmarks could be important, these pieces of information are not available. Therefore, the form of an object is only incompletely represented by landmark data. Lele (1992) proposed a method utilizing Euclidean distance matrix analysis, which is capable of identifying the possible loci of morphological differences between forms. He also presented a technique for ranking the areas according to their influence. With a view to determining the usefulness of Lele's proposal, we provide an overview below of the most important mathematical concept of landmark-based shape analysis.

Euclidean Distance Matrix Analysis

The purpose of this method is to facilitate the representation and comparison of descriptive distances of human bodies and postures of limbs. The mathematical concept is as follows. Let a given two-dimensional or three-dimensional object be specified by k landmarks. Then, this object can be represented as a k*2 or k*3 matrix of landmark coordinates. A coordinate-free representation of this object can be given in terms of a Euclidean distance matrix (Mardia et al., 1979).

$$F(X) = \begin{bmatrix} 0 & d(1,2) & \dots & d(1,k) \\ d(2,1) & 0 & d(2,3) & d(2,k) \\ d(k,1) & \dots & & 0 \end{bmatrix} = \left[F_{ij}(X)\right]_{\substack{i=1,2,..k \\ j=1,2,..k}}$$

where d_{ij} is the Euclidean distance between landmarks *i* and *j*. Given this matrix, one can construct the original landmark configuration. The Euclidean distance matrix is a symmetric matrix of dimension k*k with the *(i, j)*th entry corresponding to the distance between landmarks *i* and *j*.

Let X and Y be two K*3 or K*2 matrices of homologous landmark coordinates located on two objects under comparison. Let F(X) and F(Y) be the corresponding form matrices. Equality of forms and equality of shapes are now defined in terms of F(X) and F(Y). A new matrix is also defined, called Form Difference Matrix, to represent the difference between forms X and Y. By definition, it is said that two objects, X and Y, have the same shape if and only if $F_{ij}(X)/F_{ij}(Y) = c$ for some $c > 0$, and for all $i > j = 1, 2, \ldots k$. If $c = 1$, then X and Y have the same form. The ratios of the matrix of $F_{ij}(X)/F_{ij}(Y)$ were referred to as a Form Difference Matrix. Mathematically, it can be expressed as: $D(X,Y) = \left[D_{ij}(X,Y)\right] = \left[F_j(X)/F_j(Y)\right]$, which are actually called a Statistical Model.

Lele and Richtsmeier (1992) proposed a mathematical approach for comparing biological shapes using landmarks. A unique feature of the approach is that it is coordinate-free. An extension of their method to surface data (using surface

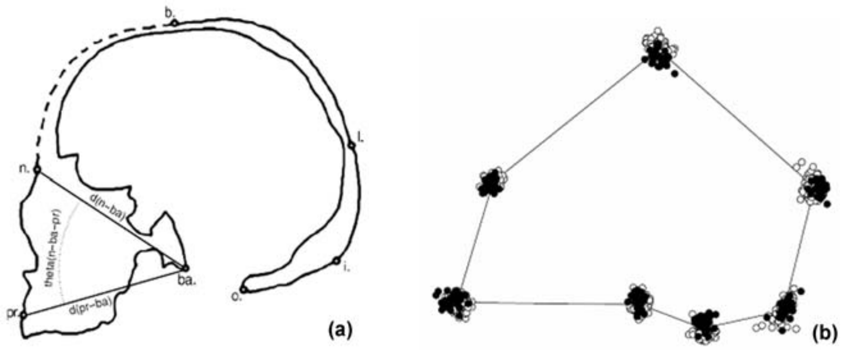


Figure 2-11 Morphology research: (a) Morphometric data; (b) GPA of seven landmarks in two dimensions (Slice et al., 2004).

curvature) is likely to produce interesting developments.

Slice et al. (2004) presented a method of landmark-based geometric morphometrics to analyze human variation relevant to the building of accurate human models for safety and injury research. Figure 2-11.a illustrates the morphometric data with Landmarks (pr = prosthion, n = nasion, b = basion, l = lambda, I = inion, o = opisthion, ba = basion), distances (d(nba) = basion-nasion length, d (pr-ba) = basion-prosthion length), and angles (theta (n-ba-pr) = basion angle) and Figure 2-11.b shows GPA (Generalized procrustes analysis) of seven two-dimensional, mid-sagittal, craniometric landmarks for mixed-sex samples of 94 adult Austrians (open circles) and 31 Khoi-San Africans (filled circles).

2.6 Mathematical instruments for the representation of the morphology of human body

Advance techniques of surface reconstruction are gaining more attention nowadays. It can be explained by the industry-wide introduction and proliferation of 3D scanners that are fast and accurate (Chui, 2003). The task of computer modeling of the human body based on 3D scanned data is actually a surface fitting problem. The objective of data reduction is to achieve an optimal fit using the smallest number of data points (Jones et al., 1995). There are of course many further considerations in practice, depending on the application and aims of modeling. Chui (2003) analyzed and compared three surface reconstruction methods. They are based on (i) Bezier curves and patches, (ii) radial basis functions, and (iii) active contour representation. Application of Bezier curves and patches is accompanied by several problems in terms of representing local shapes and of rendering. Multiple patches are combined to form a description of a complex shape. There may be problems with normal interpolation across patch boundaries and with cracks forming at patch boundaries (Farin, 2002).

The main idea behind radial basic functions is to construct a single function from surface data that can be considered as a volume function (Farfield Tech, www.

farfieldtechnology.com/products/toolbox/theory/) (Ohtake et al., 2004). This function represents a signed "distance" from the object's surface and is an explicit function of position. However, during rendering of the object, errors can occur if the normal vectors in some area (for instance, in the armpit) cannot be calculated properly (www.aranz.com/research/modelling/theory/). Active contour representation is based on Greedy's idea and algorithm (Liang et al., 1999) (Jones et al., 2000) (Chen et al., 2000). This representation is advantageous in solving problems related to incomplete meshes if the energy functions are chosen carefully. In those cases, for instance, where the holes in the raw scanned data are not too large, snakes will find the contour easily. When the holes are large, the uncertainty of the hidden contour is large. The snake has difficulties in finding these contours. Active Contour Models therefore do not offer a surface reconstruction method that solves all problems. The following context will survey the four main surface reconstruction methods on human body scanned data to date.

2.6.1 Representation by point cloud and mesh

The concept of point cloud and polygonal mesh comes from reverse engineering. Reverse engineering plays a prominent role in computer-aided engineering systems. The geometric model of an object is generated from a cloud of points, which can be obtained based on three main equipment platforms: (i) coordinate measuring machines; (ii) 3D laser scanners; and (iii) digital photo-grammetry systems. Laser scanning is the most wide-spread solution, because it is fast and robust relative to other methods. Moreover, the data scanned by the laser device provides explicit information about the exact spatial position of points, from which a 3D geometric model can be reconstructed (Wang et al., 2003).

Constructing the geometric model of parts of the human body from a cloud of points takes a great deal of work. For example, Ko et al. (1994) proposed a method for modeling a human face from a set of points. Their work concentrated on the reorganization of the points, facet-oriented modeling, and tool path generation. Sienz et al. (2000) developed a fitting technique to generate geometric models of 3D objects defined in the form of a point cloud. Doncesu (2000) meshed the surface of an object from a cloud of points using the Delaunay triangulation. Rodriguez et al. (2000) developed another method for Delaunay triangulation based on a surface reconstruction algorithm. All the above approaches are boundary-oriented, rather than volume-

Figure 2-1 Incomplete meshes on the top of the head and the ears area of the sample acquired by 3D surface anthropometry

oriented.

The CAESAR project was the first anthropometric-driven work towards the reconstruction of complete 3D human models form bulky point clouds, as input data (Figure 2-11). In the case of bulky point clouds, some sort of incompleteness. may occur. The left subfigure of Figure 2-12 shows the as-scanned point cloud of a human head. The middle subfigure shows the generated polygonal mesh. The subfigure on the right shows the smoothed and rendered surface model (Daanen and Robinette, 2001). However, there are incomplete meshes on the top of the head and the ear area of the sample point cloud, because the laser device could not reach those parts of the human head.

Most of the current techniques for converting bulky point clouds to polygonal meshes or to a composition of parametric surface patches assume ordered or semi-ordered clouds. Surface reconstruction from unorganized point sets is a major topic of computational geometry (de Berg et al., 1997). Dozens of articles have been generated in this topic during the last decades. The interested readers may refer to some classical monographs on computational geometry (O'Rourke 1998).

2.6.2 *Representation by radial basic function*

Franke (1982) identified radial basis functions (RBFs) as one of the most accurate and stable methods for solving the scattered data interpolation problem. However, it is only very recently that radial basis functions have received interest from the computer graphics community (www.aranz.com, 2002). RBFs are suited to interpolate scattered data scanned by a laser-based device. A radial basis function, $s(x)$, has been defined by the following formula:

$$s(x) = p(x) + \sum_{i=1}^{N} \lambda_i \phi(|x - x_i|), x \in \Re^d$$

Where ***p*** is a polynomial of low degree, λ_i is a real-valued weight, $|\ |$ denotes the Euclidean norm, ϕ is a basic function, $\phi : R^+ \rightarrow R$, and $|x - x_i|$ is a distance, which indicates how far ***x*** is from the point x_i. An RBF is a weighted sum of translations of a radially symmetric basic function augmented by a polynomial term.

FastRBF, developed by the Aranz company, can smoothly interpolate scattered 2D and 3D data with Radial Basis Functions (RBFs). With FarField Technology's *FastRBF*™ software, millions of data measurements can now be interpolated by a single function - a task previously thought impossible on a desktop PC. The fitted function and its gradient can be evaluated anywhere, such as on a grid, a plane or an arbitrary surface. These capabilities make FastRBF ideal for visualizing scattered data, particularly irregular, non-uniformly sampled data and reconstructing surfaces from range data. Figure 2-13 shows the interpolation results. Figure 2-13.a shows the exact fit to mesh vertices (6400 centres), Figure 2-12.b the fit to all mesh vertices to an accuracy of 1mm (6400 centres), and Figure 2-12.c the greedy fit to an accuracy of 1mm (1800 centres).

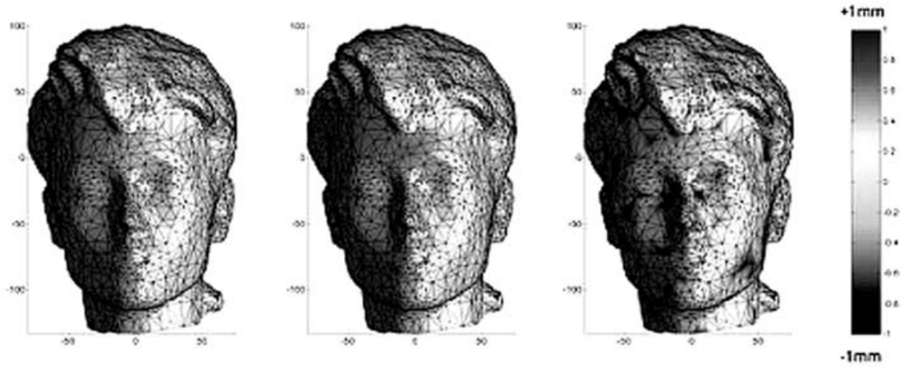


Figure 2-13 Plots of interpolation of a polygonal mesh (FastRBF)

Carr et al., (2003) showed that scattered range data can be smoothed at low cost by fitting a RBF to the data and convolving with a smoothing kernel (low pass filtering). The RBF exactly describes the range data and interpolates across holes and gaps. The data is smoothed during evaluation of the RBF by simply changing the basic function. The amount of smoothing can be varied as required without having to fit a new RBF on a fine grid, or performing a numerical convolution. Actually, the applicability of existing fast evaluation methods for certain types of smoothing kernel makes the approach computationally very effective (Carr et al., 1997).

2.6.3 Representation by B-spline surfaces

A parametric curve is a mapping of points of a 1D/2D parameter space to a 3D Euclidian space. Likewise, a parametric surface is a mapping of points of a 2D parameter space to a 3D Euclidian space. The parameter space is called the domain of the surface. It is typically a plane with a coordinate system such that every point has coordinates (u, v). The corresponding point of the 3D surface is a point which is described by the following equation:

$$x(u,v) = \begin{bmatrix} f(u,v) \\ g(u,v) \\ h(u,v) \end{bmatrix} \tag{1}$$

B-splines, or basic splines, were introduced by De Boor (1978). Rogers (2001) gave the following definition of a B-spline curve:

$$x(u) = d_0 N_0^n(u) + \ldots + d_{D-1} N_{D-1}^n(u) \tag{2}$$

This definition requires a knot sequence both in the $u-$direction and in the $v-$direction. The knot sequence is given by:

$$\begin{aligned} &u_0, u_1, u_2, \cdots, u_{R-1}; \\ &v_0, v_1, v_2, \cdots, v_{S-1}. \end{aligned} \tag{3}$$

The data points (control points) are given as $P_k; k = 0, \cdots, k-1$, and each data point P_k has a corresponding pair of parameters (u_k, v_k) These parameter pairs are expected to be in the domain of a B-spline surface.

The two fundamental methods of generation surfaces with B-splines are: interpolation and least-squares approximation. Figure 2-14 graphically illustrates these two B-spline curve and surface generation methods. Figure 2-14.a shows an example of a B-spline curve interpolation on a given set of experimental data points X^i, m = 5, with a spline of order n = 3 and with s = 5 control points. Figure 2-14.b presents B-spline least-squares approximation of the same experimental data, with n = 3 and s = 3. The approximation curve can be used to smooth data with some noise. Figure 2-14. c shows a typical control net of a B-spline surface.

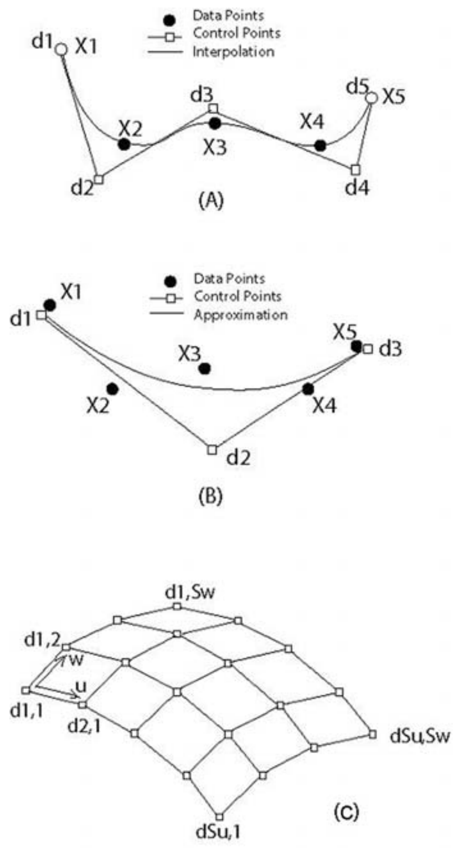


Figure 2-14 B-spline surface generation

Rogers (2001), Farin et al (2000), and Farin (2002) showed that B-spline surface definition is a very useful technique for representing and constructing free-form surfaces. Ateshian (1993) employed B-spline least-squares surface-fitting method to create geometric models of diarthrodial joint articular surfaces. His results indicated that this method is precise, highly flexible, and can be successfully applied to a large variety of surfaces. Douros et al (1999) developed an algorithm for a fast and robust surface generation process, which takes a set of B-spline curves as input, and derives a surface based on them. The surface is defined by adequately sampling the curves. The resultant smooth surface may be used to calculate body volume and surface area. Loop and De Rose (1990) presented generalizations of biquadratic and bicubic B-spline surfaces that are capable of capturing surface topology. For further details of spline theory, the reader is referred to Cohen (2001).

Most CAD software currently employs NURBS (non-uniform rational B-splines) to provide natural curvature of products (Rogers, 2001). The NURBS is known to be a specific B-spline surface. Therefore, the reconstructed representative 3D human body can be directly imported into CAD software.

2.6.4 Representation by active contour elements

The problem of contour modeling and extraction has conventionally been viewed as two separate issues in computer vision (Shih et al., 2004). Works on contour modeling typically ignore the problem of contour extraction. The starting point of extraction is usually a segmented image or an ordered set of points. Usually, edge detection and linking are attempted without reference to a contour model. In most cases, the presence of noise in images prevents detecting the boundaries, on the sole basis of intensity and contrast (Ungun et al., 2001). Active contour modeling assumes that the presence of an edge depends not only on local gradient information, but also on the long-range spatial distribution of the gradient (Yoon et al., 2004).

The active contour elements, also known as snakes, form the basis of the model reconstruction (Paragios et al., 2004). They were introduced by Kass et al. (1987). Snakes are energy-minimizing splines guided by external constraint forces and influenced by image forces that pull it towards salient image features like lines and edges. They can be looked upon as elastic curves that deform through minimization of an energy functional, and adjust their initial shapes on the basis of additional image information to provide a continuous boundary. The goal is to seek energy functions (low-level processes) whose local minima comprise the set of alternative solutions available to high-level processes. The constructed model is active because it always tries to minimize its functional and let the snake move to its desired shape. Cohen et al. (1993) are among the few researchers who applied this method in the context of surface reconstruction. They have also been working on various methods for extracting 3D models from 2D and 3D data.

2.7 Conclusions

Traditional anthropometry does not provide sufficient means and tools to treat the posture prediction problems properly. The main problem is that it is not representing the three-dimensional shape in sufficient detail and, typically, it employs manual methods in processing the human body anthropometric information. The modern 3D anthropometry gives more opportunities and advantages in capturing more information of the human body, even the dynamically changing shape of the human body. Using a 3D scanning technique provides sufficient information on the human body that describes the observable surface and the human segments in detail. This approach can be used in the development of the new solution for posture prediction based on artificial neural networks and anthropometry. However, there are problems with 3D anthropometry, because it provides a vast amount of data which are difficult to process efficiently in real time by computer. For this reason, simplification techniques are needed that keep the foundation information of human body geometry available and the same time simplify the computation. It seems to be meaningful to apply landmark-oriented processing, which means that landmarks are extracted from the scanned body surface. The changed body shapes can be reconstructed based on the landmarks using geometric techniques.

Certainly, a major problem still remains, which is how to handle population and cluster people, not only one single individual. From this point of view, statistic methods should be considered, especially those which support analysis of multi-dimensional variables. Using this technique, correlations can be found between the describable variables of the groups and the individual characteristics. Therefore, it means that in processing the data of 3D landmarks, certain statistic methods should be employed in order to achieve the most effective processing. The artificial neural networks provide a possible solution for dealing with 3D anthropometrics data directly which will be discussed in Chapter 4.

Additionally, based on the literature study, there are several geometric methods of constructing the human body based on 3D-scanned data of human body surface. The typical methods are the point clouds representation method, B-splines method, RBF method and active contour method. The point clouds representation method is the most convenient one that could be used in the research.

Chapter 3

Approaches to anthropometric digital human modeling

3.1 Introduction

Digital human modeling (DHM) is creating and manipulating virtual models of humans in a digital environment (Chaffin, 2001). There have been different digital human models developed for different applications and problems. For instance, digital human models are popular in the entertainment industry (games, movies, etc.), in medical applications, in ergonomics design, and in product usability evaluations. Product designers, engineers, ergonomists, facilities managers, workplace specialists, architects, interior designers, computer game developers, and movie animators are all on the list of digital human model users, and this list continues to grow longer each year (Laurenceau, 2001). In most of the computer graphics applications, human body modeling has to meet two main requirements or goals: (i) the created human body

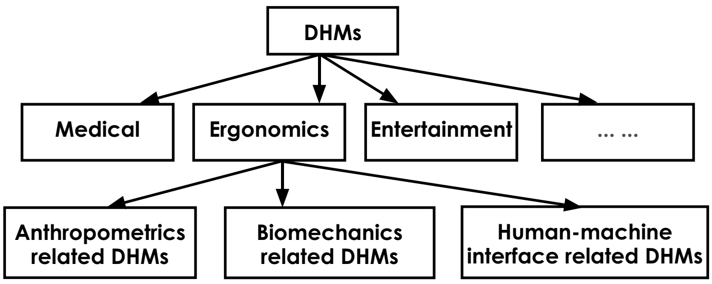


Figure 3-1 Classification of digital human modeling system

model must be animatable, and (ii) the animation must run in real time. Animation requires more complex data structures than that is typical for conventional geometric modeling (Balder et al., 1993). Consequently, modeling the human body is much more complicated than simply reconstructing its 3D shape (Thalmann et al., 1998). In the field of ergonomics design, DHM decomposes to three target fields, namely (i) anthropometrics-related DHM, (ii) biomechanics-related DHM, and (iii) human-machine interface-related DHM (Figure 3-1). In harmony with the goals of this dissertation, the research focuses on the anthropometrics-related digital human models, and will not discuss the other models.

Due to the differences in the bodies of knowledge, the methods, and the target applications, ergonomics (human factors) in the creative act of industrial design were historically treated separately (Wilson, 2000). However, with the advent of human-centered product design the two professional fields have been interlinked in multiple forms, causing some divisions between the disciplines. In current design teams, ergonomists and product designers collaborate in order to develop customized and appealing products for the customers, which are also convenient and safe to use. The goal of meeting the end-users' requirements needs effective knowledge synthesis in the early phases of the product design process (Das et al., 1995). This knowledge synthesis can be supported by digital human models, which can provide extra information both for product designers and for human factor specialists. As a result of the progress in computer technologies and information processing, it has become much easier to visualize, evaluate, and quantitatively analyze human characteristics, behaviors, and interaction in digital environments (Kakadiari et al., 1998). Important issues such as fit, stress, comfort, fatigue, and collision detection can be treated more comprehensively and deeply through the use of digital human modeling software tools (Bubb, 2002).

One of the major concerns of anthropometry-related DHM is to build representative geometric human models in different functional postures (Kroemer et al., 1988). The reason is that there is no actual human who has all features of a population of users, which have to be taken into consideration in designing a particular product. However, digital human body models are able to represent the maximal target user population of the product. Furthermore, simulating the ergonomic characteristics of person can guide the designers towards the best solution even at an early stage of the design process, even if the product exists only in a conceptual form. The advantage of simulating the spatial aspects and the behavior of users over using anthropometric data in design is that the anthropometric data tables have severe limitations. For example, you may have data about the size of the hand and the range of motion of the joints of the thumb, but it is difficult or impossible to get from that point to where the thumb of the 95th percentile hand ends up when the hand is wrapped around a device with a particular geometry (Wilcox, 2000). This definitely needs efficient posture prediction, which is one of the key functions of DHM. The conventional posture prediction methods that are usually based on angles and other traditional 1D/2D anthropometric data do not have sufficient potential to enable a fast reconstruction of the human body with complete space information.

Digital human modeling will play an important role in the future, because it becomes increasingly underpinned by the knowledge of the involved sub-disciplines, and increasingly supported by the computer and information technologies. Most probably, the issues related to continuous and real-time posture computation and prediction will also be addressed. The rest of this chapter will review the functions and the implementation approaches of DHM, focusing special attention on the methods and current applications of posture prediction within DHM. The second section will give a brief historical overview of the methodological evolution of digital human modeling. Almost 50 years will be reviewed in this short section, starting with the mid-fifties when first human mockups appear and were used, and continuing to the end of the 1990s when digital human body modeling appeared in commercialized design for ergonomics systems. In the third section, the current status of digital human modeling system will be surveyed - involving the years from 2000 to the present. The fourth section will investigate the posture prediction technologies offered by commercial software packages. The fifth section will provide an overview of the major results of academic research in the field of DHM. Finally, in the last section, I will discuss my major findings and draw conclusions about this part of the literature study.

3.2 Historical evolution and some typical problems of digital human modeling

The first body models that appeared in the mid-fifties were not digital, but mechanical or electronic replicas. Braune and Fischer (1889) were among the first researchers who developed the first linked-part models. Dempster (1955) also developed a model, which was also a link model constructed based on anthropometric data. At this time, even computers were in their infancy, so there was no opportunity to come up with an actual digital model. The first model to use a graphical display to assess workstation layouts was the system called Sammie (System for Aiding Man-Machine Interaction) developed by Case, Porter and Bonney (1969). In this system, three-dimensional models of equipment and environments could be built using geometric shapes. It had 19 connected links representing a skeleton, around which three-dimensional solids such as boxes, cones, and cylinders were placed to represent the extents of human bodies. The BOEMAN system was developed by Ryan and Springer for the Boeing Company in 1970. The kernel of this system was a computer-based model that was developed to support the design and evaluation of cockpits and other crew stations. The primary reason for its development was to assess the operator’s ability to move towards and reach the control elements in the cockpit. It included eye and digit links. Jenik and North (1978) dealt with a geometric human model for ergonomic design and evaluation which can easily be applied by users with an engineering, ergonomic, or medical background. The authors did not evaluate the different human models in relation to anthropological fidelity, but considered the feasibility of simplifying the human body features for practical applications, because of the limitations of the human-model database.

Dooley (1982) surveyed the anthropometric modeling programs until that time. The systems were improving in terms of modeling power and computational speed and had become much more effective in evaluating a variety of design concepts, without actually building a mockup of each environment concept. Wier (1989) dealt with the issues related to computer-aided anthropometric design and assessment for industrial designers. He concluded that the systems available at that time were inappropriate for industrial designers for three reasons. First, they were expensive. Second, they were too complex and had a steep learning curve. Third, the first two factors resulted in problems in application both for the practicing designers and for design education. Wier (1991) also reviewed the historical development of computer-based human simulation. From his paper I learned that a variety of computer-based human models were developed in the period starting in 1959 and continuing to 1991. They were mainly used for simulations, regardless of whether they were commercial or academic developments. This was the time when some boarder-stretching software tools such as SAMMIE, CYBERMAN, CREWCHIEF, and COMBIMAN appeared on the market and in design offices. Most of these tools were developed for specific workplace evaluation, such as a car interior or an aircraft's cockpit. The main characteristics of these software tools include: (i) a 3-D human model made of 20 or more linked parts with variable proportions; (ii) realistic body motions which could be manipulated interactively by the user of the software system; and (iii) joint movements were accurately constrained in order to comply with a real-life situation (Chaffin, 2001).

The traditional approach to human body modeling requires four steps: (i) 3D geometric modeling of the skin, (ii) modeling the material properties, (ii) mapping the skin geometry onto the skeleton, and (iv) attaching the skin to the skeleton (Thalmann, 2002). The designer first has to create a 3D geometric representation of the skin, either by modeling it from scratch, or by importing it from another system. The third step, which involves building the 3D skeleton by interactively defining the elements and the joints, and then interactively placing the 3D skin around the skeleton, is very tedious. It is so time-consuming simply because each joint of the skeleton has to be correctly placed inside the geometric model of the skin. The last operation is to attach the vertices of the skin to a segment of the skeleton. After these steps the human body model is ready to be used in animation or simulation, though there is still an additional step: the designer has to test all the skeleton's degrees of freedom. The step of linking the skin to the skeleton is quite time-consuming, in particular when the shape of the body has not been modeled in harmony with the way it will be animated.

Digital human body modeling tools are widely used in the automobile and the airplane industries to design and test vehicle interiors and cockpits (Geuss, 1997) (Hudson et al., 1998). In military applications, digital human modeling tools have been used for many years in equipment design and simulation of the activities. The systems used typically embed general anthropometric tables to support building human models. The contents of these tables typically comprise: (i) some statistical features such as mean, standard deviation, p5, and p95, etc., (ii) variables such as gender, age, profession, posture, secularization, and clothing, and (iii) a list of definitions of the variables measured and pictures of each of these (Pheasant, 1996). On the other hand, not every digital human modeling system can solve all kinds of design problems. Selection of the proper digital human modeling system is an important decision in the design process. One of the problems in relation to digital human modeling is that the geometric entities offered by the systems are not sufficient to represent all features of all humans. However, this is not only a representational problem, but also a restriction in terms of analyzing the 3D anthropometric data (Robinette et al., 1995).

Roebuck (1990) suggested a solution for overcoming some anthropometric barriers of digital human modeling. The first barrier is the lack of data on breadth, depth, and contours of limbs, and clothing. External contours of the nude human body as well as the external surfaces of clothing and the hairstyles are important for developing a graphical model that mathematically describes "enfleshment". The second barrier is insufficient data about the contours and the limited capability for generating these data. On the one hand, without an extensive set of data, an insufficiency develops that may be considered as a yawning chasm. On the other hand, when there are superfluous contour data, there will be a glut of numbers, which requires using sophisticated mathematical analysis methods as well as advanced data handling procedures for storing and retrieving data (Mascie-Taylor, 1994). Storing bulky descriptive data in different levels for different application procedures might be one solution. However, the most effective solution would be a smart selection of contours and development of proper analytical formulations.

Theoretically, many of the above problems could be solved by more complete and accurate "contour maps" of the human body. This needs more sophisticated anthropometric measurements and processing methods, using stereo video, stereo photography, or laser scanning equipment. As a result of a more extensive data acquisition, lengths, breadths, depths, circumferences, and even volume, areas, and mass properties could be calculated according to the needs of later analyses (Robinette et al., 1997). An additional problem is that many of the downstream analysis methods are still based on 1D or 2D measurement data, and therefore could not comprehensively rely on 3D information. For the above reasons, as Molenbroek (1990) argued, it is very important to choose the most appropriate anthropometric models for industrial designers and design engineers with a view to the available anthropometric data.

3.3 Current status of digital human modeling

Since the beginning of the nineties, several digital human modeling systems have been developed, marketed and applied in various fields (Wier, 1989). In the field of computer-aided ergonomic design (CAED) and simulation, the most popular commercial systems at present are SAMMIE, SAFEWORK, RAMSIS, JACK, and Anthropos, which is a human modeling system used by Boeing (Chaffin, 2001).

Laurenceau (2001) compared common features of the top DHM software packages, as well as analyzed them from the aspect of usage and from the perspective of the needs of industrial designers (Table 3-1). Table 3-1 shows a summary of this comparison for four DHM software products based on 12 common features. These features include support of 3D anthropometric data processing, which I considered as the proper basis for digital human body modeling (item 6 in Table 3-1).

Colombo et al. (2004) presented an approach to evaluating product ergonomics and safety based on the use of the JACK system for digital human modeling. They demonstrated best-practice methods through two case studies (Figure 3-2). They made various anthropometric and workplace adjustments by adjusting the joint angles that define the posture of the operator, and analyzed the comfort of executing the tasks. Once the anthropometric data were selected, a virtual mannequin was generated and located in the driver's seat. The virtual driver was set to a normal driving posture, with the right foot leaning on the accelerator pedal, and with hands on the steering wheel. They found that the JACK system is well suited for visibility and posture analysis. However, simulations requiring, for example, force feedback for the interaction between the mannequin and the scene seem to be more complex, and probably impossible at the current state of the art. Storing 3D surface anthropometric data is considered to be one of the basic requirements for a geometric design database of digital human modeling systems. For instance, RAMSIS uses a method called "blow technique" to change the shape of digital human models according to the contours of the subjects in front and side. JACK stores scanned data in its anthropometric database, and uses them for accurate visualization of human digital models.

Another solution has been borrowed from biology (Slice et al., 2004). The analogy of comparing biological shapes has been applied to human body shapes, which means that principles similar to those used in biological research have been built into the system to analyze differences between two races or one race in different growth periods. As a critique, it should be mentioned that this approach cannot be the ultimate one, since anthropometric analyses usually look for common characteristics rather than for differences. Nevertheless, the form difference matrices used for the

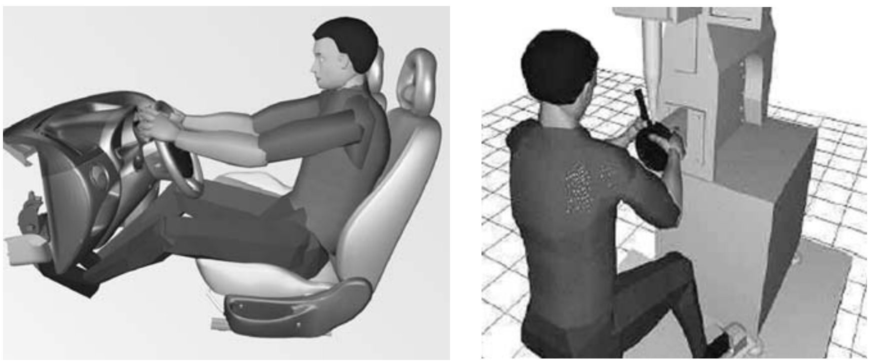


Figure 3-2 Testing car interior for usability: (a) virtual human in the driver's seat; (b) the digital human at work (Colombo et al., 2004)

Table 3-1 General functionality of leading DHM system (Laurenceau, 2001)

	Company Name	Dassault Systems	TechMath	Boston Dynamics	Unigraphics/EAI
1	Product Name	SAFEWORK	Anthropos, RAMSIS	DI-Guy, PeopleShop	JACK
2	System requirements	Stand alone package, can be integrated with CATIA, DELMIA ENOVIA Silicon Graphics IBM HP workstation systems	(3D studio plug-in Anthropos only) (Silicon Graphics IBM, HP workstations, Sun for RAMSIS	Windows NT and 95, Linux Silicon Graphics DI-GUY plug-in modules available for visual simulation products	Windown NT, 95 Linux Silicon Graphics
3	Degrees of freedom	148 degrees of freedom, 100 independent links, fully articulated hand and spine model	86 joints, 6 kinematic chains, 24 spine segments, joints have up to 5 degrees of freedom	realistic simulated movement, DBL model has multiple degrees of freedom depending on the complexity required to simulate motion	135 degrees of freedom. 69 segments, 68 joints, 17 spine segment, and16 hand segments
4	Anthro-pometric database support	YesOver 100 databases available upon request	Yes	Yes	Yes
*5	3D anthro-pometric database support	No	Yes	No	Yes
6	Selection of model type	Able to describe any gender, any height, and any somatype	Data from 10 nations, 19 global regions, any gender, children of age 10, any height, any somatype (Anthropos) 90 adult types, children in different ages (Ramsis)	A wide range of model types from military personnel to ordinary people (DI-Guy) A scenario simulator creating environments for DI-Guy models, DBL model, (PeopleShop)	Large medical simulations, humans based on SAE J833 human dimensions. Short and tall man and woman. Japanese humans based on recognized Japanese data. Body types can be chosen from a boundary manikin set of 77 figures
7	Ergonomic functions	Posture simulations, reach analysis, force analysis, vision and mirror analysis, comfort analysis; lifting/carrying; collision detection; functional clothing analysis	Reach analysis; posture simulations; lifting/carrying; leg force; collision detection; vision and mirror (Ramsis). Reach analysis; force analysis; Belt analysis; Vision and mirror analysis; health and comfort, posture simulations, leg force.	Physics based simulation of biomechanic movement based on robotic control theory Performs: Functional clothing analysis Effectiveness of footwear and equipment designs DBL: does ground force evaluations	Posture simulations; reach analysis; force analysis; vision and mirror analysis; comfort analysis; lifting/carrying; collision; detection; functional; clothing analysis
8	Model Structure	Link reprentation; ellipses; lines; flat and Gourad shading	Wireframe; shaded or 3D scan Glass and skeletal view sub-object structure	Rigid link model with body shapes and mass properties	Wireframe shaded transparent solid model
9	CAD import file formats	IGES, STL, STEP, OBJ, DXF, SAT, COOR, SWX	ASE, DWG, DXF, WRL, WRZ, AI, STL, 3DS, Ramsis: IGES, VDA, SAT	N/A	IGES, STL,IV,VRML
10	Geometric modeling	Use spatial ACIS geometry modeler that integrates wireframe, surface and solid models. Imports all major universal CAD file formats	CAD anthropos: Autocad, Cadkey, Cadds, Catia	DI-Guy, has predefined graphic models, textures clothing, equipment PeopleShop,(N/A) DBL includes loadable CAD equipment models	Import models from CAD and simulations
11	Editor for handicapped models	Yes	Yes	N/A	Yes
12	Documentation output	Single pictures; movie with sound; composite video; real time VR simulation; Alphanumeric(CAD); Graphic (CAD)	Single pictures; movie with sound; composite video; Cave simulation(VR) Alphanumeric(CAD) Graphic (CAD)	Single pictures; movie with sound; composite video; real time VR simulation; Alphanumeric(CAD); Graphic(CAD); Cave Simulation (VR)	Single pictures; Movie with sound; composite fideo; real time VR simulation; Alphanumeric(CAD); Graphic (CAD)

comparison of two samples can used to identify the influential landmarks.

Van Scherpenzeel and Boelens (2003) also compared several digital human modeling systems in terms of geometric modeling capabilities for digital human body modeling. They found that SAFEWORK is not suitable for designing person-mounted products, in particular head-mounted products, because there are only 11 variables to represent a human head. This number of parameters is definitely not sufficient for designing a head-mounted product. They also concluded that different digital human

Variables	Boundary Modeling							
A	Min (5%)				Max (95%)			
B	Min (5%)		Max (95%)		Min (5%)		Max (95%)	
C	Min (5%)	Max (95%)	Min (5%)	Max (95%)	Min (5%)	Max (95%)	Min (5%)	Max (95%)
Number	1	2	3	4	5	6	7	8

Figure 3-3 Method of generating boundary models by SAFEWORK system

models should be developed for different design tasks.

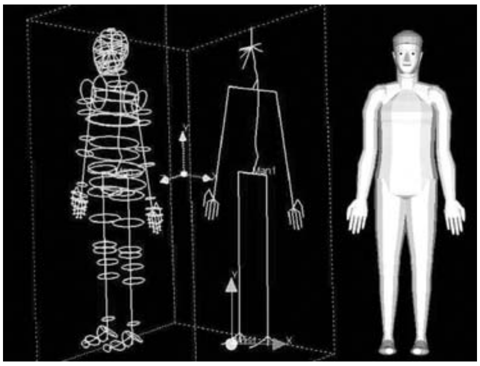


Figure 3-4 Three displaying methods of SAFEWORK (Safework 2.0)

Figure 3-3 illustrates the method of generating boundary models by the SAFEWORK system. In this case the model is composed of 8 component boundary models, according to the three main design variables derived from the design requirements (variables A, B, and C). Figure 3-4 shows the three displaying methods that can be used for displaying human models in SAFEWORK (Safework 2.0). As it can be seen from the above discussion, SAFEWORK was built with due consideration of traditional 1D/2D anthropometric measurements. This is why the surface of the modeled body is approximated by a few ellipses. This approximation is accompanied by many limitations. The segment measurements, which are necessary for anthropometric modeling in SAFEWORK, are managed on percentiles.

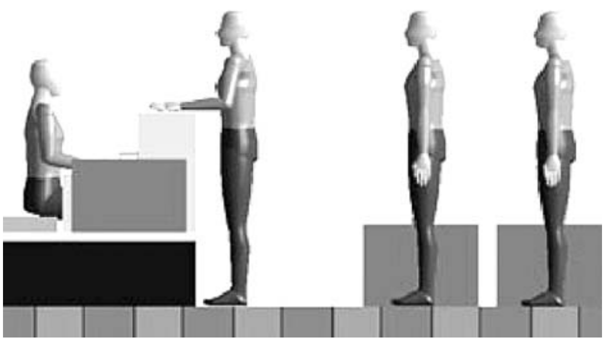


Figure 3-5 The simulation of check-in quenes (Liem and Yan, 2004)

It is known that there are also some inconveniences withDHMin3Denvironments that will need to be overcome by future research. One example is described in the paper by Liem and Yan (2004). They discussed how DHMs have been applied in the work system simulation of rapid transit stations. It was difficult to manipulate the location of a larger number of human models merely by using hinge points. An auxiliary method was therefore developed based on the queuing level-of-service standards. They represented the space that a human body would occupy by a 45.7 times 61.0 cm ellipse, representing a space belonging to a straight elliptical cylinder. The advantage is that the size of elliptical cylinders can be adjusted as different populations need to be considered for human modeling. This is much easier to do than adjusting a large amount of hinge points of human models. Although it is considered more convenient to locate a wide range of human models, the models remain approximations.

3.4 Survey of posture prediction technologies offered by commercial digital human modeling systems

The approaches of current digital human modeling systems (such as SAMMIE, SAFEWORK, RAMSIS, JACK, and Anthropos) to human posture prediction are different. It comes from the fact that different means are available in these systems for geometrically modeling the human body and geometrically transforming the geometries. Nevertheless, each of them has some sort of functions for posture transformation and prediction (Chaffin, 2001). Table 3-2 depicts the main features, the ways of predicting postures and the application fields of the popular CAED software packages listed above.

Most of the marketed systems represent general-purpose DHM systems, which can be applied for general tasks in product design. Some of them still rely on 1D or 2D anthropometric measurements, such as SAMMIE and SAFEWORK (Chaffin,

Table 3-2 Means and methods of posture prediction (Chaffin, 2001)

Name	Means	Methods to predict	Application
SAMMIE	A sophisticated statistical method to assemble the population anthropometric data is needed to predict the percentile size and shape of given subgroups.	Based on 1D anthropometric data, such as segments joints and angles of segments.	A general modeling tool for designers
SAFEWORK	Inverse kinematic method for assisting designers in selecting postures of interest and simulating simple motions. Boundary statistic model considering the multivariate correlation of anthropometric dimensions that define human size and shape.	Based on 1D anthropometric data, such as segments joints and angles of segments.	A general purpose modeling facility
RAMSIS	A sophisticated method (a scalable anthropometric model) available for representing different population subgroups. An optimization method is available based on empirical data to predict reasonable postures.	Based on 1D anthropometric data, such as segments joints and angles of segments and empirical data to predict reasonable postures.	Vehicle interior design
JACK	A means to use different published anthropometric data sets to produce a scalable linkage and hominoid. Flexible spine and multi-segmental limbs can be easily articulated and positioned through an inverse kinematic model. A method for creating a solid form environment for reach and visual interference analysis.	Based on 1D anthropometric data, such as segments joints and angles of segments, and also involves a strength guided posture and motion prediction algorithm	Complex human simulation model
BHMS	A set of human modeling and human task simulation tools that allow the user to study human motion and strength, to define design requirements in terms of human reach, vision, and strength capability, and to perform design evaluations in terms of human size accommodation.	Based on 1D anthropometric data, such as segments joints and angles of segments.	Specific for engineering applications in the aircraft industry

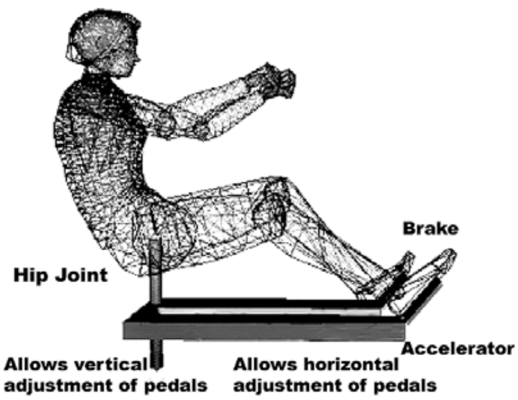


Figure 3-6 JACK created environment (Freeman et al., 2004)

2001). Thus, the scalable models they offer are not really representative of the whole population because they are based on segments representing different population subgroups. In other words, the percentile is not correctly accumulated in these systems (Robinette, 1998). RAMSIS employs an optimization method based on empirical data to predict reasonable human body size and postures (Geuss et al., 1994) (Seitz et al., 2000). RAMSIS uses photographic technology to record subject body contours in two different views. By adjusting the pre-built human body template to the contours, a new model of the subject can be generated. Nevertheless, it is possible to conclude that posture prediction in current CAED software needs to be done by designers themselves. However, this process is complex and errors are unavoidable (Assmann, 1995). JACK has more powerful posture prediction functionality since it employs a strength-guided posture and motion prediction algorithm (Tarzia et al., 2000). However, it is very time-consuming to develop the necessary model and the computational transformation also requires a long computational time (Chaffin, 2001). Additionally, all those DHM systems make use of the percentile dimensions for each gender; as has been demonstrated, percentiles are not additive, and using percentiles to represent multiple body dimensions leads to gross inaccuracy and over- or under-designing for the desired population (Dainoff et al., 1999). With the development of 3D scanning techniques, there were various proposals to use landmarks in various anthropometric and morphological manipulations of the shape of the human body. Landmarks not only rationalize the way of processing anthropometric information, but can also contain 3D relationships in 3D space (Daanen et al., 2001).

Simulations of pedal positioning, using JACK modeling software, were conducted to determine the optimal positioning of the accelerator pedal for joint comfort (hip angle, knee angle and ankle angle) (Freeman et al., 2004). It was argued that one difficulty in using version 3.1 of JACK when performing repeated trials was that the predicted postures were affected by the starting position of the mannequin. The difficulty in achieving consistent results due to the relationship between start and end postures was compounded by the fact that, when the pedals were positioned during the simulations to optimize joint angles, fine movement of the pedals was required to find the point at which the joint angles reached their limits. Additionally, it was found that the results obtained through manipulation of the mannequin's foot with the mouse differed from the results obtained when foot position values were entered via the keypad as numerical values. Freeman et al. argued the following possibilities: that JACK is not producing consistent results, that pedal positions which meet the comfort criteria do not exist for seat positions higher than 25 cm, or, more likely, that there is a deficiency in the algorithm or constraints that control mannequin movement (Figure 3-6). On the other hand, not all variables can be modified independently, making the package difficult to use for research investigations. For instance, JACK assumes that the seat is positioned on a track. It results in the mannequin's seat automatically being adjusted when the posture prediction tool is being used to predict driving posture. This means that the user cannot directly manipulate or set the horizontal distance between the pedals and hip joint. The final minor issue was the ease with which the mannequin could accidentally be moved in an undesirable plane of movement. Due to the difficulty in mapping the x,y,z planes of movement to the three buttons of the mouse, it was common to accidentally move the mannequin along the wrong plane.

According to Table 3-2, the way of predicting the posture in all the commercial software reviewed above is based mainly on 1D anthropometric data, such as adjusting the joints of body segments in special angles simulated from human beings of different genders. It is good at simulating the postures of human beings, but it is not suitable for user convenience, because the users must make all the adjustments by themselves. In other words, the software only provides the suggested scope and parameter of postures, but no suggestions about optimal postures for different design applications. JACK and RAMSIS make more of an effort to provide more complex posture prediction for users, but they need more operation on the modeling and more computer time consumption.

3.5 Survey of academic research on posture prediction

In academic research with regard to posture prediction, photography methods have been used to aid workplace design by analyzing the 2D postures of subjects (Paul et al., 1993) (Kapitaniak et al., 1996). Reynolds (1982) first illustrated the method of studying the relation between sitting posture and the geometry of the working environment, describing a three-dimensional anthropometric model as a tool for measuring geometric properties of the human body. Robbins et al. (1984) developed anthropometric-based design specifications for a family of advanced adult dummies. In that study, three-dimensional surface landmark coordinates of seated postures in vehicle occupants were measured by a photogrammetric technique. Seated surface form was constructed based on the measured landmarks by estimating the joint center, and anthropometric measurements obtained in the standard seat were used to assist in defining the shape of dummies. The work was completed for average-sized U.S. male occupants. Since the seated posture was established by clay and fiberglass, it was hard to adjust and evaluate the posture in further research in different vehicles.

Cote Gil and Tune (1987) developed a model for sitting posture which is based on recording the angles of body segments. The proposed procedure includes these specific features, allowing the identification of the different postures presented by subjects as well as their relative frequency of occurrence. However, the analysis of the recorded angle of body segments is very complex and difficult for application in design support. Chaffin et al. (2000) described how more than 3000 right-arm reaching motions of a diverse group of participants were captured and statistically modeled. The results demonstrate that stature and age have a larger effect than gender does on reach motion postures for motions chosen by the participants while reaching to targets placed throughout a typical automobile interior.

With the development of 3D-scanning techniques, working with 3D anatomical landmarks seems more promising in posture prediction for workstation design. Cerney (2003) described a statistical comparison of the characteristics of traditional, univariate anthropometric data to 3D data in the design of a seated workstation through the exploration of (i) the ability of distance data extracted from 3D landmark data to represent traditional anthropometric dimensions and (ii) the degree of similarity between the design information provided by extracted distance data and the original set of 3D landmark coordinates. The results suggest that 3D landmarks provide a more complete archive of form than the univariate descriptors.

Prediction human reach posture based on psychophysical discomfort was analyzed by Jung (1996) using a regression model. A three-dimensional reach posture prediction model using an inverse kinematics technique was developed on the basis of predicting the perceived discomfort. The model predicts the uncomfortable postures by selecting the minimum discomfort configuration from the feasible body postures reaching a target point. An efficient posture recognition method using fuzzy logic was developed by Tsang et al. (1998). Fuzzy logic is applied both in the classification and in the identification processed with the goal of coping with imprecise data. However, this form posture recognition is applied mainly for virtual reality instead of for design purposes. Cerney (2002) developed a tool which applied 3D anthropometry to a human population and visual reality technology to enable designers to explore complex datasets and examine relationships that existed among the data and digital representations of workstation prototypes (Figure 3-7). In contrast to other digital human modeling tools, his application is not a human figure poser. There is no synthetic human representative available for examination. Additionally, a joint model has not yet been implemented, so all landmarks and scanned data are static. Therefore, there is no technology for posture prediction using this tool.

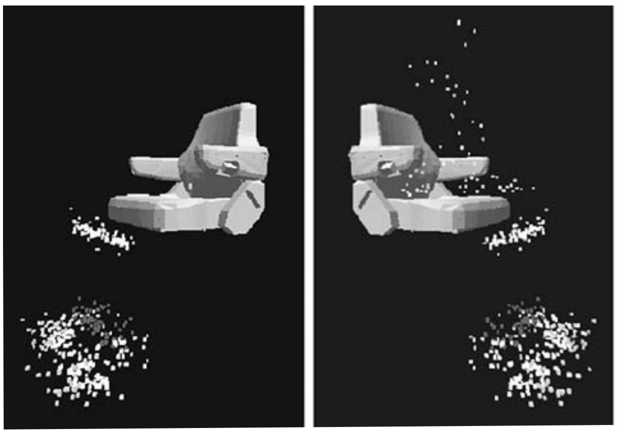


Figure 3-7 Landmark clouds: (a) Knee and foot landmark points displayed for all users; (b) All body landmarks displayed for three selected subjects (Cerney et al., 2002)

However, the current problem is that traditional statistics are not suitable for working directly on landmark coordinates of 3D anthropometry since they work with mean, standard deviation, and percentage. Therefore, a 3D solution to the 3D anthropometry problem must be considered, such as the artificial neural network (ANN) method. ANN has been proposed as an alternative to statistical methods, in particular to model non-linear functional relationships (Lim, 1996). Using the ANN method, new posture prediction technology was verified (Zhang et al., 2004). Its purpose was to overcome the shortcomings of the 1D anthropometric posture prediction method in terms of estimating joint centers, dividing segments, adding percentages, consuming computer time, and so on. All those advantages of the ANN method of posture prediction lead to accuracy and time savings in applications of specific design for designers, since it predicts the specific posture by directly inputting demographic variables and aided 1D anthropometric variables as well as posture variables. Representation of work posture for workspace design is one of the main issues of ergonomics (Vayrynen et al., 1990) (Bridger, 1991) (Haslegrave, 1994). However, a limited set of postural stereotypes may be culturally biased, and does not reflect the true limitations and possibilities of human anatomy (Hedge et al., 1999) (Chaffin et al., 2000). The currently popular 3D ergonomics aided design software packages, such as SAFEWORK, JACK, and RAMSIS, support posture modeling based typically on regression analysis and statistical models (Hoekstra, 1997) (Chaffin, 2001).

Zhang et al. (1994) found that it is advantageous to use a 3D humanoid display with posture performance. It helps improve the congruency of the interface when the pre-analysis of the collected posture data cannot be realized. The major challenge for computational posture generation originates in the inherent complexity of the shape of human bodies. Generating one model with one posture is relatively easy with 3D scanning and 3D reverse engineering (Katsuraki et al., 1995). However, generating one model which is representative of the whole population with all the possible postures is extremely difficult, if not impossible, when traditional statistical methods are used such as mean, percentage, or standard deviation. Such tasks require dedicated 3D digital human body modeling and analysis methods, which have the potential to work directly on the 3D scanned surface of the human body.

Various methodologies for measuring postures have been suggested by many researchers. Assmann et al. (1995) applied a system equipped with six video cameras to measure the body dimensions, postures, and movements of drivers without contact. The video images were superimposed and analyzed in the human model RAMSIS. The analysis leads to statistics on the driver’s joint angles which are related to the results of a comfort questionnaire. Bush et al. (1998) also employed a video-based motion measurement system to collect seated occupant posture data for assisting in automotive seat evaluation and development. The technique using a two-dimensional computer model of the human body was developed for predicting the occupant’s postures. A comparison of a 2D photographic method and a 3D scanning method can be found in Paul (1993). The conclusion of the authors was that the 2D method is valid, and cheaper than 3D scanning, as long as some guidelines for the reduction of the perspective error are followed. Since both the sitting and the standing postures of the human body can be described in terms of features, many studies used feature-based techniques to represent and investigate human postures (Gil and Tunes, 1989) (Rys and Konz, 1994). Other studies were conducted to see the spinal shrinkage during working in a sitting posture compared to working in a standing posture (Leivseth, 1997).

Prediction of human reach posture based on psychophysical discomfort was analyzed by using a regression model (Jung, 1996). A three-dimensional reach posture prediction model was developed on the basis of an inverse kinematics technique to predict the perceived discomfort. The model predicts the uncomfortable postures by selecting the minimum discomfort configuration from the feasible body postures when reaching a target point. The abdomens of obese and slim people were compared in standing and seated positions with the help of real-time visualization. The dataset produced in the CAESAR project contains scans of each subject in three positions: two seated and one standing. Ressler and Wang (2002) simply sliced out the subject's abdomen in one of the seated positions and compared that to the abdomen of the same subject while standing. A radial difference map was generated by the "beer belly" analysis, which indicated the difference between two surfaces with colors. An efficient posture recognition method using fuzzy logic was developed by Tsang and Sun (1998). With the goal of coping with imprecise data, fuzzy logic is applied both in the classification and in the identification**.**

3D human models of various anthropometries and evaluative techniques to assess reach and postures were presented in the ergonomics analysis of motorcycles (Barone et al., 2004). A parametric mannequin was modeled in a commercial CAD environment to represent various anthropometries and to assess postures and reach in virtual prototypes of motorcycles. The human model consists of an internal structure, which is defined as a connection of straight lines of proportionate length, and external body parts which represent anthropometric shape. The human model was constructed using 19 segments and 16 joints. The external bone structure was modeled using a top-down approach, using the skeleton as a support that contains data coordinate systems to assemble parametric solid models of the body parts (e.g. arms, legs, hands, feet, bust, head, joints) to define positions and orientations of body posture. Anthropometric dimensions of various potential motorcycle users are grouped in the database on the basis of age, nationality, gender, and percentile. The ergonomics analysis system offers three methods of posture modeling: joint angle entry,

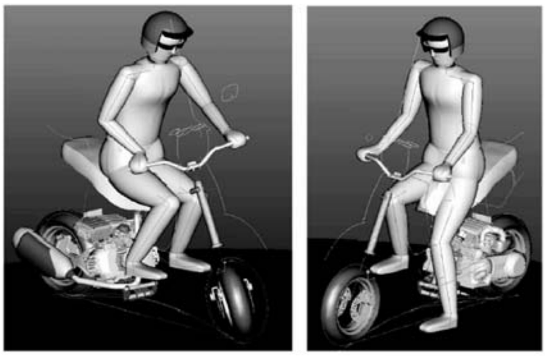


Figure 3-8 Posture analysis simulating different vehicle manoeuvres: wheel turning (a) and foot on ground (b) (Barone and Curcio, 2004)

direct manipulation, and behavioral modeling. The first method enables specific joint angles measured in predefined planes to be entered directly into the program. In this way, the human posture generated by the program can provide a rough check for the accuracy of data entry. If specific joint angles cannot be determined accurately, direct manipulation may be used to rapidly approximate a posture-changing joint or link positions by pointing and clicking using a computer mouse. The behavioral criteria were developed relating experimental joint angles to vehicle parameters and driver anthropometrics data, because the reference points on the vehicle model do not enable the mannequin to assume a unique posture (Figure 3-8).

However, in the design of vehicle layouts, the driver's posture is generally unknown. Instead, the designer must select a posture judged to be reasonable and likely for the vehicle being conceived. For this purpose, the ergonomics analysis system also incorporates a behavioral protocol to "predict" the posture that a driver would adopt given the locations of the link points and the driver's anthropometry. The behavioral model relies on correlating experimentally measured joint angles with subjective judgments expressed by test drivers and anthropometric data.

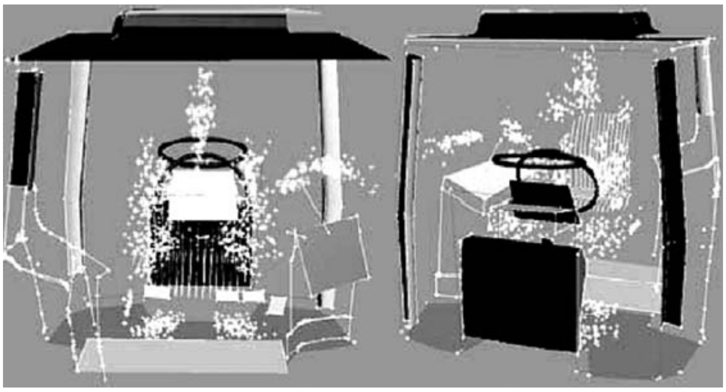


Figure 3-9 View of the tractor workspace populated with subject data landmark locations according to their seating preference and anthropometry (Whitestone et al., 2004).

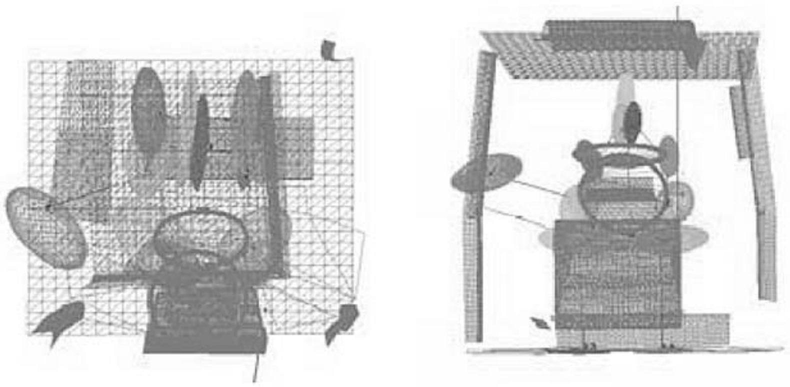


Figure 3-10 Bottom and front views of the 95% ellipsoidal representations of the feature envelopes for the 15 subjects in the tractor workspace as visualized in integrate (Whitestone et al., 2004).

Consequently, the posture prediction process was very complex and needed the designers' operation on the joints based on suggested segments angles.

A feature-envelope technique is a method that describes the spatial location and orientation of areas or landmarks of interest with respect to a duplicated coordinate system. Lafferty et al. (2004) employed this technique in an evaluation of farm tractor design. Fifteen of the subjects, representing the extremes plus one mean, were recruited again and seated in the tractor workstation, and their anatomical landmarks were digitized using Faro arm technology. Fourteen landmark point clouds were further simplified using principal component analysis to generate feature ellipsoids for each landmark location with respect to the workstation (Figure 3-9). Each feature envelope can be thought of as an ellipsoid enclosing a cloud of 3D data points representing the variability in a landmark location (Figure 3-10).

The postures in the pilot study included a "natural" seated position and a "scrunched" seated position to simulate postures that might be found in the tractor environment, and to capture the volume of those postures. The landmarks were selected based on the criteria that they would provide joint center information, segment lengths, and/or the ability to create linkage systems for modeling subjects in the future. A principal component analysis method was used in this context as a means of data reduction, which efficiently and effectively described the point clouds of landmarks. While a point cloud of 3D coordinate locations of the anatomical landmarks of subjects selected for their extreme body size proportions may provide some insight into tractor workspace design, simply plotting the landmarks of these features in 3D space does not give the designer enough information regarding the distribution. Visualization of the feature envelopes is important for understanding the utility of statistically representing point cloud data. The 15 subjects represented the extremes of the variability found in the tractor-related critical dimensions for this population. However, their research is oriented towards joint links in building

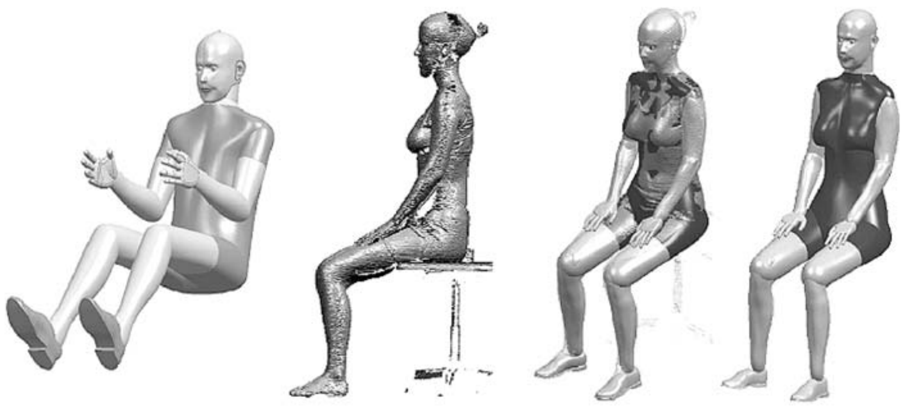


Figure 3-11 Porting scanned data as an ERL human body model: 1) 3D solid model for the average neutral male CAD model; 2) original CAESAR laser scan data; 3) overlay of ERL human body model and original CAESAR laser scan data; 4) final ERL human body model (Brodeur et al., 2004)

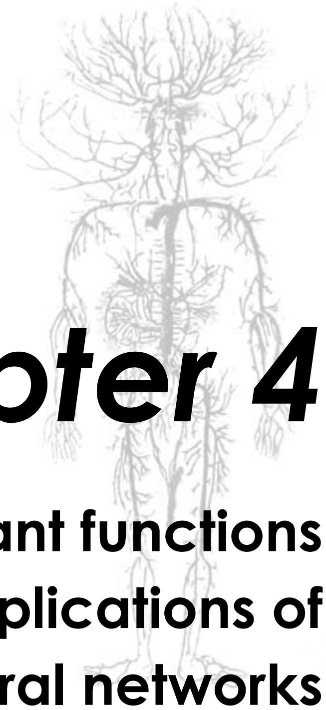
models, even with the 3D landmarks coordinates. This method is still complex and limited.

Additionally, using a designed template of modeling and transforming the template to match the scanned 3D anthropometric data also provide a new way to predict postures, even though this method is approximation-based. Brodeur et al. (2004) presented a method for converting the CAESAR full-body scanned data into human body models for use in the ERL (a comprehensive interior automobile design tool) design software (Figure 3-11). The 3D CAD occupants in ERL were generated-form anatomical cross-sections at comparable landmarks and spinal shapes. Skeletal landmarks in the CAESAR data are used to establish segmental coordinates from which cross-sections are defined. The anatomical cross-sections are used to regenerate the external shape of the body. Additional skeletal landmarks are calculated using regression equations. Therefore, once converted to an ERL human body model, the CAESAR data can be incorporated into the ERL software for ergonomic design and evaluation. However, it is very time-consuming if there are a large number of scanned subjects.

3.6 Conclusions

Traditional anthropometry does not provide sufficient means and tools to treat the posture prediction problems properly. The main problem is that it does not represent the three-dimensional shape in sufficient detail, and, typically, it employs manual methods in processing the human-body anthropometric information. Modern 3D anthropometry creates more opportunities and advantages to capture more information on the human body, even the dynamically changing shape of the human body. Using a 3D scanning technique provides sufficient information on the human body that describes the observable surface and the human segments in detail. This approach can be used in the development of the new solution for posture prediction based on artificial neural networks and anthropometry. However, there are problems with 3D anthropometry, because it provides such a large amount of data which are difficult to process efficiently in real-time by computer. For this reason, simplification techniques are needed which keep the foundation information of the human body geometric and the same time simplify the computation. It seems to be meaningful to apply landmark-oriented processing, which means that landmarks are extracted from the scanned body surface. The changed body shapes can be reconstructed using geometric techniques based on the landmarks.

Certainly, a major problem remains, which is how to handle population and classed people not only one single individual. From this point of view, statistic methods should be considered, especially those which support multi-variate analyses. Using this technique, correlations can be found between the describable variables of the groups and the individual characteristics. Therefore, it means that certain statistic methods should be employed in processing the data on 3D landmarks in order to achieve the most effective processing. The artificial neural networks provide a possible solution for dealing with 3D anthropometrics data directly, which will be discussed in Chapter 4.



Chapter 4

Analysis of relevant functions and applications of artificial neural networks

4.1 Introduction

The concept of artificial neural networks (ANNs) was introduced in 1943 (McCulloch and Pitts, 1943). Since that time, several types of neural networks have been developed and applied in areas such as image recognition, process control, decision making, and object classification (Spelt, 1992) (Arcand, 1994). Artificial neural networks belong to the branch of advanced information processing technology that attempts to simulate the operation of the human brain and nervous system. ANNs learn "by example", in which an actual measured set of input variables and the corresponding outputs are presented to determine the rules that govern the relationship between the variables. Consequently, ANNs are well suited to modeling complex problems where the relationships between the variables are unknown and where non-linearity is suspected. After a slow proliferation period, research into the transfer mechanisms and applications of ANNs started to blossom when the back-propagation training algorithm for feed-forward ANNs was introduced in 1986 (Rumelhart et al. 1986). Contrary to the widespread applications, ANNs can be considered a relatively new tool in the field of prediction and forecasting, in particular in the context of ergonomics and product design.

ANNs are composed of arrangements (layers) of simple elements (neurons) operating in parallel. Some commercialized software packages, such as Neural Networks Tool Box 3.0 or MATLAB 6.5 (NNTB, 1998) make it possible to define various network architectures. Using neurons as active processing elements is inspired by the analogy of biological nervous systems. As in nature, the function (operation) of the network is largely determined by the connections between elements. It is possible to train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, ANNs are adjusted, or trained, so that a particular input leads to a specific target output. The scheme of this transformation process is shown graphically in Figure 4-1. Based on a comparison of the output and the target, the network is adjusted until its output matches the target. Usually, a large number of such input/target pairs are used to train a network in a process that is called supervised learning.

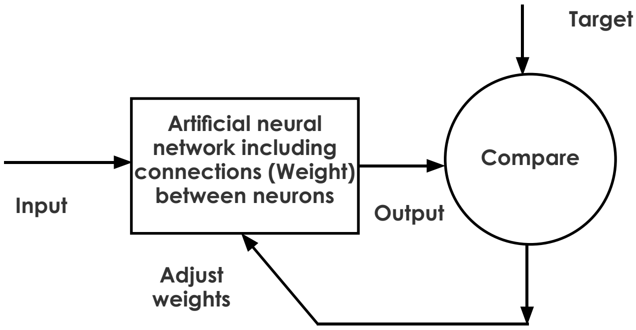


Figure 4-1 Graphical illustration of the concept of ANN

The simplest ANN architecture is a one-layer network. It is a construct with R input elements and S neurons as shown in Figure 4-2. In this network, each element of the input vector P is connected to each neuron input through the weight matrix W. The i th neuron has an adder that gathers its weighted inputs and bias to form its own scalar output $n(i)$. The various $n(i)$ taken together form an S-element net input vector n. Finally, the neuron layer outputs form a column vector a ($a = f(W_p + b)$) (NNTB, 1998).

The further parts of this chapter analyze the supporting theories of ANNs and survey the related applications of ANNs. The goal of studying the literature of ANNs is to look for possible functions and algorithms to solve the problem of transforming and predicting the 3D landmark coordinates in different postures. The following sections will investigate what kinds of ANNs have been applied and how they have been applied in data mining, regression analysis, and classification, especially in the field of digital human modeling. In my literature study on this topic, I looked

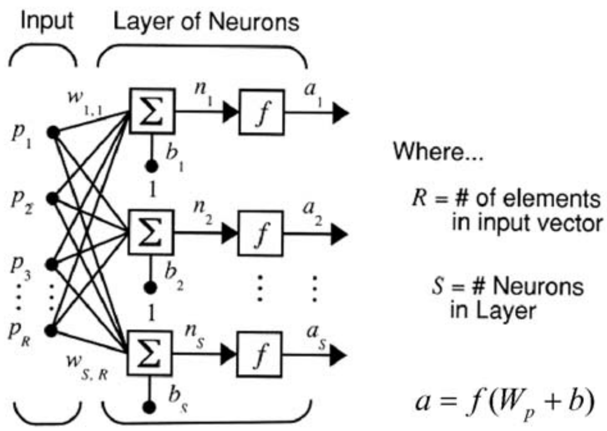


Figure 4-2 A one-layer network with ***R*** input elements and ***S*** neurons

for answers to three main questions: (i) what kind of problems the other researchers faced, (ii) what solutions they developed, and (iii) what applications of ANNs proved to be successful in practice. I assumed that the answers to these questions would help me to reason out the best approach to using ANNs in a landmark-based posture prediction.

4.2 Analysis of the functions offered by artificial neural networks

Learning in ANNs is usually achieved in two ways: (i) supervised learning, or (ii) unsupervised learning (NeuroSolutions, 2002). In the case of supervised learning, the network is presented with a historical set of inputs (samples, patterns or models) and the corresponding (desired) outputs. The actual output of the network is compared with the desired output and an error is calculated. This error is used to adjust the connection weights between the model inputs and outputs to reduce the error between the historical outputs and those predicted by the ANNs. In unsupervised learning, the network is only presented with the input stimuli and there are no desired outputs. The network itself adjusts the connection weights according to the input values. The idea of training in unsupervised networks is to cluster the input records into classes of similar features.

ANNs can be categorized on the basis of two major criteria: (i) the learning rule used, and (ii) the connections between processing elements (neurons) (NNTB, 1998). As mentioned above, ANNs can be divided into supervised and unsupervised networks based on learning rules. One example of a supervised network is multi-layer perceptrons (MPLs). An example of an unsupervised network is the self-organizing map (SOM). Based on connections between processing elements (neurons), ANNs can be divided into feed-forward and feedback networks. In feed-forward networks, the connections between processing elements (neurons) are in the forward direction only, whereas, in feedback networks, connections between processing elements (neurons) are in both the forward and the backward directions (NNTB, 1998).

The back-propagation algorithm is the best-known training algorithm for neural networks, devised independently by Rumelhart (1986), Werbos (1974), and Parker (1985). A BP network has lower memory requirements than most of the algorithms and usually reaches an acceptable error level quite quickly, although it can then be very slow to converge properly on an error minimum. It can be used on most types of networks, although it is most appropriate for training multi-layer perceptrons. Back-propagation was created by generalizing the Widrow-Hoff learning rule to multi-layer networks and nonlinear differentiable transfer functions. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

MLPs trained with the back-propagation algorithm have a high capability for data mapping and are currently the most commonly used neural networks (Simpson,

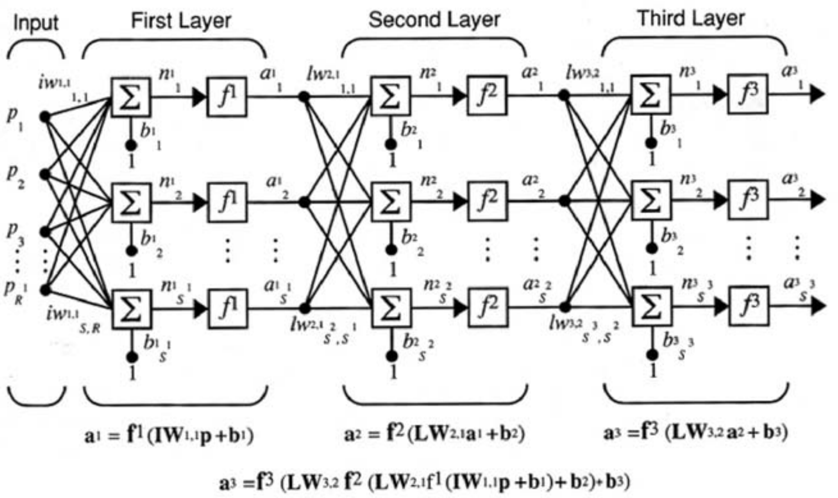


Figure 4-3 Construct of multiple layers neural networks

1990). MLPs belong to the class of supervised feed-forward networks in which the processing elements (neurons) are arranged in a multi-layered structure (Figure 4-3). The architecture of MLPs consists of an input layer, one or more hidden layers, and an output layer. The input from each neuron in the previous layer is multiplied by a connection weight. These connection weights are adjustable and may be likened to the coefficients in statistical models. At each neuron, the weighted input signals are summed and a bias or threshold value is added or subtracted. This combined input is then passed through a non-linear transfer function (e.g. logistic sigmoid or hyperbolic tangent) to produce the output of the neuron (NNTB, 1998). The output of one neuron provides the input to the neurons in the next layer. The global error between the output predicted by the network and the desired output is calculated using an error function. For example, the error function for node J is calculated using the following equation: $E = \frac{1}{2}\sum(y_j - d_j)^2$, where $E =$ the global error function, y_j = the predicted output by the networks and d_j = the desired (historical or target) actual output.

Multi-layered perceptron neural networks (MLPs) are capable of performing just about any linear or nonlinear computation, and can approximate any reasonable function arbitrarily well (NNTB, 1998). Properly trained back-propagation networks tend to give reasonable answers when presented with inputs that they have never seen (Venno, 1993). Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs (Simpson, 1990). A class of ANNs relying on back-propagation was created by generalizing the Widrow-Hoff learning rule to multi-layer networks and nonlinear differentiable transfer functions (NNTB, 1998). The term back-propagation refers to the manner in which the gradient is computed for nonlinear multi-layer networks. As mentioned above, the MLP architectures are capable of performing any linear or nonlinear computation, and can approximate any reasonable regression function sufficiently well. Input vectors and the corresponding target vectors are used to (a) train a network until it properly approximates a regression function, (b) associate input vectors with specific output vectors, or (c) classify input vectors in an appropriate way as defined by the user. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities (NNTB, 1998).

Cybenko and Funahashi (1989) have proved that arbitrary continuous mapping can be approximated by employing a feed-forward ANN with one hidden layer. Recently, many ANNs have been used in motion detection and hand-gesture recognition studies (Laviola Jr., 1999). Pallbo (1994) presents an approach in which motion is viewed as a stable pattern propagating over the image - a technique that makes the model unusually insensitive to noisy input sequences. Even the results of simulation are better than that of other approaches, but the speed is extremely slow when the software runs on a sequential computer and 300,000 or more nodes are used. Lamar et al. (2000) proved that by defining an input space that can optimize the global performance of the structure of neural network. The results obtained show that the use of interclass distance measurement criterion can improve the classification capability of the network. The recognition rate of hand gestures has improved from 91.2% to 96.5%. However, it is only suitable for solving classification problems which they have obtained, though the same structure of neural networks can be used to solve regression problems. A randomized self-organizing map algorithm was used to recognize the posture images of hand gestures (Tobely et al., 2000). Using this algorithm, the recognition time of one image reduced to 12.4% of the normal self-organizing map competition algorithm with 100% accuracy and allowed the network to recognize images within the range of normal video rates. However, a competitive network learns to categorize the input vectors presented to it. In other words, if a neural network only needs to learn to categorize its input vectors, then a competitive network will do. However, the posture transformation and prediction problem is more than just a categorization problem. Therefore, other functions that are offered by ANNs must also be considered.

Despite the effectiveness of MLPs that are trained with the back-propagation algorithm for solving many engineering problems, they suffer from a number of shortcomings. For example, MLPs can get trapped in a local minimum when they try to find the global minimum of the error surface (Burwick, 1994). However, there are several ways proposed in the literature to escape local minima, including increasing the learning rate, adding a momentum term, adding a small amount of random noise to the input patterns to shake the network from the line of steepest descent, adding more hidden nodes, and relocating the network along the error surface by randomizing the initial weights and retraining (Sarkar, 1995). Another limitation of MLPs is that feed-forward neural networks that are trained with the back-propagation algorithm are often criticized for being *black boxes* (Shahin et al. 2003). The knowledge acquired by these networks during training is stored in their connection weights and bias values in a complex manner that is often difficult to interpret (Brown and Harris 1995). Consequently, the rules governing the relationships between the input/output variables are difficult to quantify, especially for large networks that have a large number of processing elements.

Shahin et al. (2003) discussed the strength and limitations of ANNs compared with other modeling approaches in foundation engineering. It was proved that one way to overcome the shortcoming of MPLs is to use neuro-fuzzy networks, which are supposed to provide a better understanding of the relationships between the model inputs and outputs of an ANN. An adaptive neuro-fuzzy inference system (ANFIS) was employed to estimate anthropometric measurements (Kaya, 2003). It was found that ANFIS performs better than the step-by-step regression method (traditional statistical method). However, the algorithm is more complex than ANNs.

Various methods based on artificial intelligence have also been proposed as alternatives to statistical methods, in particular for modeling non-linear functional relationships. Fraser (2000) reviewed artificial neural networks from a statistical perspective. It was found that there is greater interest in using networks as problem-solving algorithms than in developing them as accurate representations of the human nervous system. By subjecting an ANN to various supervised or unsupervised training paradigms, the network "learns" to generalize a correct predictive response to a given data set. In mathematical terms, this can be seen as a form of (non-linear) function approximation. Additionally, it was also surveyed that the actual construction of a network, as well as the determination of the number of hidden layers and the determination of the overall number of units, is something of a trial-and-error process, determined by the nature of the problem at hand. Another observation is that alternative methods for training ANNs by "natural selection" via genetic algorithms are also possible (NeuroSolutions, 2002). Furthermore, similarities between ANNs and statistical methods definitely exist. Indeed, ANNs have been categorized as a form of nonlinear regression. It has also been observed that multiple linear regression, which is a standard technique in statistics, can be expressed in terms of a simple ANN node (Olden et al., 2004). For example, given the linear equation: $y = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n$, the x_i can be taken as the inputs to a node, the β_i taken as the corresponding weights, and β_0 as the activation function.

There are, however, at least two key differences between ANNs and statistical methods. One aspect often remarked upon as a major drawback of ANNs is the fact that their internal functional structure remains unknown once they have been trained. In effect, a neural network remains a "black

Table 4-1 Classification algorithm types ranked for 22 different data sets by error rate

Rank	Algorithm Type		
	Statistical	Neural network	Machine learning
1	15	1	6
2	7	8	7
3	11	4	7
4	10	5	7
5	6	8	7

box" that may produce useful results, but cannot be precisely understood. Statistical procedures do not exhibit this sort of opaque design. Whereas the construction of a neural network is also something of an ad-hoc process, there are commonly formalized guidelines for fitting the best model in statistics. The performance of ANNs has been extensively compared to that of various statistical methods within the areas of prediction and classification. In particular in time series forecasting, basic neural networks substantially outperform conventional statistical methods.

Table 4-2 Artificial neural networks versus general linear modeling (Goodman, 1999, www.scs.unr.edu/nevprop)

Advantages	**Limitations**
Same link function as linear logistic regression	Predictive more computationally demanding
Capture predictor nonlinearity	Nonlinear effects more difficulty to interpret
Capture interactions	Interactions maybe difficult to identify
Minimize pre-processing biases	Minimize pre-processing biases
Inherent Bayesian attributes	Overfitting occurs if not properly regularized
Minimize FP associations due to data snooping	Full Bayesian requires multiple ANNs
Screen large data sets for meaningful nonlinearities & interactions	Inference on predictive effects more difficult to draw
Capability may be expected by collaborators	Less established theory and accepted software

In a comprehensive study of classification techniques, Mitchie et al. (1994) rated the performance of a large selection of ANNs, statistical, and machine-learning algorithms on a variety of data sets. In the analysis of their results, they present the top five algorithms for the twenty-two different data sets based on error rates. The number of each type of algorithm falling into each rank (1-5) is summarized in Table 4-1 below. Though not conclusive, the study would seem to suggest that neural networks are not necessarily replacements for, or even preferable alternatives to, standard statistical classification techniques (Sargent, 2001).

The current generation of ANNs may be conceptualized as nonlinearly-linked general linear modeling systematic structures. Goodman (1999) came to the conclusion that, if properly regularized, ANNs will therefore reduce to general linear modeling in the absence of significant predictor nonlinearity and interaction (Table 4-2). When a properly regularized and bias-adjusted ANN outperforms the corresponding general modeling, its superior predictive performance makes it a valuable addition to the armamentarium of the biostatistician.

Marcle et al. (1999) employed a constrained generative ANN for hand posture recognition for real-time computer visualization purposes. The goal of the constrained generative learning was to closely fit the probability distribution of the set of hands by using a non-linear compression neural network. A small set of hand postures was selected (5 kinds of postures), and a database of thousand different hand posture images with both uniform and complex backgrounds was built. The research results showed that the constrained generative ANN was capable of effectively recognizing hand postures. The mean detection rate was 93.4%.

We can conclude that ANNs have gained much more attention in the last two decades as an effective approach to solving artificial intelligence problems. There are of course a large number of engineering, ergonomics, and even design applications, but the applicability of ANNs in specific posture transformation had not received sufficient attention. At the same time, there is agreement on the fact that the opportunities are enormous. ANNs have been used in many kinds of applications requiring non-deterministic information processing.

4.3 Comparison of back-propagation artificial neural networks and radial basis artificial neural networks

The concept of back-propagation (BP) was created by generalizing the Widrow-Hoff learning rule to multi-layer networks and non-linear differentiable transfer functions. Input vectors and the corresponding output vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities (NNTB, 1998).

Trained BP networks tend to give reasonable answers when presented with inputs that they have never seen before. Typically, a new input will lead to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs. The BP training may lead to a local rather than a global error minimum. The local error minimum that has been found may be satisfactory, but if it is not, a network with more neurons may do a better job. However, the number of neurons or layers to add may not be obvious (NeuroSolution, 2002).

The BP learning rule is used to train nonlinear, multi-layered networks to perform function approximation, pattern association, and pattern classification (Winther et al, 1997). The BP learning rule can be used to adjust the weights and biases of networks in order to minimize the sum-squared error of the network. This is done by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error. Unfortunately, simple BP (learnbp) is very slow because it requires small learning rates for stable learning (NNTB, 1998). The good news is that there are ways to improve the speed and general performance of BP. As we already know, multi-layered networks are capable of performing just about any linear or nonlinear computation, and can approximate any reasonable function arbitrarily well. Such networks overcome the problems associated with the perceptron and linear networks (Figure 4-3). However, while the network being trained may be theoretically capable of performing correctly, BP may not always find a solution. In any case, be cautioned that although a multilayered BP network with enough neurons can implement just about any function, BP will not always find the correct weights for the optimum solution.

Networks are also sensitive to the number of neurons in their hidden layers (Olden et al., 1997). Too few neurons can lead to underfitting. Too many neurons can contribute to overfitting, in which all training points are well fit, but the fitting curve oscillates wildly between these points. Various ways of dealing with these issues are discussed in the section on Levenberg-Marquardt optimization. BP can be improved in two different ways: by heuristics, and by using more powerful methods of optimization (NNTB, 1998). The function trainbpx uses techniques called momentum and an adaptive learning rate to increase the speed and reliability of BP. Momentum decreases BP's sensitivity to small details in the error surface. This helps the network avoid getting stuck in shallow minima which would prevent the network from finding a lower error solution. Standard BP is a gradient descent algorithm (as is governed by the Widrow-Hoff learning rule), in which the network weights are moved along the negative of the gradient of the performance function. There are a number of variations on the basic algorithm that are based on other standard optimization techniques such as the conjugate gradient method and the Newton method (Kecman, 2001).

Properly trained BP-based networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for the original input vectors used in training whenever the new input being presented is somewhat similar to the original input vectors (Coblenz et al., 1991). This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs (NNTB, 1998).

Radial basis (RB) networks may require more neurons than standard feed-forward BP networks, but they can often be designed in a fraction of the time it takes to train standard feed-forward networks (NNTB, 1998). They work best when many training vectors are available. The transfer function for a radial basis neuron is *radbas*. The expression for the net input of a *radbas* neuron is not the same as for neurons in BP. The net input that a radial basis neuron receives is the vector distance between its weight vector w and the input vector p, multiplied by the bias b. Radial basis networks consist of two layers: a hidden *radbas* layer of s1 neurons and an output *purelin* layer of s2 neurons. If *simurb* is called with one output argument, it will return just the output of the second layer. A2 = *simurb* (p, w1, b1, w2, b2). If an input vector is presented to such a network, each neuron in the *radbas* layer will output a value according to how close the input vector is to each neuron's weight vector. The function *solverb* iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons has been reached. The function *solverb* takes matrices of input and target vectors, P and T, and design parameters *dp*, and returns weights and biases for a radial basis network, the number of neurons in the *radbas* layer nr, and a record of design errors dr. The design parameters dictate the maximum number of neurons for the *radbas* layer, the sum-squared error goal, and the spread of the *radbas* neurons. Some or all parameters may be passed to *solverb*; missing parameters and *NaN* values will be replaced with default values. The design method of *solverb* is similar to that of *solverb*. The difference is that *solverb* creates neurons one at a time. In each iteration, the input vector that contributes the most to lowering the network error is used to create a *radbas* neuron. The error of the new network is checked; if it is low enough, *solverb* is finished. Otherwise, the next neuron is added. This procedure is repeated until the error goal is met, or the maximum number of neurons is reached.

Based on the above discussion, it is obvious to ask why a radial basis network should not always be used, instead of a standard feed-forward network. Radial basis networks, even when designed efficiently with *solverb*, tend to have many times more neurons than a comparable feed-forward network with *tansig* or *logsig* neurons in the hidden layer. This is because sigmoid neurons can have outputs over a large region of the input space, while *radbas* neurons only respond to relatively small regions of the input space. The result is that the larger the input space (in terms of number of inputs, and the ranges those inputs vary over), the more *radbas* neurons required. On the other hand, designing a radial basis network often takes much less time than training a sigmoid/linear network and can sometimes result in fewer neurons to be used. The only real design decision for a radial basis network, besides picking an error goal, is finding a good value for the spread constant. This constant determines how wide the radial basis functions are. It is important that the radial basis functions of the hidden layer overlap so as to allow good generalization. However, the radial basis functions should not be spread out so as the radial basis neurons return output near 1 for all the input vectors used in design. Ideally, the spread constant should be much larger than the minimum distance and much smaller than the maximum distance between input vectors (NNTB, 1998).

Radial basis networks may require more neurons than the standard feed-forward back-propagation networks. Because the number of radial basis neurons is proportional to the size of the input space, and the complexity of the problem, radial basis networks can still be larger than back-propagation networks. There are two main variants of radial basis networks, Generalized Regression networks (GRNN) and Probabilistic networks (PNN). GRNN is often used for function approximation. It has a radial basis layer and a special linear layer. PNN can be used for classification problems. A PNN is guaranteed to provide coverage to a Bayesian classifier providing it is given enough training data. These networks generalize well. The GRNN and PNN have many advantages, but they both suffer from one major disadvantage. They are slower to operate because they use more computation than other kinds of networks to do their function approximation or classification (NNTB, 1998).

4.4 Applications of artificial neural networks in ergonomics and digital human modeling

Artificial neural networks (ANNs) have been used in various applications in the field of ergonomics (Spelt, 1992). Representation of work posture for workspace design is one of the main issues of ergonomics (Vayrynen et al., 1990) (Bridger, 1991) (Haslegrave, 1994). However, a limited set of postural stereotypes are usually culturally biased, and do not reflect the true limitations and possibilities of human anatomy (Hedge et al., 1999) (Chaffin et al., 2000). Nussbaum et al. (1995) developed a model employing ANNs for the prediction of lumbar muscle activity in response to steady-state static external moment loads. The model is constructed using standard feed-forward networks and trained with available data using the standard back-propagation algorithm. Training with a limited set of exemplars allowed accurate prediction of muscle activity for novel moment loads (generalization). Sensitivity analyses during training and testing phases showed that the choice of specific network parameters was not critical except at extreme values of those parameters. Model predictions correlated better with experimental data than predictions made using two optimization-based methods (average $r^2 = 0.8$ using ANNs and 0.65 using optimization). ANNs present a useful alternative to experimental measures of myoelectric activity and optimization-based approaches by being both "reality-based" and predictive.

Jung et al. (1995) reported an inverse kinematic method for predicting the reach envelope for the upper limbs. However, the limitation of this approach is that its motions are based on a robotic type of linkage system. Lim et al. (1996) examined the potential of neural network analysis to predict the range of anatomical joint motion for the design of workstations and tasks. Simulated assembling tasks were carried out on a custom-built multi-adjustable workstation, and the posture and motion data were recorded with a flexible electro-goniometric system. In this approach, the layout of the workstation and/or the configuration of tasks were based on the criteria of comfortable reach, optimum range of motion, and a balanced posture for the operator. A multi-layered, feed-forwarded back-propagation neural network was trained to predict the extreme wrist and elbow motions associated with the given bin locations, subject to table height and anthropometrics characteristics. The trained neural network was capable of memorizing and predicting the maximum and minimum angles of joint motions associated with a range of workstation configurations. The average prediction accuracy was found to be around 10 degrees. Table 4-3 depicts the input and target/output parameters of the ANNs. However, when the competency of the trained networks in generalization was tested with data outside the domain of the training set, the errors in the predicted ulna/radial angles were

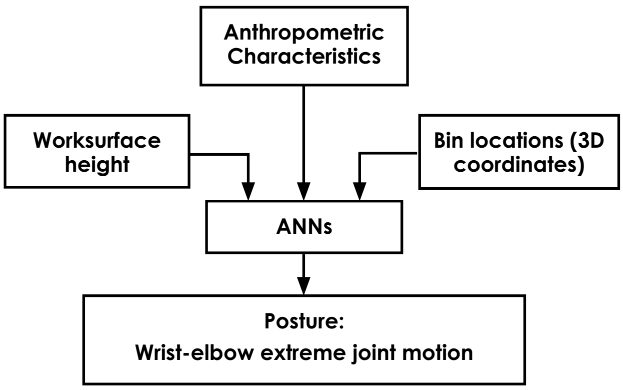


Figure 4-4 ANNs for prediction of wrist-elbow posture (Lim et al., 1996)

around 25 degrees. Flexion/extension of the wrist had an error of up to 40 degrees, while the error for the elbow was less than 20 degrees.

Table 4-3 Input and output parameters of the artificial neural network (Lim et al., 1996)

Input	Output
Anthropometrics characteristics: . Stature . Sitting elbow height . Elbow-fingertip length . Shoulder-fingertip length	Wrist: . Ulna/radial angle (max) . Ulna/radial angle (min) . Flexion/extension (max) . Flexion/extension (min).
Workstation : Height of work surface	Elbow: . Flexion/extension (max) . Flexion/extension (min)
Bin Locations : .x location of bin . y location of bin . z location of bin	

Magnotta et al. (1999) evaluated the ability of an artificial neural network to identify brain structures. This ANN was applied to post-processed magnetic resonance (MR) images to segment various brain structures in both two- and three-dimensional applications. Table 4-4 shows the demographic data used in training and testing sets. The corpus callosum demonstrates a two-dimensional application of ANN, whereas the other structures show the ability to define three-dimensional structures. An ANN was designed that learned from experience to define the corpus callosum, whole brain, caudate, and putamen. Manual segmentation was used as a training set for the ANN. The reliability of the ANN was compared against manual segmentations made by two technicians. It was found that the ANN was able to identify the structures used in this study as well as the two technicians involved. Because the ANN is trained with a stable, anatomically accurate data set, it is less prone to error propagation than, for instance, human technicians are. ANNs offer an automated and efficient approach to quantification of brain morphology and detection of morphologic abnormalities that eliminates inter- and intra-variabilities and ensures reproducibility of results over time.

Table 4-4 Demographic data used in training and testing sets (Magnotta et al., 1999)

Data	Corpus callosum	Whole brain	Caudate	Putamen
Training set (patients)				
No. of men	21	13	4	4
No. of women	0	5	0	0
Total no.	21	18	4	4
Mean age (y)	30.2	33.8	25.7	25.7
Control subjects				
No. of men	21	7	11	11
No. of women	6	5	5	5
Total no.	27	12	16	16
Mean age (y)	28.3	38.3	27.0	27.0
Testing set (patients)				
No. of men	11	7	4	3
No. of women	0	4	0	0
Total no.	11	11	4	3
Mean age (y)	29.4	28.0	32.7	27.3
Control subjects				
No. of men	10	2	3	3
No. of women	2	2	3	3
Total no.	12	4	6	6
Mean age (y)	25.7	31.0	30.5	30.5

The surface asymmetry of scoliosis seems to be caused by the mechanical deformability of the underlying scoliotic spine and ribcage, though this complex spine-surface relation is extremely difficult

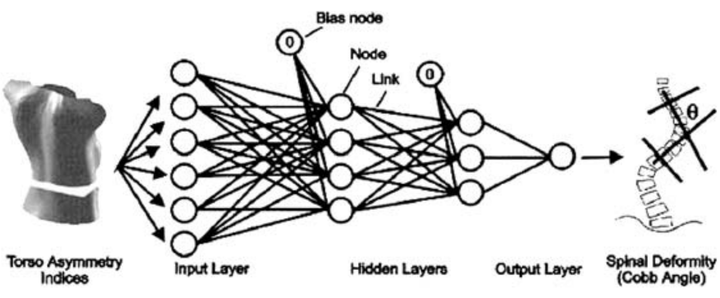


Figure 4-5 ANN architecture (Jaremko et al., 2002)

to model directly (e.g. through a finite element model). Jaremko et al. (2002) have developed a genetic algorithm neural network (GA-ANN) to relate spine and surface deformity based on the assumption that the mechanical links (through ribs and intervening tissues) between spine and surface give rise to common patterns of surface-spine relation that enable consistent estimation of spinal deformity from changes in surface shape. Figure 4-5 illustrates the ANN architecture employed. The input layer accepted indices of torso asymmetry. In the hidden or processing layers, each node produced an output if the sum of inputs from connected links, multiplied by the link weights, was sufficiently large. Bias nodes functioned as constant terms in the ANN, like y-intercepts in linear regression models. The use of hidden layers enabled nonlinear calculations recognizing features of the input data. The ANN output in this study was an estimate of the Cobb angle.

Figure 4-6 depicts the calculation procedure of selected torso asymmetry indices. (*a*) Cross-sections were cut through the torso surface model. PSIS axis = line joining skin markers on posterior superior iliac spines. (*b*) The quasi-Cobb angle (ϑ) was computed for each index of asymmetry between the most appropriate pair of points of inflection on the index curve. (*c*) Angles of principal axis (PAX) rotation (ϑ_1), back surface rotation (BSR, ϑ_2), and the difference between BSR and PAX rotation (ϑ_3) were recorded relative to the PSIS axis along with the "i hump" (d_L–d_R). (*d*) Half-areas were cut relative to the PAX

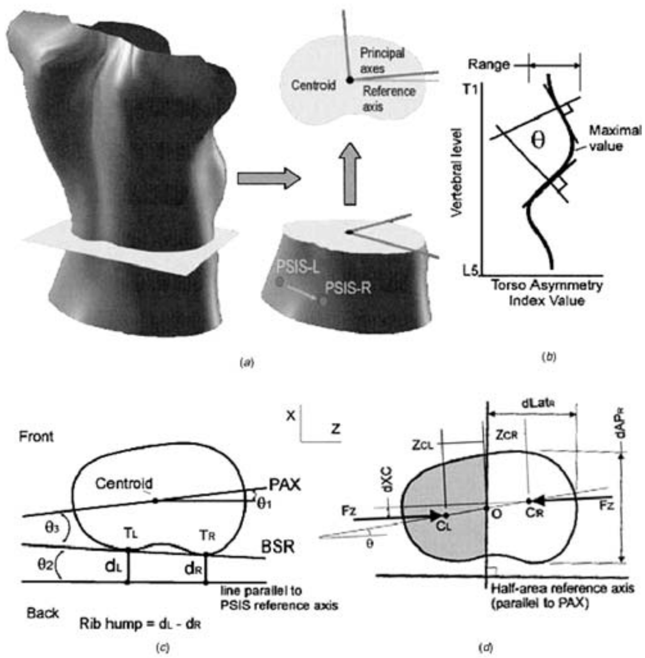


Figure 4-6 Calculation of selected torso asymmetry indices (Jaremko et al., 2002)

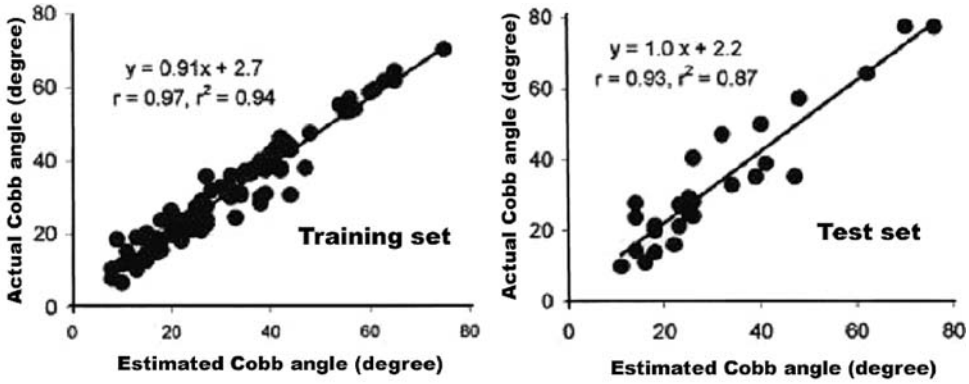


Figure 4-7 Actual Cobb angle vs. ANN-estimate of Cobb angle, in (a) training set and (b) test set. ANN results were better in the training set; this "over-fitting" would be reduced by use of a larger data set (Jaremko et al., 2002).

reference axis. Asymmetry of half-centroids C_L and C_R was measured in the antero-posterior (dXC) and lateral (Z_{CL} vs. Z_{CR}) directions. The angle of rotation of the line joining the half-centroids (ϑ) and the difference in aspect ratios (dAP/dLat) between left and right half-areas were also computed. Their conclusion is that the genetic ANN analysis was 30% more accurate than step-by-step regression, and while the genetic method was much more time-consuming than regression, the extra processing time required for genetic-algorithm index selection would be unimportant in clinical use of the system, since the genetic algorithm would not need to be repeated for each new scan (Figure 4-7).

A constrained generative ANN model was applied to hand-posture recognition with the aim of achieving real-time computer visualization (Marcel and Bernier, 1999). The research results showed that an ANN can effectively recognize these hand postures. Rigotti (2001) used ANNs to generate the movements of a virtual mannequin for the analysis of the human seated working posture.

4.5 Conclusions

It has become evident from my literature research related to ANNs that they have been applied successfully to general data mining, but also to specific problems of ergonomics. Based on the results of the studies of other researchers, it can be seen that ANNs perform better than, or at least as well as, the conventional methods for modeling multi-dimensional nonlinear relationships. In ergonomics and 3D anthropometrics data analysis, it is most likely that problems are encountered that are very complex and not well understood. By and large, ANNs are based on the data alone, in which the model can be trained on input-output data pairs to determine the structure and parameters of the model. Moreover, ANNs can always be updated to obtain better results by presenting new training examples to them, whenever new data become available.

The Bayesian networks are the applications of Bayesian statistics to the multi-layer perceptron. In fact, the Bayesian algorithm is a set of rules for using evidence (data). The major difference is the way that the error is measured or the accuracy of the network is calculated. In a conventional MLP, the learning rule changes the weights on the connections to minimize the amount of error. This measure of error is usually a sum of squared error. Because the training sets are finite, there is a risk that the networks will learn the noise as well as the underlying function. Bayesian theory adds an extra term to the error measure in order to reduce the impact of noise on the network. This enables the network to generalize without the need to use a validation data set. Bayesian rules state that the probability of the network being in a state w, given that an event *D* has occurred, is equal to the likelihood that the event *D* would occur if the network was in state *W*, multiplied by the probability of the network being in the state w regardless of any events, divided by the probability of the event *D* occurring regardless of the state of the network. The shortcoming of the Bayesian MLP is the complex connection between neurons, which makes it more computation- and memory-intensive than that of the simple MLP.

Despite their good performance in many situations, ANNs suffer from a number of shortcomings, notably from the lack of theory to help their development. It is also a fact that success in finding a good solution is not always guaranteed, and ANNs have only a limited capability of explaining the way they use the available information to arrive at a solution. Consequently, there is a need to develop some guidelines that can help the process of designing ANNs. In addition, there is also a need for more research to give a comprehensive explanation of how ANNs arrive at a reliable and robust prediction.

Based on the literature review in the field of ANNs, it is possible to reach the final conclusion that anthropometric characteristics and landmark coordinates, as well as demographic information, can be taught to and learned by ANNs to predict postures. Chapter 5 will present the concept of a new posture prediction technology that is based on ANNs and landmark-based geometric data processing.

Chapter 5

Concept and pilot system development for posture prediction

5.1 Introduction to the framework of knowledge processing

It was clarified earlier that the aim of this doctoral research project is to implement and develop a new posture prediction technology (PPT) and to verify

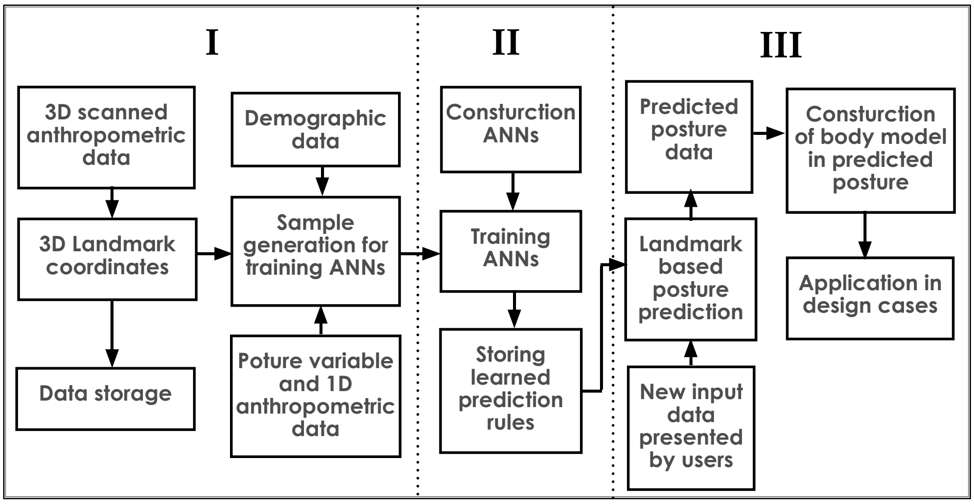


Figure 5-1 Framework of landmark-based and ANNs-based posture prediction technology

it with computer experiments. The development of a conceptual solution therefore needed to involve feasibility studies, neural network architecture development, and operational testing. This chapter describes the concept of the proposed posture prediction technology that incorporates landmark-based geometric data processing, using ANNs to predict the posture data. This chapter also deals with many aspects of implementing PPT. Since the ultimate goal is to develop a pilot system and to optimize the performance of this system through testing in various design cases, the concept has to be not only feasible, but also effectively usable.

Figure 5-1 illustrates the three stages of concept development. Stage I involves the procedures for input data processing. Stage II is about artificial neural network-based knowledge processing. Stage III is related to the reconstruction and prediction of human body postures. In the following sections, these three stages will be discussed from the aspects of problem-solving and feasibility of implementation respectively. Section 5.4 presents an experimental investigation on the effects of local body deformation. The experiments were conducted in the Applied Ergonomic Laboratory of the IDE Faculty at the Delft University of Technology. In these experiments, a 3D Microscribe device was used as well as the functions of the 3D CAD software,

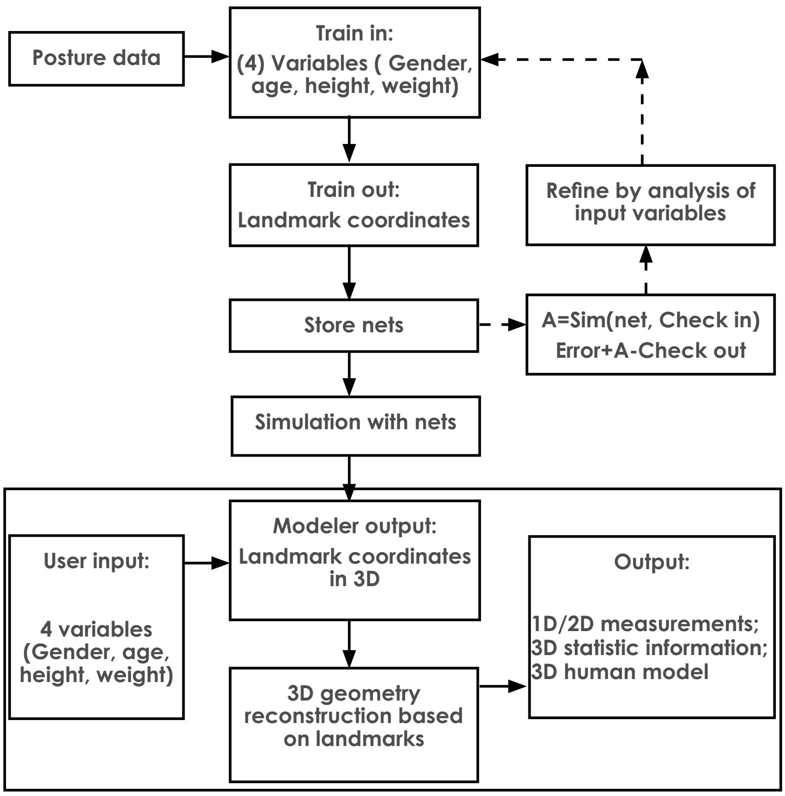


Figure 5-2 Workflow of realization of the proposed posture prediction technology

Rhinoceros 1.1. In section 5.5, a preliminary feasibility study is presented and the results are analyzed. A radial basis artificial neural network (RB-ANN) was employed in the experiments.

Figure 5-2 describes the general workflow of the data processing and the process of ANNs and 3D landmark coordinates-based posture prediction technology.

5.2 Procedures for input data processing

There are two fields of attention related to input data processing. The first is pre-processing of anthropometric data as a source of input for the pilot system. The second is preparation of data samples for teaching the neural network.

5.2.1 Pre-processing of anthropometric data

The shape of an object is the spatial layout of an uncountable set of geometric points in the 3D Euclidian space. The points can be defined in multiple ways depending on the type of the embedding reference frame. Most often, they are defined by three orthogonal coordinates, but they can also be defined by spherical coordinates. The observable shape is invariant for linear transformations such as translation, scaling, and rotation. In preparing the input data for ANN processing, it is assumed that the 3D orthogonal coordinates (x, y, z) of each geometric point are available and the limit set of points available provides a discrete representation of the shape with sufficient fidelity. The measured set of geometric points is referred to as raw data from an anthropometric point of view.

The raw anthropometric data of the 3D surface of the human body is available in many common formats, which are easily transferable and can be processed by computer (Robinette et al., 1997). A shape can be approximated by locating a finite number of points of the human body, which are called landmarks. A landmark is a point of correspondence on each object that matches between and within populations and has significance from an anatomical or from an anthropometric point of view. The literature distinguishes between anatomical and mathematical landmarks.

Anatomical landmarks are usually type A or B, and mathematical landmarks are usually type B or C. Type-A landmarks occur at the joints of tissues/bones. Type-B landmarks are defined by local properties such as maximal curvatures. Type-C landmarks occur at external points or constructed landmarks, such as maximal diameters and centroids. In addition, pseudo-landmarks are also involved. These landmarks are commonly taken as equi-spaced points along outlines between pairs of landmarks of type A and B. In this case, the pseudo-landmarks are type-C landmarks. In the following part of this dissertation, the above definitions of landmarks are applied. Type-A landmarks can easily and reliably be specified on a point cloud measured on the human body. However, landmarks of type C are the most difficult and least reliable to locate.

Due to the rapid development of 3D anthropometric techniques, it became

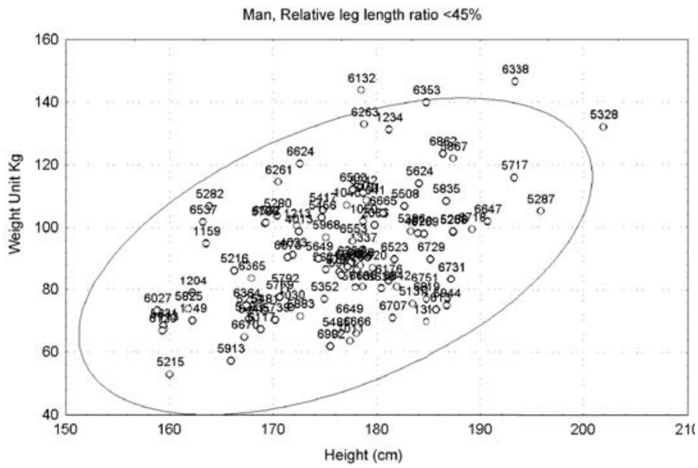


Figure 5-3 Samples of subjects who have a ratio of leg length to height <45%.

possible to operate directly on the landmark coordinates. Computer software can process the coordinates of huge sets of data in reasonable times. These are the opportunities which were utilized in concept development and implementation in this research. More specifically, the geometric shape is defined in terms of landmark coordinates, assuming that they maintain the geometry of a point configuration. This approach to shape analysis, which progressed rapidly around the late 1970s and early 1980s, is called geometric shape analysis (Bookstein, 1991). To perform a shape analysis, biologists traditionally selected ratios of distances between landmarks or angles, and applied a multivariate analysis to these data. This approach has been called "multivariate morphometrics" in biology. In multivariate morphometrics studies, one deals exclusively with positive variables (length, angles, and ratios of lengths) (Robinette et al., 1997). A considerable amount of work was carried out in multivariate morphometrics using distances, ratios, angles, etc., and it is very commonly used in both biology and anthropometry (Roebuck, 1995). However, in abovementioned approaches, the geometry is abandoned when only distances and angles are considered. Interpreting important linear combinations of ratios of lengths and angles can sometimes be difficult. This is why it was decided to explicitly use the coordinates of the landmarks. Ratios of distances can easily be calculated from coordinates, whereas the converse is generally not true.

The landmarks can be recognized directly by the computer program. A set of landmarks that can be found on a particular object is called a configuration. Landmarks can be arranged in various mathematical (relational) formations. It is also possible to talk about the configuration space of landmarks. A configuration X can be described by a $k \times m$ matrix of Cartesian coordinates of k landmarks in m dimensions. The configuration space is the space of all relevant landmark coordinates (Dryden and Mardia, 1998). The research relied on 73 landmarks, i.e. k = 73, and the dimension of the configuration space, m, was 3.

5.2.2 *Preparation of data samples for teaching the neural network*

For the implementation of the ANN and landmark-based posture prediction technology, input data and target/output data of ANNs should be prepared with care. The reason is that the ANNs are sensitive to input and output data construction.

Table 5-1 Samples with 4 input variables and 3 target/output variables (x, y, z)

A	B	C	D	E	F	G	H
number	x1Gender	x2 Age	x3 Height	x4 Weight	x	y	z
1248	1	42	190	65	-39,25	8,57	777
1251	1	47	194	85	-39,8	-9,39	816,82
1449	2	26	143	52	60,69	27,03	353,04
4042	1	53	178,5	87	-21,15	43,72	658,82
5208	2	36	180	88	-2,19	19,9	673,24
5282	1	59	167	105	44,81	48,2	543,19
5287	1	47	196	100	-11,94	9,44	866,37
5317	1	46	185	91	-20,26	17,6	757,49
5440	2	59	166	122	41,63	18,85	537,61
5514	2	39	186	70	-4,33	12,82	758,62
5525	2	33	176	105	1,31	31,35	666,44
5590	2	51	168	92	-2,06	3,9	558,02
5649	1	45	178	87	25,6	57,86	673
5903	2	40	195	81	11,47	8,6	837,08
5913	1	68	170	55	-60,32	-12,88	564,76
5953	2	60	168	78	33,2	22,33	528,18
6023	2	27	174	60	-6,86	-12,37	598,84
6027	1	50	160	74	50,79	23,15	502,4
6114	1	38	205	100	-12,86	-2,2	916,57
6268	2	62	155	67	1	43,07	461,22
6353	1	39	187	135	-17,02	18,67	733,44
6486	2	22	169	50	1,46	8	578,43
6550	2	47	175	126	-1,88	39,09	629,17
6551	1	43	203	80	-23,14	12,23	911,71
6562	2	55	150	92	47,6	47,99	411,66
6624	1	57	172	110	-13,15	-28,52	609,48
6701	2	22	182	57	-20,46	-28,83	682,26
6738	1	23	174	65	-11,65	4,42	664,92
6754	2	23	159	49	32,83	31,22	526,85
6803	1	22	192	80	-14,55	6,44	774,01
6950	2	32	176	63	4,73	7,93	618,15
6992	1	21	180	65	17,81	46,45	655,68

The input data for posture prediction includes three parts in this study (Figure 5-1). The first subset of input data is landmark coordinates from the scanned surface of the human body in a standing posture. The second subset of input data is demographic information on the subjects, for example, gender, age, race, occupancies, etc. The third subset of input data is 1D or 2D anthropometric variables such as weight, height, sitting height, and waist of the subjects. The target/output data are corresponding landmarks coordinates in the sitting posture. All the input data and the target/output data need to be pre-processed since the raw data obtained from scanners may be noisy or incomplete. The pre-processing needs the following steps:

1) Obtain the point cloud of the whole body of the subjects in the source and target postures;

2) Select the landmarks on the source posture and on the target posture;

3) Estimate the missed landmarks coordinates according to anthropometric rules;

4) Calibrate the landmark coordinates of both postures in order to eliminate any errors in the source data;

5) Select important demographic information and encode it into samples for training the appropriate ANNs;

6) Select 1D/2D anthropometric data which are important for describing the shape of human body;

7) Normalize all the input and target (output) data.

The point clouds obtained by measurements of the whole body in the source and target postures are used for teaching. These point clouds are different for each subject.

Figure 5-3 shows data on samples of various subjects. The scanned 3D coordinate data of the surface of human bodies are from the CAESAR project (Civilian American and European Surface Anthropometry Resource). The body measurements were made on people aged between 18 and 65 in three countries, namely the United States, the Netherlands, and Italy. The raw data were obtained in STL format, which is actually a polygonal (triangular) mesh. The total number of the scanned data sets in the research was 32, from which 28 scans were used to train the neural network, and 4 scans were used to test the performance of the neural network (Table 5-1).

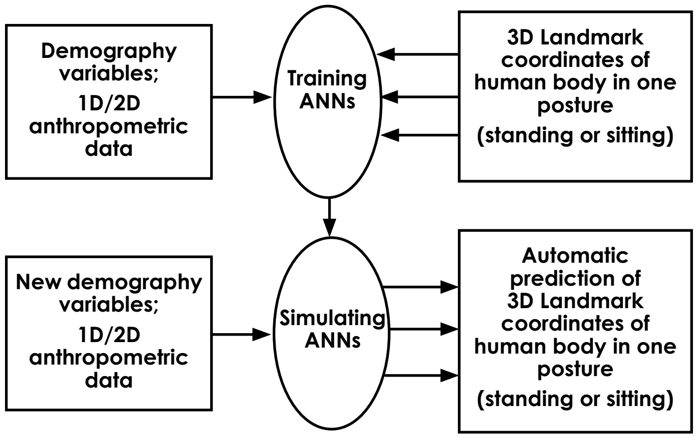


Figure 5-4 Automatic prediction of landmark coordinates based on 3D scanning

When ANNs are used as the means of posture transformation, there are two main actions: (i) to teach the ANNs in order to get the transfer rules and (ii) to store these rules for future simulation. For teaching the neural network, one landmark was used from the total of 73 landmarks describing the whole body. Using the learned rule, the system is able to generate the anthropometric data for the posture based on new input data, which is needed for product design. In addition to the landmark data, various demographic variables were also used as input variables to teach the network. In the training experiments, these variables were gender, age, weight, and height. The output is the expected coordinates of the respective landmarks. The coordinates of landmarks can also be used to reconstruct the 3D geometric model of the human body. This, however, needs extra geometric computation, for which the neural networks as well as specific geometric modeling methods can be utilized. When explicit posture data are used as input to the ANN, the landmark coordinates can be predicted automatically in different postures. Figure 5-4 illustrates the principle of this automatic prediction of the 3D landmark coordinates of human body.

5.3 Knowledge processing by dedicated artificial neural networks

This research project exploited the fact that ANNs can learn rules for transforming data. From the many possible working principles, the one which is called the multi-layer feed-forward network back-propagation algorithm was used. This type of ANN works according to the following principle. An elementary neuron with R inputs is shown in Figure 5-5. Each input is weighted with an appropriate ω (weight value). The sum of the weighted inputs and the bias forms the input to the transfer function f. This research used two differentiable transfer functions f to generate their outputs. One is *Tansig* (tan-sigmoid transfer function), the other is *Purlin* (linear transfer function).

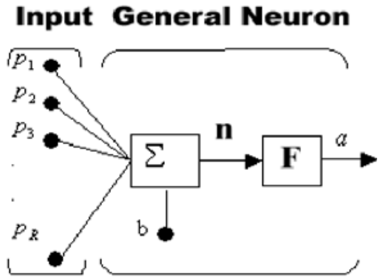


Figure 5-5 Neuron model

In Figure 5-5, R is the number of elements in the input vector. When all the input and target (output) data are correctly prepared for training the ANNs, the architecture of the ANNs should be designed. This procedure includes selecting the suitable transfer function, designing the structure of networks, selecting the suitable learning rate, and other training parameters. Based on the discussion in Chapter 4, a regression function was used in the computer experiments for posture prediction, since it was supposed that it would be an effective 3D solution to transform 3D landmarks directly.

The main reason for selecting BP-MLP-ANN was that, according to the literature and my own experience, building all the connections between neurons in a Bayesian NN is much more time-comsuming than with the BP-MLP-ANN. The assumption was that this way the time that the knowledge engineer would spend on training the ANN could be reduced.

Feed-forward networks usually have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. For this research, a feed-forward network with one input layer, one hidden layer, and one output layer was chosen. Both the input layer and the hidden layer have sigmoid neurons with Tansig transfer functions; the output layer has linear neurons with Purlin transfer functions. As the algorithm TrainLM appears to be the fastest method of training moderate-sized feed-forward neural networks (up to several hundred weights), TrainLM was employed in the research. The architecture is shown in Figure 5-6. There are one input layer, one hidden layer, and one output layer, which have 4, 8, and 3 neurons respectively, as shown by S1=4, S2=8, and S3=3 in Figure 5-6. The selection of the ANN architecture is based on the fact that simple architecture has the best support from generalization results. The sigmoid transfer function was used because it has a selective feature in learning.

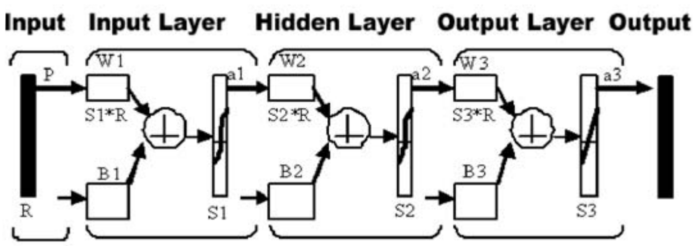


Figure 5-6 Network architecture design

The next step was the training of the ANNs by presenting them with the normalized input and target/output data. During the training experiments, some parameters should be adjusted in order to get the best weights for the neurons of the trained nets. The best weights were then stored, which actually means that the ANNs have learned the rule for posture prediction. In order to prove that these best weights indeed result in a sufficiently generalized rule for posture prediction, it was tested by presenting test samples. These were new input data to the learned rule for the simulation procedure. If the simulated/predicted results are close or match the known data, then it confirms the training was valid. After that, it is justified to use this ANN as a tool for posture prediction. In Figure 5-6, P is input, R is the number of input vectors, S is the number of neurons in layers, W is the input weight, and B is the input bias.

5.4 Experimental investigation of the effect of local body deformation

It is known that certain landmarks of the human body show special behavior when the posture of the body is changing. This behavior can be characterized by two observable phenomena. First, due to the local body deformations, certain landmarks will be hidden by the neighboring parts of the human body, which causes the landmarks to be undetectable to the digital scan. It means that in sitting postures, for instance, the scanned point clouds will not contain sufficient information about the covered landmarks. In order to provide this information, additional measurements are needed, based on which the missing information can be provided and the incomplete point clouds can be extended.

Consequently, one of the reasons for the experiment described in this section is to investigate the position changes and visibility of the landmarks in the abdominal and pelvic region of the human body, which is known to suffer the largest geometric deformation when the body posture changes from standing to sitting. Secondly, another important aspect in posture prediction is the magnitude of changes in the location of the landmarks. As will be analyzed further in Chapter 6, there are regions of the human body where the magnitude of repositioning in the landmarks is much larger then that of the landmarks in other regions. This lends itself to a classification of the landmarks, and to the development of a posture prediction approach that benefits from the

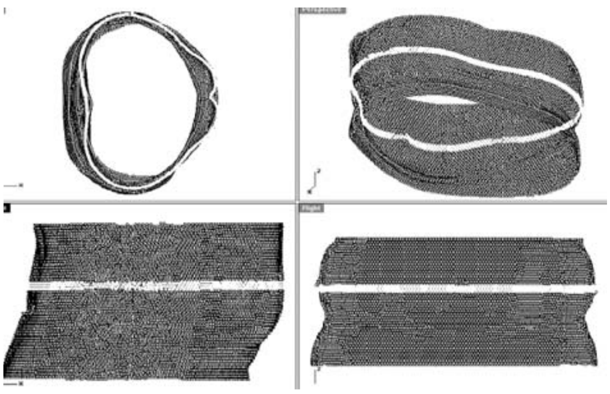


Figure 5-7 Abdominal region with lighted waist of one item of scanned data

opportunity of clustering the landmarks. The related issues are discussed in Chapter 6.

The investigation was done by digitizing the relevant part of the human body with a Microscribe device. The data was then modeled into 3D surface modeling (Rhinoceros 1.1). The waist region was measured and modeled in both standing and sitting postures. The intention was to generate information to describe the difference in shape between different postures (which had not yet been studied in-depth by other researchers).

This is especially true for obese people, for whom even the traditional measurement of the waist is not valid, because the abdomen may descend relative to the normal case. This repositioning of the waist is illustrated in Figure 5-7. The experiment empirically studied the local deformation of the waist region (the abdomen and the pelvis) for people of average weight and build, and the repositioning of the corresponding landmarks. Contrary to the parts of the body where the anthropometric measurements typically obey standard (normal) distribution, the measurements in the waist region show skewed distribution.

5.4.1 Method

The participants were 10 adult Dutch males and females over the age of twenty who are students at the Delft University of Technology (Table 5-2). The first issue to be elaborated on here is how the region was designed for measurement. The focal region is described as the region around the waist. This region of the human body is defined on the geometric model by an upper and a lower boundary. The upper boundary is the waistline. This is the horizontal plane at the height of the Natural Indentation (NI). The lower boundary is the horizontal plane at the height of the point where the lowest part of the spine is pointed most outward to the back. You can determine this part by feeling the most outward point of the bone. You can feel two little knobs at either side; this called the sacral hiatus. It is possible to make measurements in this specified region in both the standing and sitting posture. There are several known landmarks located in this region.

Table 5-2 Anthropometric data in the experiment

Anthropometric Items	Mean	SD	Min.	Max.
Age(years)	22.7	301	20	29
Height (mm)	1739.8	106.2	1609	1955
Weight(kg)	66.9	11.9	54.4	89.1
Waist circ.(mm)	736.2	87.8	645	865
Waist width(mm)	250.6	36.5	226	298
Hip circ.(mm)	972.3	36.4	900	1025
Hip width (mm)	342.6	12.7	324	360

The next issue is to locate the points of measurement. There are two types of points which are needed to reconstruct the body surface: landmark points and other characteristic body surface points. However, for an efficient and precise reconstruction, it is necessary to know not only the points but also the curves between them. All points of

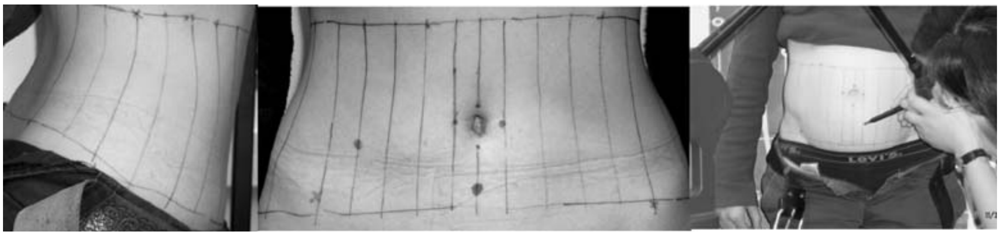


Figure 5-8 3D anthropometric measurement with Mircroscribe

measurement are located and marked in a standing posture. The orientation used in the descriptions is the orientation as seen from the subject's point of view.

Waist-points on the left and right sides are the points on the outer left and right sides of the waistline. From the subject's point of view, the points are also called NIs. These points can be found where the middle portion of the upper body is narrowest (as seen from the front or back) and where the circumference is generally smallest. The subject is placed in a standing posture against the wall. The anthropometer is placed horizontally at the NIs. The points where the anthropometer touches the subject's side first must be marked.

Sometimes the NI cannot be located on very obese people. The alternative method for locating the NI is to place an elastic cord that has a round cross-section around the middle of the upper body, adjust the cord's length to apply moderate tension, and then release the tension. The cord will seek the height with the smallest circumference. The anthropometer is placed horizontally at this height. The points where the anthropometer touches the subject's left and right sides must be marked. The navel center is a characteristic point in the middle of the measurement area, which can be found in the middle of the navel when the subject is in a standing posture. The navel top and bottom points should be marked where the skin starts to go inward, while the subject is in standing position. The navel left and right points should be marked as well where the skin starts to go inward in both the left and right side of the navel.

The anterior superior left and right iliac spine points are the points of the hipbone which are most to the front on the left and right side of the subject's coax. These points are just beneath the skin. A knob can be determined by touching the subject's skin. The sacral hiatus is used to determine the lower boundary. This point can be found by locating the two knobs of the skeleton at the end of the spine. These knobs are at the start of the buttocks, pointing most outward compared with the spine. They are located at the same height. The point in between these knobs has to be marked for further measurements.

The body surface points are on the same height as the two landmarks at the waist-point on the left and right. The horizontal position of the body surface points is based on the landmarks. The body surface points are above all the landmarks. There are ten landmarks; two of them, the waist-points, are equal body surface points, so there are eight body surface points created by known landmarks. Some distances between the ten body surface points are too big. That is because the grid is based on these points. This means that the areas between them must be divided. Figure 5-8 shows the landmarks and the body surface points based on the landmarks and deviation.

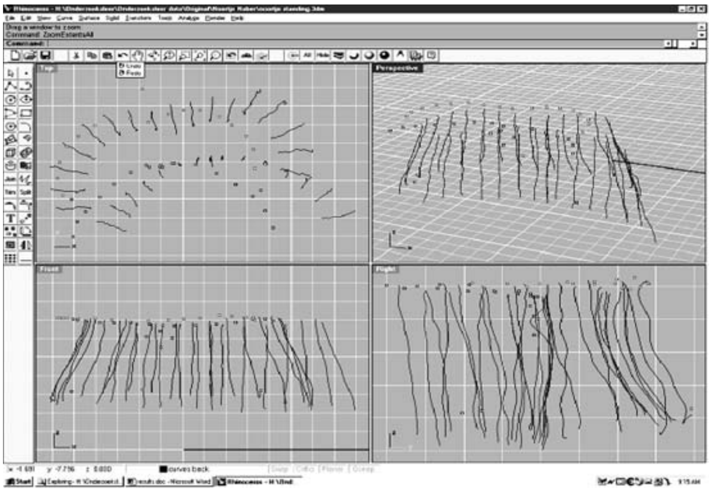


Figure 5-9 Plots of the original data directly from the measurements in Rhinoceros 3D software

A grid is made of lines drawn on the subject's body. The grid contains two horizontal lines, an upper and lower boundary line, and thirty vertical lines. The upper boundary line passes through the two waist-points. The anthropometer and the level were used to get a horizontal line between the points. The lower boundary line passes through the sacral hiatus landmark; this line is a horizontal line which describes the lower boundary. The vertical lines are based on the body surface points. Every body surface point gets a vertical line. Some lines should be on a surface point and on a landmark. The line starts on the upper boundary and ends at the lower boundary.

The grid was used to define the locations of the body surface points to be measured. The data was collected with a Microscribe 3D. The Rhinoceros software was used to calculate the data needed for a graphical representation of the

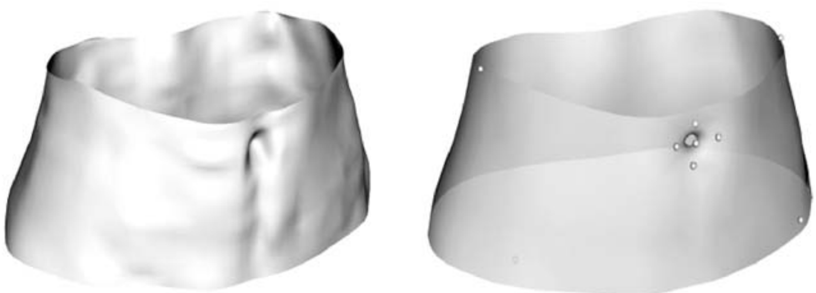
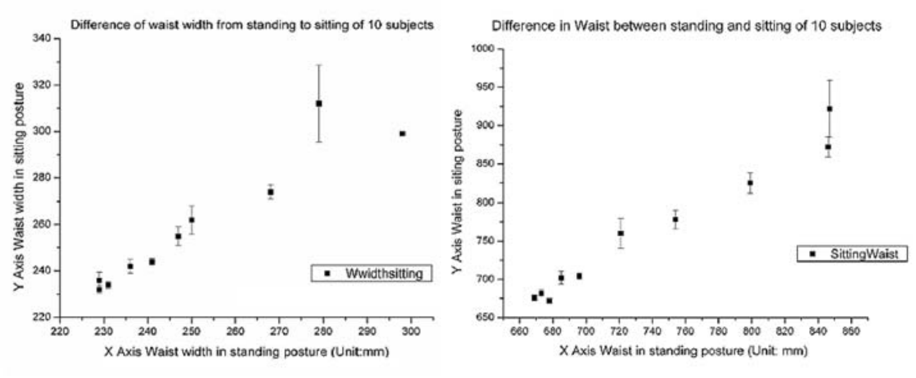


Figure 5-10 Modelling the measured domain: (a) The measured data converted into a surface (in standing posture); (b) the smoothed surface model of the measure region (in standing posture).



(a) (b)

Figure 5-11 Plots of changes in waist region: (a) Plots of the change in waist width individually and (b) plots of change in waist circumference individually.

surface and to create additional lines and points. There are two types of input data sets: (i) measurements of body points and landmarks and (ii) measurements of grid lines. The Appendix includes a more detailed description of the measurements.

5.4.2 Results and discussion

First the results obtained in measuring the waist region on various human bodies using the 3D Microscribe device will be presented. The reason why this more conventional technology was used is that regions which can not be accessed by a laser scanner can be conveniently accessed by the Microscribe machine.

10 subjects were measured and the surfaces were modeled in Rhinoceros1.1. There were ten landmarks on each surface. Actually, 10 of the surfaces represented measurements in a standing posture and 10 of them were for measurements in a sitting posture. Six of the participants were female and four were male. The data was processed graphically in the three stages of the measurement-based modeling: (i) the original raw data from the measurements (Figure 5-9); (ii) the data converted into a

Table 5-3 T-Test of differences of in waist width and waist between standing and sitting posture

Sample	**N**	**Mean (mm)**	**SD**	**SE**	**t**	**P Value**
1. Waist width_standing	10	250.8	23.55	7.447	-2.7969	0.02082
2. Waist width_sitting	10	259	28	8.854		
1. Waist_standing	10	736.8	70.675	22.35	-3.17125	0.01134
2. Waist_sitting	10	759.3	88.642	28.03		

surface (Figure 5-10 a); and (iii) the smoothed surface model of the region (Figure 5-10 b).

As a next step, the difference in the distances between standing and sitting postures was analyzed. The changes in the measurable distances obviously indicated the intensity of deformations. The changes could be measured between the same landmarks on the surfaces representing the standing and sitting positions. Different relative changes could be observed, for instance: (i) the relative change in waist width; (ii) the relative change in waist circumference; (iii) the translation of the 10 landmarks from standing to sitting; (iv) the position of the navel relative to iliocristale left and right.

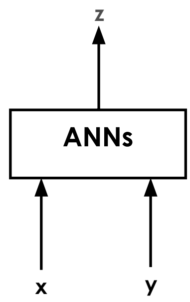


Figure 5-12 Employed ANN architecture (Where x, y, z are the 3D coordinates of scanned landmarks on the head)

The first thing that could be observed was the change in shape of the waist region. In a sitting posture, it became wider. The changes in the waist width were plotted for the ten people who participated in the research. This graph is in Figure 5-11.a.

As can be seen in Figure 5-11.a, the average increase in waist width from standing to sitting posture is 3.1%. The same changes apply to the waist circumference (Figure 5-11. b). This also becomes larger in sitting position. The average increase in waist circumference from standing to sitting is 2.9%. The change in posture is described by the change in position of ten landmarks. The results are given in a unit vector for the direction and a scalar for the distance in mm. This gives a vector description of the change in posture for the landmarks (Figure 5-11.b). According to the Two Sample Paired t-Test, at the 0.05 level, the differences in waist and waist width between standing and sitting are significant (Table 5-3).

5.5 Preliminary feasibility study

Anthropometry is the research and technique of human body measurement. 3D surface anthropometry extends the study of the human body to 3D geometry and morphology of external body tissues (Robinette et al, 1997). It includes the acquisition, indexing, transmission, archiving, retrieval, and analysis of body surfaces and their variability. New technological advances both in 3D surface digitization and other areas such as computer graphics technology, automated manufacturing, and electronic communications are radically changing the field of anthropometry.

The structuring model of the 3D human-body scanning database recommended in this paper is still under work and constantly improving. The database reduced from full-resolution raw 3D data may be one of those forms, which are integrated polygonal models, or model-based CAD models as well as statistical database. Nevertheless, it is still not clear yet which model is the best format to choose for use by product designers. For example, with statistical 3D human body data, there is the problem of using percentiles in solving multi-variables (Robinette, 1998). A newly emerging type of mathematical model for human systems engineering is the "multivariate model" or series of models such as CADRE. Additionally, the simulation of the human body both in static situations (with regard to comfort rating and centre of gravity) and in dynamic situations (with regard to deformable joint link issues) is the current hot research domain, which can offer designers more opportunities in product creation.

5.5.1 Method

We did a pilot study based on 10 scanned human-body data samples downloaded from the CAESAR Project free download website. However, because these 10 samples were chosen from the populations, it does not make sense to do statistical analysis on them. Therefore, they were only used in ANN training and to prove that ANN can help study the human body form for product design purposes. The ANN architecture is employed as shown in Figure 5-12.

The data format is Cyberware PLY (Standford). To transfer the data into a format that could be used in the training of Neural Networks, several pieces of software were involved: Rhino, Inventor V2.1 ASCII, and Microsoft Word. As a result, the accuracy of the ANN training may have been influenced by the chosen transfer process. This should be taken into account. In this pilot study of the human head form with Neural Network, Radial Basis Neural Network (RB-ANN) is employed to learn 3D human head surface landmarks. In the Neural Network Toolbox of Matlab5.3, *NEWRB* designs a radial basis network. RB-ANN can be used to approximate functions. *NEWRB* adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal. *NEWRB* creates a two-layer network. The first layer has *Radbas* neurons and calculates its weighted inputs with Dist and its net input with *Netprod*. The second layer has *Purelin* neurons and calculates its weighted input with *Dotprod* and its net inputs with *Netsum*. Both layers have biases.

Initially, the *Radbas* layer has no neurons. The following steps are repeated

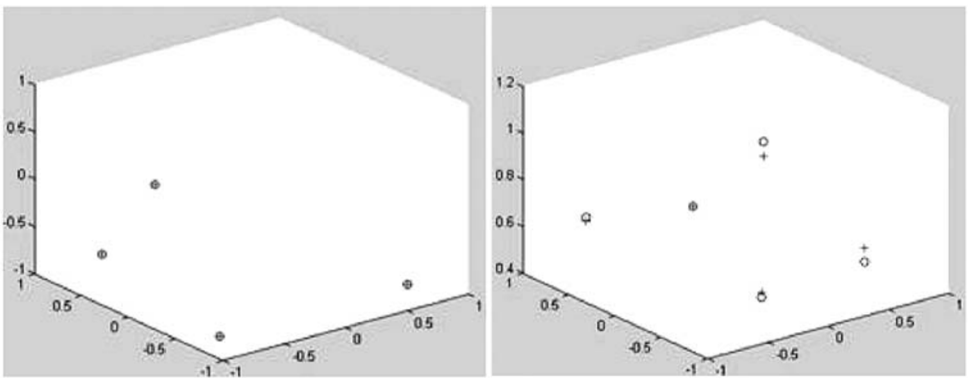


Figure 5-13 The left picture is the result of training 4 landmarks of the human head (in normalized 3D space), the right is the predicted result of 5 other landmarks of the human head.

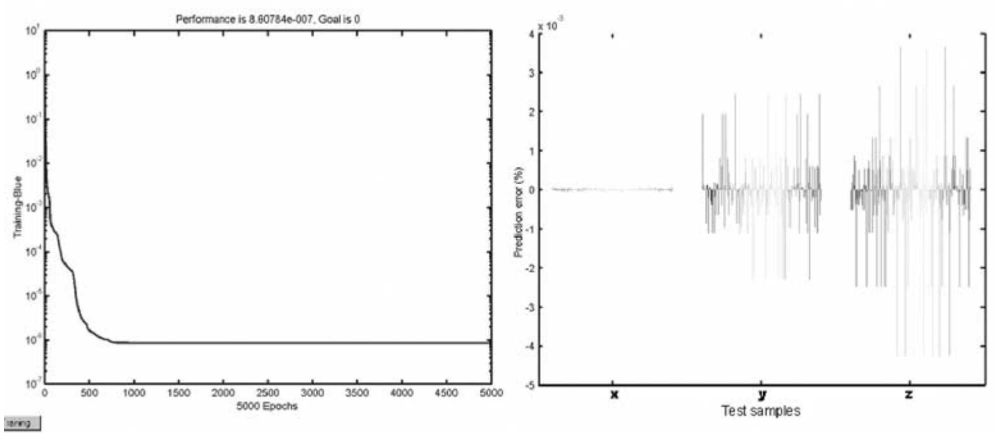


Figure5-14 Performance analysis: (a) Development of the error while training;
(b) The prediction error (*10^{-3})

until the network's mean squared error falls below target value.

1) The network is simulated.

2) The input vector with the greatest error is found.

3) A *Radbas* neuron is added with weights equal to that vector.

4) The *Purelin* layer weights are redesigned to minimize error.

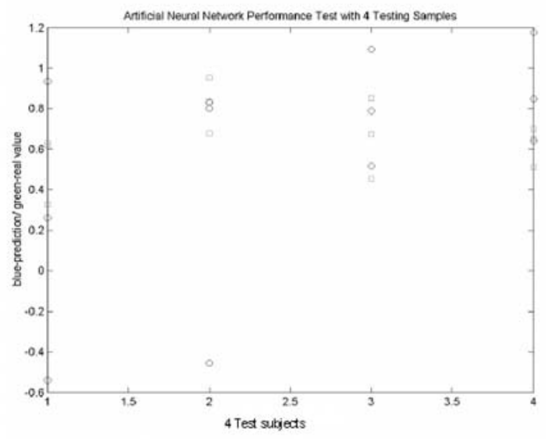


Figure 5-15 Feed-forward back-propagation artificial neural network performance checked with 4 testing samples (squares are prediction value, circles are real value)

An M.File is programmed to use the ANN Toolbox in Matlab5.3. The M.File includes three parts, normalization and training as well as analysis, where eg = 0.5, sc = 0.1 (e.g: mean squared error goal; sc: spread of radial basis functions).

5.5.2 Results and discussion

The two pictures here are the RB NN training and predicted results (Figure 5-13). The original scanned coordinates are shown almost overlapping new coordinates predicted by RB NN. The pilot study proves that NN can be used to approximate human head surface function precisely. Much work remains to be done before 3D anthropometric data systems can be used successfully in the product design process and other design applications. An ANN can be used to approximate any functions which have been proved by rigid mathematical theory. This pilot study proves that an ANN can be used to research 3D scanned human body surface. Everything has two sides. Many detailed ANN studies will be completed in further research projects, for instance on how to acquire human body surface characteristics for building a CAE tool to solve the fit problems and the shift variants in changing postures.

5.6 Performance analysis of the implemented neural network

In total, three different types of BP neural networks with different numbers of neurons in the hidden layer were trained with the same inputs. They are 4*6*3 neurons BP-ANN, 4*8*3 neurons BP-ANN, and 4*10*3 neurons BP-NN. Training results show that the 4*6*3 neurons BP-NN was more stable than the other two kinds of BP-ANN during this research.

Figure 5-14.a illustrates that the training errors were consistent to 10^{-6} with 5000 epochs. Figure 5-14.b shows the prediction errors in x, y and z respectively. The training results of 4*8*6 BP-NN show that the feed-forward BP neural networks can be employed to predict landmark coordinates using demographic information and 1D anthropometric data effectively. Figure 5-15 shows the landmark coordinates of 4 testing scans in testing. The blue squares are prediction values and the green circles are the real values of the 4 test samples. The insufficiency of the input data is the main cause of inaccurate results. In other words, the number of scans is very important for the training accuracy. In this research, only 28 scans enlarged 50 times were done first and then randomly sent to input neurons to train them.

5.7 Reconstruction of predicted human body posture

Based on the stored best weights, when new input data, such as 3D landmarks coordinates in standing, posture variables (standing), demographic information, and 1D/2D anthropometric measurements, are presented to the ANNs by users (designers, ergonomists, etc.), 3D landmark coordinates in a sitting posture of the corresponding subject can be predicted (Figure 5-1). Furthermore, based on the predicted 3D coordinates of landmarks, a simplified human body model in a sitting posture can be constructed and applied further in design evaluation procedure. The simplified model is similar to the skeleton model but not the same, because the landmarks are on the model surface and they are not at the same points as the joints of human body. In order to construct a vivid human body model, more landmarks and points between known landmarks should be predicted.

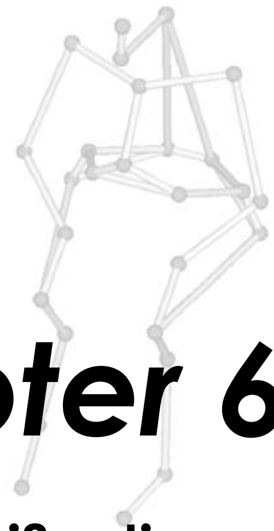
5.8 Conclusions

Considering that the framework of posture prediction is supported to clarify the foundation of the system's method and the method of data processing, three stages have been identified, namely input data processing, ANN-based posture prediction, and reconstruction. The test indicated that point clouds derived from 3D anthropometric scanned data could not be transformed as a whole input. Utilizing the landmark concept significantly reduced complexity in terms of training the ANN and using it for posture prediction directly.

The experiments using Microscribe showed that there are certain regions of the human body where the landmarks undergo intensive positive changes. In other regions of the human body, the change of the relative position of the landmarks is almost negligible. This oriented my attention to the implementation of a cluster-oriented posture prediction. The critical implementation was tested from the point of view of feasibility and performance. Since the result of this experiment was positive, this concept was applied in the final implementation of ANN-based and landmark-based posture prediction.

The results of preliminary research indicate that BP-MLP neural networks are capable of memorizing and predicting the landmarks of the surface of the human body. ANN learning is not stable with different numbers of neurons in the hidden layer. In other words, once the function of *Newff* runs, the initialization of the ANN kept changing, which leads to inaccurate results. The BP neural network analysis is being refined to improve the prediction accuracy.

An implementation study of posture changing based on ANN and scanned anatomical landmarks of the human body as well as demographic information was conducted. The results of this research indicate that back-propagation artificial neural networks (BP-ANN) are capable of memorizing and predicting the landmarks of the surface of the human body with considerable accuracy, although ANN learning is not stable with different numbers of neurons in the hidden layer. In this chapter, the concepts of shape, size and shape, landmarks, and configuration space were defined before the experiments were conducted.



Chapter 6

Verification of posture prediction technology

6.1 Introduction

This chapter describes the verification of posture prediction technology (PPT). Chapter 6 presents two research projects: an approach for transforming scanned body data between various postures, and algorithm comparison of multi-layer BP-ANNs. In this verification research, the scanned human body is substituted by a proper set of landmarks, which is used as a basis for transforming the data, as they are needed to describe specific body postures. Multi-layer BP-ANNs have been used for the actual data conversion. The input is a set of demographic data and the coordinates of the landmarks characterizing a given posture. The output is another set of landmarks characterizing the transformed posture.

Explanations of the fact that there are certain groups of landmarks on specific parts of the human body (e.g. on the head, shoulder, etc.) show similar displacements when the body posture changes. At the same time, other groups of landmarks exhibit a large difference in the location when the body is deformed. Of course the deformation here is the result of the change in the posture of the body. Recognizing this phenomenon, it is possible to divide the landmarks into two types: (a) small changes in location when the posture changes and (b) large changes in location when the posture changes. Based on this observation, the idea was that these two types of landmarks can be treated differently in the ANN-based and landmark-based posture prediction. Actually, two dedicated techniques were developed for handling landmarks with small and large changes in location. As a result, in addition to the fact that the technique must consider all landmarks of the human body simultaneously in posture prediction, a second one was worked out, which benefits from the classification of the landmarks. This technique is called landmark cluster-oriented posture prediction.

The following parts of the dissertation compare and investigate the two techniques from a functional point of view. The main area of interest is the functional performance in application.

6.2 Elaboration on the two techniques of posture prediction

6.2.1 Whole body-oriented posture prediction

Our preliminary investigations indicated that there are no obvious solutions for the posture transformation problem, that is, for transforming data points between postures. In order to be able to investigate the achievable efficiency in the neural network-based computation for transforming data points between postures, two distinct methods were developed. The first method considered the total number of landmarks of the whole body in the posture transformation process, while the other method focused on clusters of landmarks that share similar characteristics from the point of view of posture transformation. In other words, one approach is when all data points are considered simultaneously in the transformation process.

Another approach is when subsets of the data points are considered in various transformations and the results are recombined. The first approach is called "whole body transformation", and the second one is called "cluster-based body transformation". A multi-layered perceptron neural network was used in the research. The network was based on the principle of back-propagation. The number of layers was set to three. The number of neurons in the input, intermediate, and output layers were different. The number of neurons in the output layer was chosen depending on the number of output variables. In this case, it was the product of the number of output coordinates and the number of landmarks. In total, the data of 40 subjects (20 males and 20 females) were

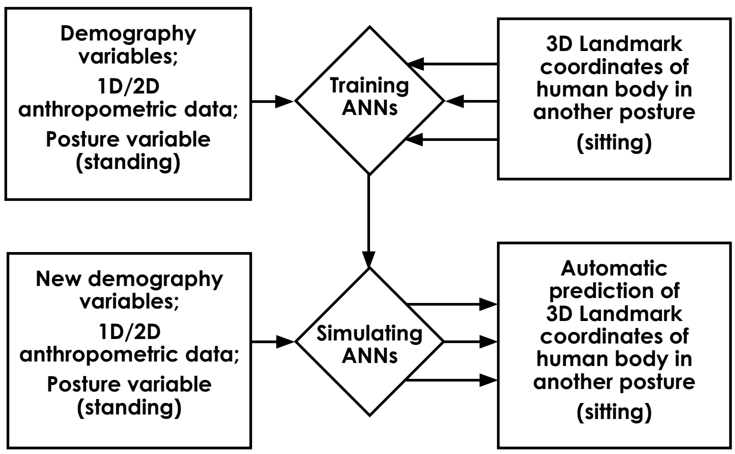


Figure 6-1 Preparation of ANN to transform 3D landmarks of the human body between postures

used in the network teaching experiments in 4 groups, which were formed according to the leg and height ratio of the subjects. The whole-body transformation approach was based on 27 landmarks, selected from a total of 73 landmarks, which were identified from the measured data of the human body.

The posture transformation concerned the landmark coordinates only. The steps of the whole body-oriented posture transformation were as follows:

1. Obtain the point cloud of the whole body in the source and target postures;
2. Find the landmarks on the source posture and on the target postures;
3. Generate a set of descriptive input variables;
4. Use the descriptive parameters and the source and target posture landmarks to teach the artificial neural network;
5. Regenerate the point cloud representing the target posture based on the transformed landmarks.

The input in the ANN was the landmark coordinates of the whole body of 32 subjects in standing posture, together with characteristic demographic features, such as gender, weight, height, head width, shoulder width, and waist. The compiled multi-layer perceptrons of the ANN formed a layered feed-forward network. The network was typically trained by employing static back-propagation. The desired/target values were landmark coordinates of the whole body of the 32 subjects in sitting posture (Figure 6-1). In the simulation mode, the ANN was used to transform the 3D landmark coordinates of the human body in different postures automatically.

6.2.2 Landmark cluster-oriented posture prediction

The main difference between this approach and the previous whole body-oriented approach is that first clusters of landmarks are identified based on anthropometric, morphological, and behavioral consideration of the human body, and then the transformation is completed based on the neural network. The landmark cluster-oriented body-posture transformation was implemented in the following steps:

1) Obtain the point cloud of the whole body in the source and target postures;
2) Find the landmarks on the source posture and on the target postures;
3) Cluster the landmarks by anthropometric subdivisions into units, such as head, upper torso, pelvis, and so on;
4) Transform the clustered landmarks by using the artificial neural network;
5) Regenerate the point cloud representing the geometry of the target posture based on the transformed landmarks.

In the training process, the coordinates of the clustered landmarks of the human body formed one part of the samples. Related to this, the other part was the characteristic anthropometric surface features of the human body in a standing posture. The expected/desired values were the clustered landmark coordinates of the human body in a sitting posture. Having trained the ANN with an appropriate number of samples of the clustered landmark coordinates of the human body in a standing posture, it was possible to achieve a reasonably good prediction of the corresponding landmark coordinates in a sitting posture, and vice versa. The results indicated that the ANN-based approach is not only unique, but can also be a useful tool for designers. However, this assumption needed to be verified in experiments. In the next part of the paper, these experimental investigations and their results will be presented, together with a description of the use of ANN for posture transformation.

6.3 Issues of verifying the ANN-based posture prediction

The success of applying an artificial neural network-based approach for posture transformation depends on many issues, such as: (a) fidelity of the measured input data (or, in other words, the raw data); (b) preparation of the input data for teaching the neural network; (c) optimal exploitation of the learning capabilities of the network; and (d) the amount of data to be processed by the net. The following section will concentrate on these issues and explain how they contribute to an efficient implementation of the ANN-based posture transformation.

6.3.1 Investigation of the fidelity of input data

We first investigated the measured data for fidelity. In this investigation, individual landmarks were taken into consideration. One of them was the Lt. Acromion landmark, which is identified as landmark #41. The positional distribution of this landmark #41 was plotted for the sample of 40 subjects in a 3D space, as shown in Figure 6-2. Here, the density of the points is related to the number of subjects. The results showed that the positional distribution of this landmark of the human body over the sampled subjects formed a point cloud in the 3D space. This is a natural distribution, depending and influenced by the normal body heights. However, noise and errors were also observed in the raw data, which can be traced back, for instance, to the fact that subjects stood and sat in non-standard postures during the scanning procedure.

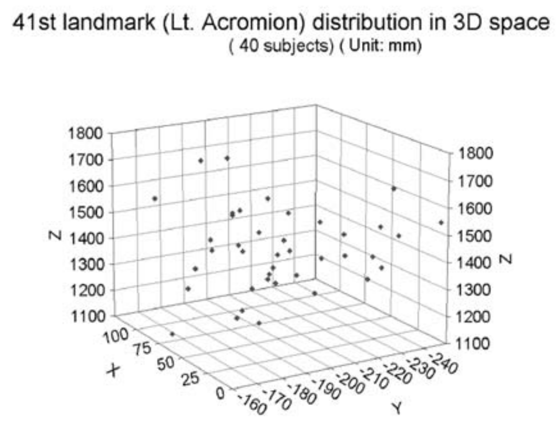


Figure 6-2 The positional distribution of landmark #41, Lt. Acromion, of 40 subjects in a 3D space

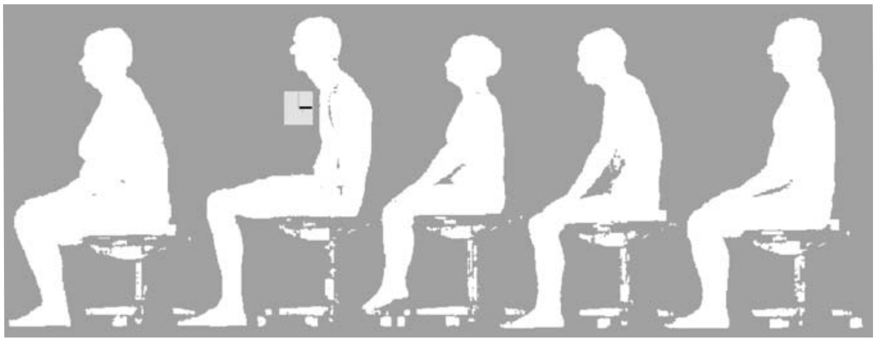


Figure 6-3 Subjects in different sitting postures

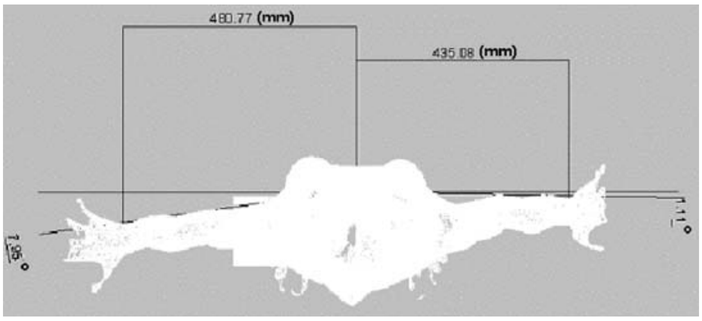


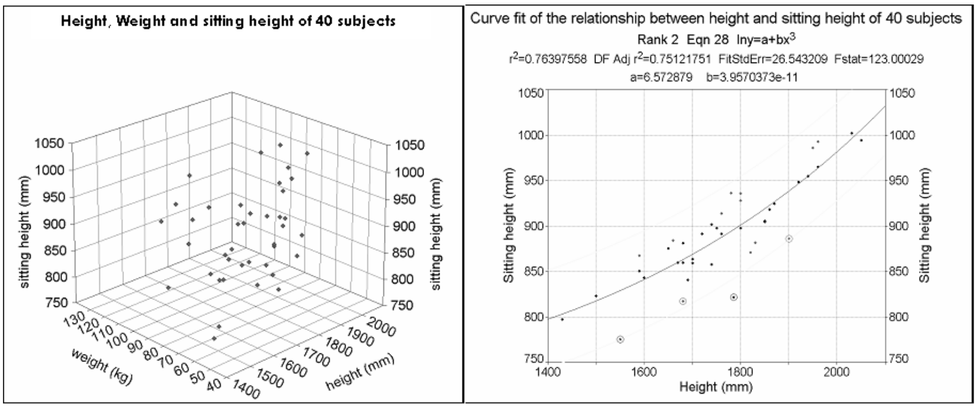
Figure 6-4 Errors in scanning of body data (unit: mm)

As an illustration, Figure 6-3 depicts different subjects sitting relaxed, leaning forwards or backwards, or unable to make their feet reach the floor. Figure 6-4 shows another example of the deviation from the absolute position in scanning. This subject was scanned in an asymmetrical standing posture, where the arms were lifted to different heights, and the hands stretched at different angles. These individual deviations can hardly be eliminated from the anthropometric measurements, and they also have an influence on the results of the posture transformation.

6.3.2 Clustering body landmarks on the basis of predictable posi tional changes

In order to facilitate the application and operation of the neural network, the input raw data were analyzed and pre-processed. Among other things, the analysis involved the completeness and numerical appropriateness of the data, and interpretation of the data from anthropometric aspects. My hypothesis was that the efficiency of the computation with the neural network can be increased if the nature of changes in the body postures in terms of the positional changes of the landmarks is taken into consideration. For this reason, the relationship between the body heights in standing posture (normal heights) and in sitting posture (that is, the sitting heights) was analyzed.

Figure 6-5 shows the distributions of the analyzed anthropometric data. Figure 6-5.a shows the plot of the height, weight, and sitting height of 40 subjects in a 3D space. Figure 6-5.b shows the curve that represents the correlation function describing



(a) (b)

Figure 6-5 Analysis of the correlation between two 1D anthropometric characteristics for 40 subjects: (a) plot of height, weight, and sitting height in a 3D space; (b) curve representing the correlation function between the body height and the sitting height.

the relationship between the body heights and sitting height for all subjects. The bestfitting correlation function is the non-linear function of form $\ln y=a+bx^3$, where $a=6.573$, $b=3.957e^{-11}$, $r^2=0.7698$. Statistically, only four subjects fell out of the interval of fitting with a 90% confidence level. These are marked by 4 circles in Figure 6-5.

In the analysis and pre-processing, 73 landmarks on the whole body were considered at the beginning. From this set, the most characteristic 27 landmarks were selected, with the aim of using them for teaching the ANN. With a view to the cluster-oriented body transformation, the important action was the clustering of the landmarks. It is obvious that the position, for instance the height (z) coordinates of the landmarks, changes differently in various postures. The change is most intensive on those parts of the body which undergo large mechanical deformation, and less intensive or completely non-essential for those body parts that are mechanically hardly deformed at all. Consequently, the variation of the landmark coordinates in posture was adapted as the basic principle of landmark clustering.

Figure 6-6 shows the distribution of the observable changes in the height coordinates of all the 73 landmarks when the human body posture changes from standing to sitting. Based on the intensity (actually the magnitude) of changes of the 'z' value, the landmarks were clustered in three groups and identified as group A, B, and C. The landmarks in group A feature large changes, the landmarks in group B show less changes, while those in group C display the least changes in the value of the 'z' coordinate. Further investigation of the landmarks in these groups (refer to Appendices 1 and 2) showed that group A includes landmarks that are for the head and the main torso. Group B primarily includes landmarks for the arms and the hands, and group C includes landmarks for the thighs and the feet. As shown in Figure 8, the changes of the 'z' values are characteristic of the different body segments, and this fact can be exploited in the application of a neural network for

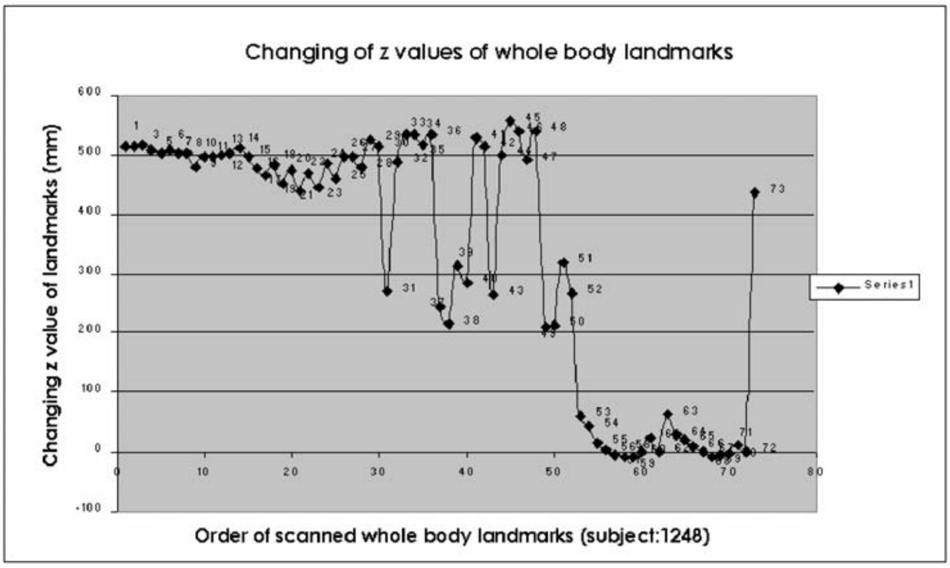


Figure 6-6 The changing of z values(Zstanding -Zsitting) of whole body landmarks

transforming body postures from, say, standing to sitting. What this means is that the human body can be divided according to the change that can be expected in the values of the 'z' coordinates. This segmentation will, however, be different then the traditional anthropometric segmentation of the body. This new type of segmentation proved to be much more advantageous in teaching artificial neural networks for 3D landmark=based posture transformation. The advantages were observed in terms of the shorter times that the ANN needed for the numerical computations.

6.3.3 Estimation of non-measured/non-measurable body landmarks

In the phase of data pre-processing, in addition to the analysis of the values of the landmarks' coordinates and clustering of the landmarks according to the changes in the coordinates, the consideration of the errors in data acquisition, and calibration based on the global coordinate system and local coordinate system respectively, it was necessary to deal with the issue of the directly unavailable landmarks. In the measured data, the group of directly unavailable landmarks is the landmarks that either were not measured, or could not be measured properly. It can happen due to imperfections in the scanning technology, for instance because the laser rays could not reach a particular region of the body. In practice, it means that the coordinates of some landmarks could not be directly identified in the scanned data. However, in order to achieve sufficient completeness, the missing landmarks have to be supplied by geometric estimation. For the purpose of geometric estimation, a CAD software package was used. The estimation considered the anatomical definition of the missing landmark, as well as the geometric information available about the region of the human body where the non-identified landmark was supposed to be. There were two typical reasons for the missing landmarks: (a) incomplete measurement of a certain

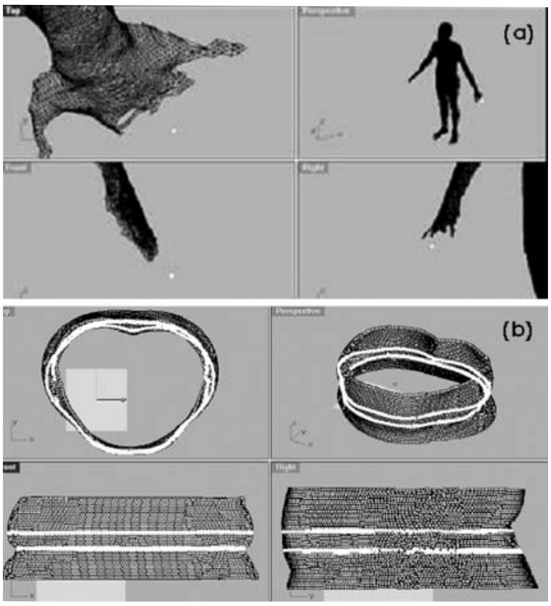


Figure 6-7 Pre-processing of input data: (a) Acquiring missed landmarks; (b) Acquiring waist

part of the body, in which case the estimation included extrapolation from available information (Figure 6-7a), and (b) imperfect measurement of a certain body part, in which case the estimation was based on interpolation. Figure 6-7 (b) shows an example of this latter case, and the anthropometric features which had to be taken into consideration. As can be seen, the waist of subject was imperfectly measured and the missing data (the coordinates of the needed landmark) had to be acquired by a specific method.

In principle, the simplest method is slicing the torso with horizontal planes that pass through the reference landmarks of the waist. However, this method cannot be applied straightforwardly, since the anthropometric characteristics of various subjects have a strong influence on the actual position of the waist landmarks. Specifically, in the case of subjects with thin and standard body shapes, the slicing plane can pass through the navel point. However, for subjects with large abdomens, the slicing plane should not be through the navel point, but somewhere above, in the upper part of the abdomen. This can be explained by physical reasons, that is, by the fact that gravity causes the position of the abdomen of obese subjects to be lower than that of thinner subjects. Consequently, the navel point of obese subjects is in a lower position than normal. A proper estimation of the physical position of the waist landmark point should take this factor into consideration. In addition, the best method is to measure or scan the waist differently for different subjects with different abdomen shapes.

6.4 Experiments with the optimal architecture of the neural network

As it was mentioned earlier, a multi-layered back-propagation-based neural network architecture was used in the research. The goal was to investigate the best architecture for the problem at hand, from the point of view of efficiency and reliability. The experiments involved not only different numbers of (hidden) layers and different numbers of neurons, but also different momentums and step intervals on the different layers of the multi-layer perceptron (MLP). From the point of computational efficiency, it was important to use the optimum architecture. In practice, it meant a neural network with a minimum number of free weights, that, on the one hand, still makes it possible for the network to learn the problem rapidly, and, on the other hand, to be a kind of "minimal network", which is able to generalize well with different input data.

The following discussion summarizes the results of the application of the multi-layered back-propagation-based neural network for the whole body-oriented posture transformation and for the cluster-based posture transformation respectively.

6.4.1 *Whole body-oriented posture transformation*

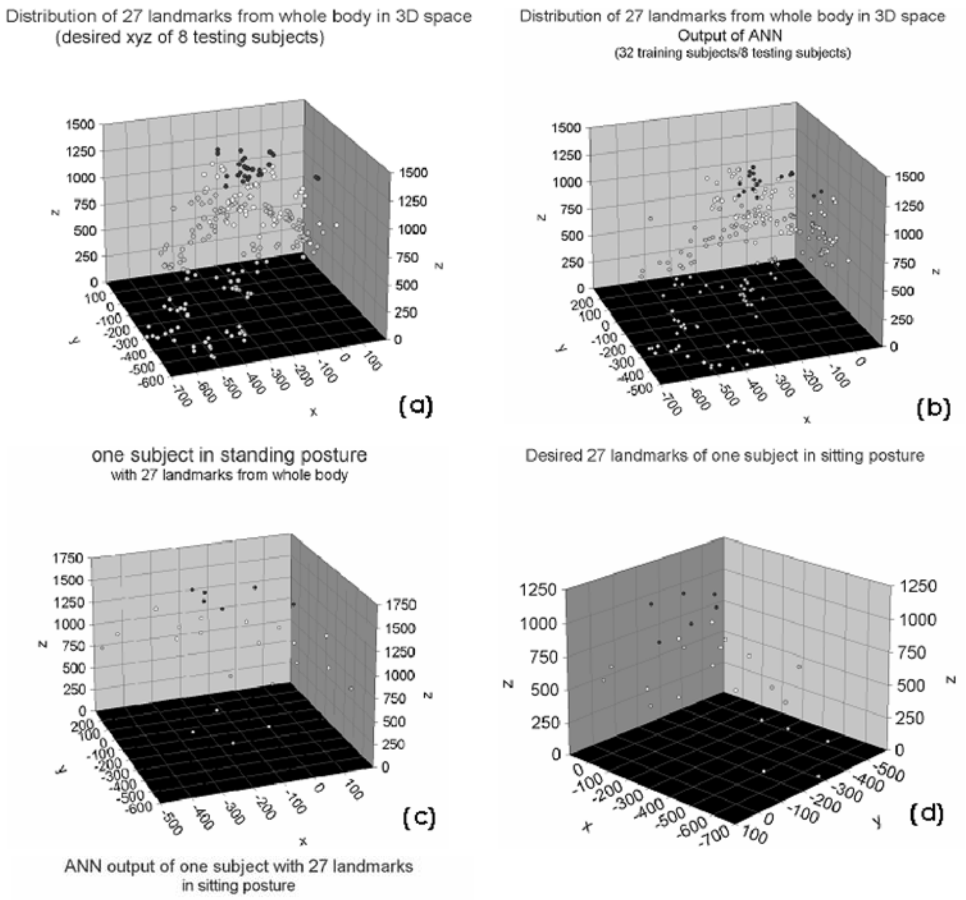
We used the individual neural network training sessions to optimize the operation of the neural network. Actually, this optimization concerned the weights applied to the transfer functions of the neurons. Setting the weights proved to be an effective means of increasing the global computational efficiency of the neural network. The best results could be achieved with the MLP when two hidden layers and the minimal number of neurons on the layers were used, and the weights were set accordingly. The weights were empirically modified, that is, based on the comparison of the values of the input and output coordinates. Having found the best values of the weight in the process of training, the operation of the neural network was tested with 8 new subjects. The results of these tests of the whole body-oriented posture transformation are shown in Figure 6-8. As can be seen, the posture transformation concerned 27 landmarks of the 8 subjects. The captions of Figures 8a – 8e explains the data for which the spatial distribution is visualized in the sub-figures. The deviations between the target output data and the ANN-generated output data can be observed by comparing the corresponding sub-figures. The deviations were statistically analyzed by means of the mean squared error (MSE) method.

Figure 6-8 shows the visualization of the results of whole body-oriented posture transformation by ANN in a 3D space: (a) spatial distribution of the expected (x, y, z) coordinate values of the 27 landmarks of the 8 tested subjects; (b) spatial distribution of ANN-generated (x, y, z) output coordinate values of the 27 landmarks of the 8 tested subjects; (c) spatial distribution of the 27 landmarks of one subject in a standing posture; (d) spatial distribution of the expected 27 landmarks of one subject in a sitting posture; and (e) the ANN-generated output coordinate values of the 27 landmarks of one subject in a sitting posture. The errors in teaching were evaluated in the whole body-oriented posture prediction. This analysis was done to find the relationship between the number of teaching epochs and the mean squared errors. The mean squared error was computed by the following formula :

$$MSE = \frac{\sum_{j=0}^{P} \sum_{N=0}^{N} (d_j - y_j)^2}{NP}$$

(MSE is the mean squared error; P = number of output processing elements (neurons); N = number of exemplars in the data set; y_j = network output for exemplar i at processing element j .; d_j = expected output for exemplar i at processing element j .)

Figure 6-9 shows the learning curves and errors of the ANN in the case of whole body-oriented posture transformation. The ANN was used to transform the coordinates of landmarks from a standing posture to a sitting posture. Computer-based training experiments were employed, which were based on the data of 8 test subjects. The two sub-figures plot the learning curves of training, in terms of the average MSE with standard deviation boundaries for 3 runs. The average MSE is asymptotically



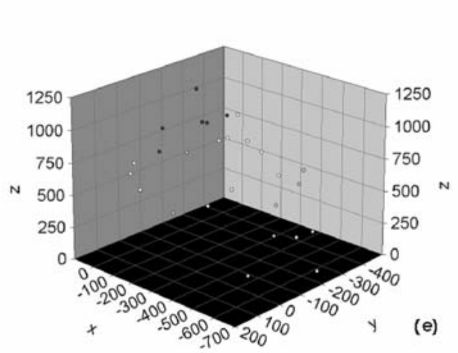


Figure 6-8 Visualization of the results of whole body-oriented posture transformation by ANN in a 3D space: (Explanation of the subfigures see in the text)

decreasing, and after 500 teaching epochs there is no significant improvement.

Table 6-1 gives the various MSE values of training. It shows that after 1198 teaching epochs the learning capabilities of the network were exhausted and the training MSEs have become minimal, likewise the average MSE at the last epoch. The best network (with optimum architecture and weighting) produced the minimum value of MSE, which was 0.0354. In the experiments, the training was stopped when the condition that MSE < %Error/2 was met. It means that the MLP was trained efficiently enough, although for the 27 landmarks considered in the whole body-oriented posture transformation, the total value of r was only 0.462969. This will be discussed in more detail below.

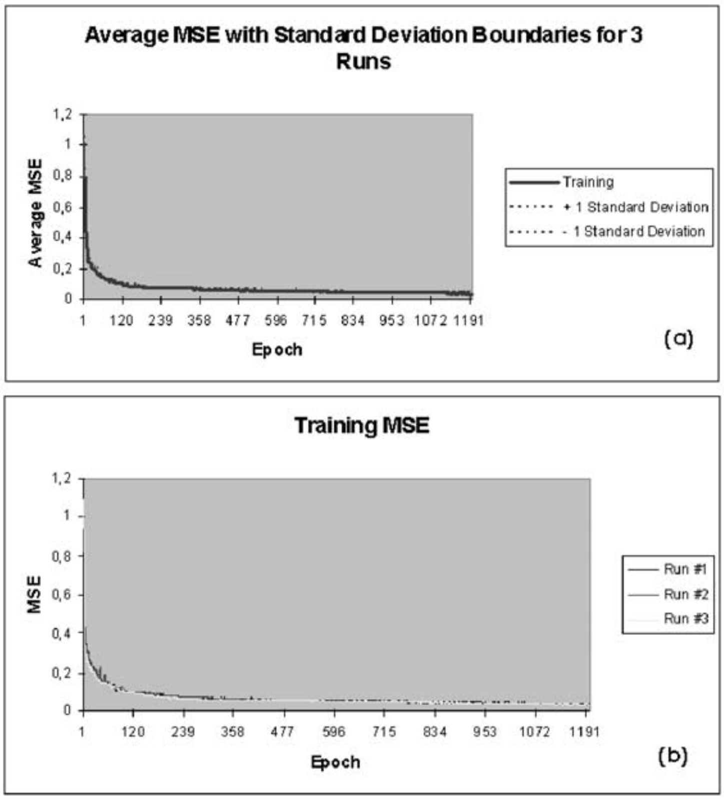


Figure 6-9 Learning curves and errors of the ANN in the case of whole body-oriented posture transformation: (a) average MSE with standard deviation boundaries for 3 runs; (b) training MSE of 3 runs.

We evaluated the correlation between the expected and the actual output values generated by the neural network. Table 6-2 gives the values of the normalized mean squared error (NMSE), and the correlation coefficient (r). The correlation coefficient expresses the relationship between the expected (desired) values of the landmark coordinates and the actual output values generated by the ANN. As mentioned in section 5.1, the correlation coefficient was r = 0.462969 in this case. The value of the MSE can be used to determine how well the actual output generated by the neural network fits the expected output. However, it does not necessarily reflect whether the two sets of data change in the same direction. The correlation coefficient (r) is supposed to indicate whether the expected and the actual output of the neural network are converging, and if so, how well. The correlation coefficient is confined to the range [-1, 1]. When r = 1, there is a perfect positive linear correlation between the requested output and the actual output of the network, which means that their difference varies by the same amount. When r = -1, their difference varies in the opposite way. When r = 0, there is no correlation between the actual output and the requested output of the network.

Below, the obtained results are analyzed further. It is important, because there are many other factors that had an influence on the formation of the results. Only the most important ones are mentioned here.

Table 6-1 Learning errors of the ANN in the case of whole body-oriented posture transformation

All Runs	*Training Minimum*	*Training Standard Deviation*
Average of minimum MSEs	0,0374	0,00237
Average of final MSEs	0,0376	0,00232
Best Network	***Training***	
Run #	3	
Epoch #	1198	
Minimum MSE	0,0354	
Final MSE	0,0356	

1) Transformation of the human body is geometrically non-linear for many parts (surfaces) of the human body. The whole body-oriented posture transformation could not represent this non-linearity with 100% accuracy using a single function. Therefore, the total value of r (0.462969) that was received for the 27 landmarks considered in the whole body-oriented posture transformation seems to be a reasonable and acceptable value.

Table 6-2 Testing errors of the ANN

MSE	**0.2275**
NMSE	**1.2045**
R	**0.462969**
%Error	**35.4196**

2) The number of training subjects was not enough to be a statistically representative set of the characteristics of the whole population. Figure 6-10 indicates an obvious problem. When two subjects had the same height but different weights, and when one was used as the training sample, and the other was used as a testing sample, the result of the test necessarily show some imprecision, since the ANN was not taught to know all characteristics of the possible subjects.

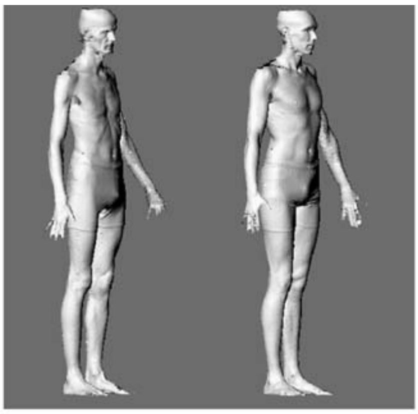


Figure 6-10 Serving as training subject and as testing subject, respectively, the two subjects with same height but different weights cause imprecision in the output

3) The raw data acquired by scanning is typically noisy and might have errors due to the physical limitations of the scanning technologies. In addition, non-standard standing and sitting postures of human beings also cause deviations from the ideal situation.

4) The input variables for training the neural network for the whole body-oriented posture transformation are limited in terms

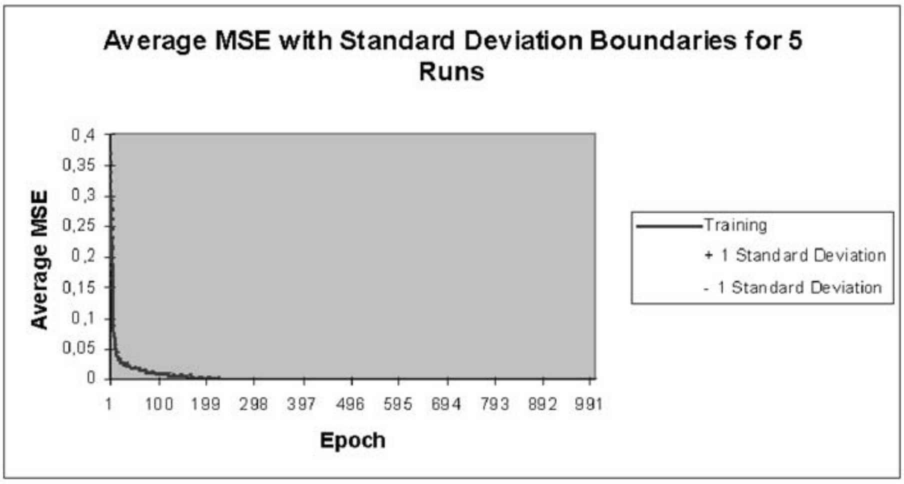


Figure 6-11 Learning curves of average MSE, with standard deviation boundaries, for 5 runs

of describing the relationship between anatomical landmarks. For example, the waist could not show the width of the pelvis in the training of the deformation of the pelvis.

5) The design of the architecture of the back-propagation-based MLP plays an important role in the quality of teaching of the neural network. It is worth mentioning, since there is a possibility to use varying number of neurons on every hidden layer, and the number of times of teaching the neural network with samples can also be set in the computer-based teaching experiments. Actually, the minimum number of

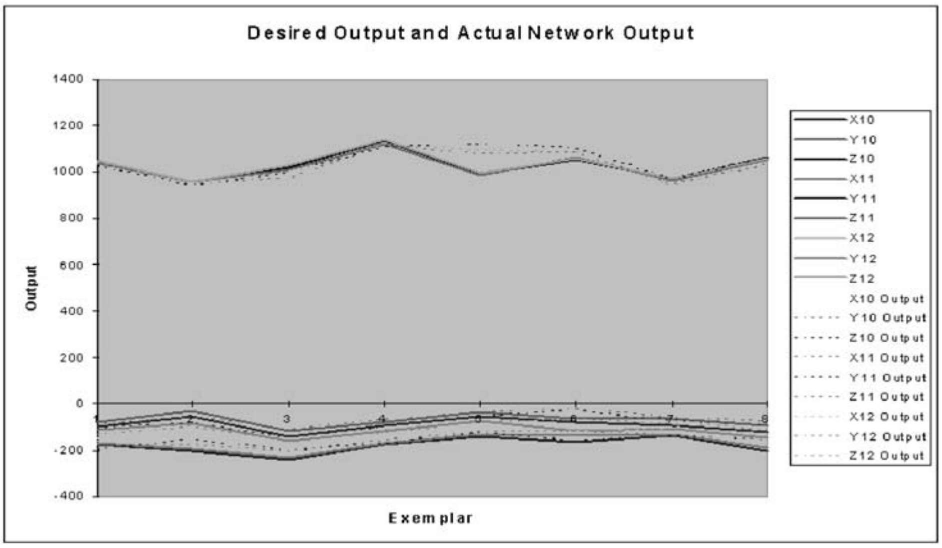


Figure 6-12 Plotting of desired output and actual ANN output

Table 6-3 Errors of the ANN in the case of learning one cluster of landmarks (shoulder) in the case of cluster-oriented posture transformation

All Runs	*Training Minimum*	*Training Standard Deviation*
Average of Minimum MSEs	0,00032	9,421E-05
Average of Final MSEs	0,00032	9,421E-05
Best Network	*Training*	
Run #	3	
Epoch #	1000	
Minimum MSE	0,000197	
Final MSE	0,000197	

Table 6-4 Testing errors of the ANN

MSE	0.1156
NMSE	0.6551
r	0.644449
%Error	15.2735

neurons and layers are determined in the experiments repeated N times. This is called the epoch number. When fewer hidden layers are used, more neurons are needed on every hidden layer; moreover, the epoch number N should not be too high, otherwise the network becomes over-taught and loses its ability to adapt to new input. This can easily lead to incorrect test results in the simulation phase of the use of the neural network. When fewer neurons are used, more hidden layers are needed to achieve a certain level of ”knowing” by teaching the network. Usually, the epoch number N needs to be set to a higher value, which should be higher than the number of weights (w) divided by performance error (%error). Random initialization can make optimization of the computer-based training experiments uncertain.

Table 6-5 Performance characteristics of teaching the coordinates of three landmarks of the shoulder

Performance	***X10***	***Y10***	***Z10***
MSE	736,2201	461,5249	2806,1481
NMSE	0,6816	0,7027	0,9853
MAE	20,9987	17,1825	38,5428
Min Abs Error	0,2648	1,01682	6,2629
Max Abs Error	43,04282	41,8609	129,4848
r	0,6951	0,7367	0,6263
Performance	***X11***	***Y11***	***Z11***
MSE	669,1977	602,4619	1507,1528
NMSE	0,6141	0,7116	0,5175
MAE	19,9169	20,8202	28,9264
Min Abs Error	3,7382	0,9828	0,7204
Max Abs Error	31,8639	43,8747	91,0424
r	0,9128	0,7543	0,7901
Performance	***X12***	***Y12***	***Z12***
MSE	695,1571	649,6999	1793,7776
NMSE	0,7146	0,8649	0,6134
MAE	22,6980	23,1927	35,4023
Min Abs Error	4,5083	5,9030	8,7721
Max Abs Error	41,1000	44,5067	96,8075
r	0,8695	0,6524	0,7532

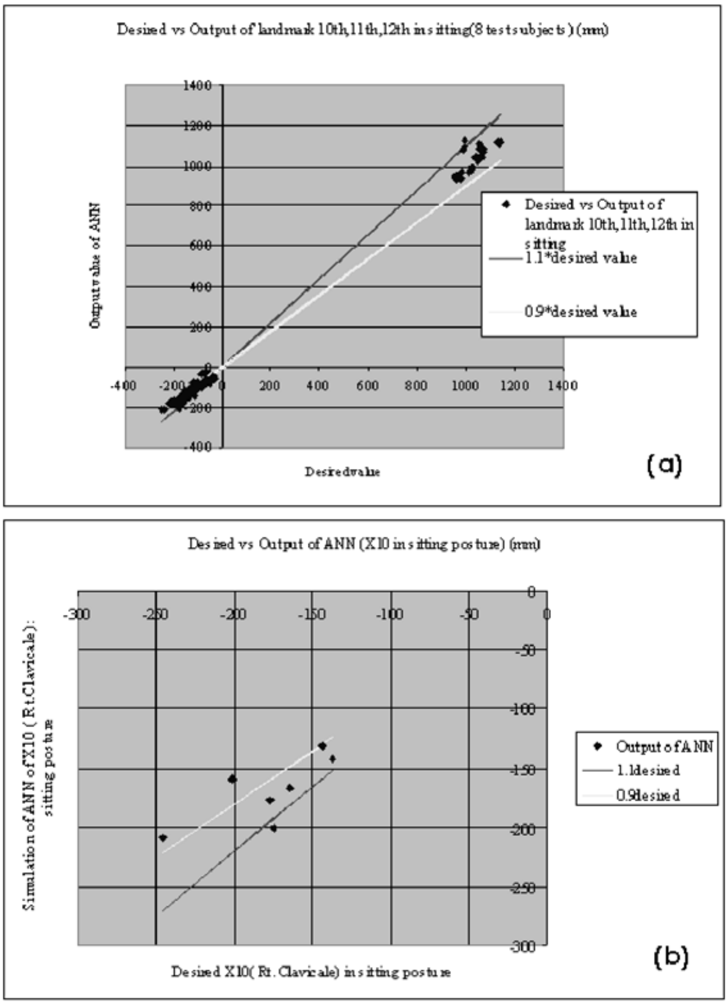
6) Our observation is that, when the number of epochs increased to a level during the training experiments, more epochs meant more risks for training with a ”singular matrix”. This appeared at a very late stage of teaching and caused the training to fail in the end. This phenomenon could be explained by the nature of the general algorithm. When the number of training examples is not large enough, the selection of examples in the training carries a risk of working with the same matrix. This problem

could be avoided by training with large examples from a large population.

The above experiences indicate that there is a need to experiment with the design as well as the training of the MLP neural network in order to gain better insight into the operation, to improve the efficiency of operation, to shorten the necessary computational times, and, finally, to reduce the training errors.

6.4.2 *Landmark cluster-oriented posture transformation*

In the case of the whole body-oriented posture transformation experience, the complete predefined set of body landmarks was considered. The approach discussed below differs from this in that it operates with specific clusters of landmarks. The clusters are based on the magnitude of change in the values of coordinates of the landmarks in posture transformation.



First, the results obtained in the experiments are presented. Figure 6-11 shows the results of computer-based teaching of the neural network for landmark cluster-based posture transformation. The plotted curves are the learning curves of average MSE, with standard deviation boundaries, for 5 runs, with randomized initialization. In the teaching process, as the number of epochs increases, the MSE gradually drops and approaches to 0. Compared with the MSE in teaching the neural network for whole body-oriented posture transformation, the MSE obtained in the case of landmark cluster-based posture transformation was much smaller (in particular, for the #10, #11, and #12 landmarks). Expressed in numerical values, it was only 0.000196966, instead of 0.035391979. After the best values of weights were found in the teaching experiments, they were used in the testing, which involved 8 test subjects.

Again, the relationship between the expected output and the actual output of the neural network was studied. Figure 6-12 graphically represents the relationship for #10, #11, and #12 landmarks. (The names of these and the other landmarks are listed in the Appendix 1.) It was observed that the actual output of the neural network almost matched the expected (desired) output, except for subject #5, the data of which did not show a sufficiently good match of the values of the 'z' coordinates.

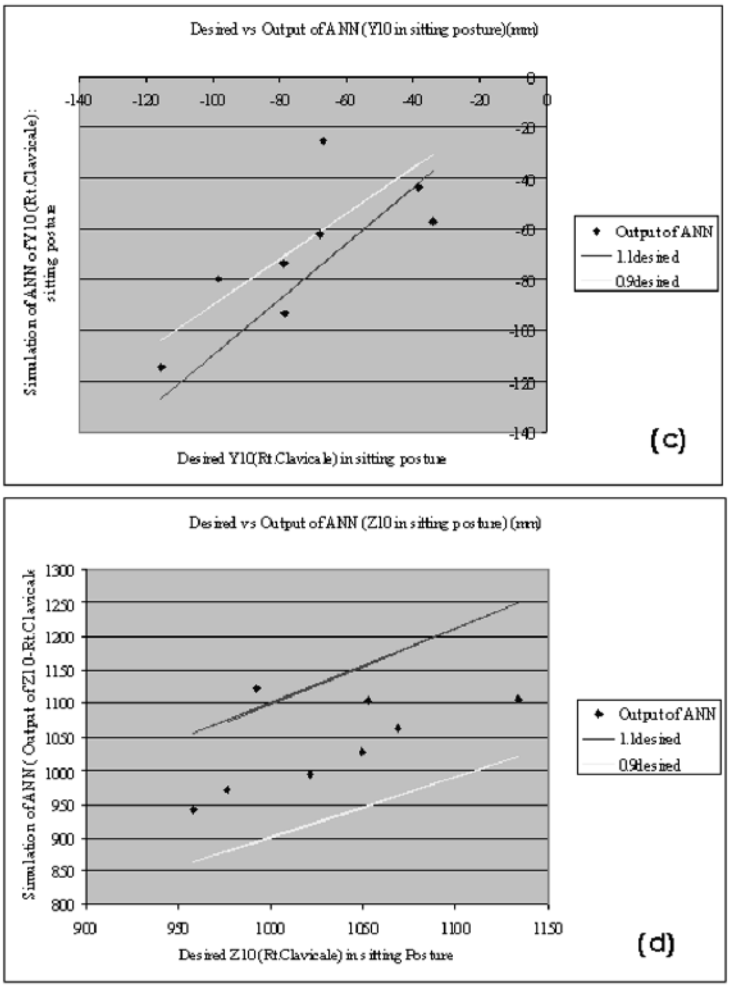


Figure 6-13 Requested and actual output of the neural network for landmarks #10, #11, and #12 for 8 test subjects. ((Explanation of the subfigures see in the text)

In order to evaluate the errors of teaching, the errors for the landmark cluster-based posture transformation were also analyzed. Table 6-3 summarizes the figures. The optimal number of neurons was determined by manual search, and the minimum value of MSE for this best neural network was 0.000197 after 1000 epochs.

In Table 6-4, the MSE values for testing the network with 8 test subjects are given. The mean squared error was 0.1156, and the normalized mean squared error was 0.6551. The correlation coefficient 'r' between the expected and the actual output values produced by the neural network was 0.644449, which is much higher than the value of the whole body-oriented posture transformation experiment. The results for teaching the MLP-based neural network for three coordinates of the previously discussed three landmarks are shown separately in Table 6-5.

Table 6-6 Errors of the neural network in testing a cluster of four landmarks of the back part of the human body.

MSE	0.1391
NMSE	0.6132
r	0.581218
%Error	46.7411

As a next step of verification, the learning precision of the ANN architecture was evaluated. More specifically, the learning precision in landmark cluster-based posture transformation was studied, focusing on the results belonging to the 90% confidence interval. Most of the testing results were satisfactory, although the prediction of the 'x' and the 'y' coordinate values was less precise than that of the 'z' coordinate value of the landmarks concerned. In other words, the results proved that the prediction of the 'z' coordinate values of landmarks should be statistically more precise than the prediction of the 'x' and 'y' values, since it has a higher correlation coefficient in terms of the expected 'z' value. Figure 6-13 plots the requested and the actual output values of the neural network for landmarks #10, #11, and #12. The values are for transformation from a standing posture to a sitting posture, and the intervals are formed by the 90% confidence lines. Figure 6-13a shows the (x, y) values of the three shoulder landmarks in a sitting posture after transformation (considering 90% confidence interval).

Table 6-7 Performance characteristics of teaching the coordinates of four landmarks of the back part of the human body

Performance	*X25*	*Y25*	*Z25*
MSE	122,2684093	120,5577474	1854,587089
NMSE	0,784757732	0,687694046	0,417630478
MAE	8,203054649	9,139215871	39,73212244
Min Abs Error	0,261633205	1,769478226	19,43103516
Max Abs Error	25,06928497	20,87191109	80,82318604
r	0,525056317	0,708123756	0,767191214
Performance	*X26*	*Y26*	*Z26*
MSE	309,188941	130,8829232	1211,133087
NMSE	2,078602385	2,339619573	0,246246636
MAE	12,79069862	8,704302311	29,56382423
Min Abs Error	1,980690842	0,86850174	3,244528809
Max Abs Error	14,56529175	20,8627829	53,82762695
r	0,740779161	0,883926636	0,898184397
Performance	*X27*	*Y27*	*Z27*
MSE	232,9770625	236,2729933	619,4883843
NMSE	3,460320741	1,577674938	0,129872904
MAE	11,52906333	13,5384972	19,06142073
Min Abs Error	1,566787109	5,433051453	0,455527344
Max Abs Error	13,70848297	29,2413588	51,18941406
r	0,501972621	0,64012502	0,943912987
Performance	*X28*	*Y28*	*Z28*
MSE	77,45355151	9,698326795	2001,213068
NMSE	*	*	0,247942484
MAE	2,480478807	0,414471893	39,39959875
Min Abs Error	0,002355993	0,033427596	2,354128418
Max Abs Error	0,214969158	0,289075971	73,15334229
r	*	*	0,883397258

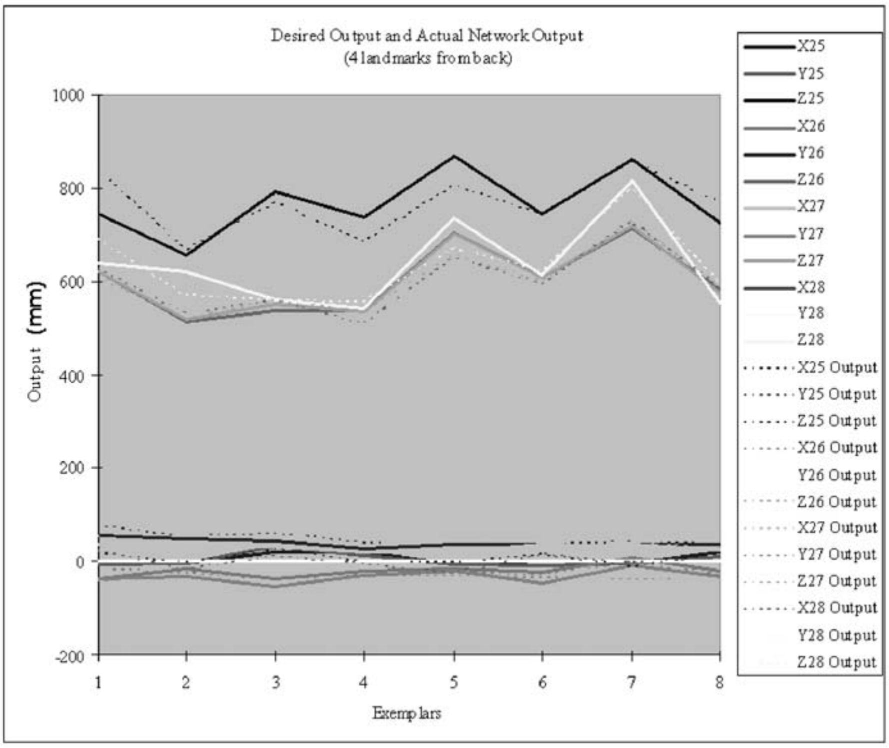


Figure 6-14 The requested output and the actual output of the neural network for the cluster of four landmarks representing the back part of the human body (Uni: mm)

Figure 6-13b shows the distribution of the 'x' coordinate values, and Figure 6-13c shows the 'y' coordinate values of landmark #10 in sitting posture. Finally, in Figure 6-13d, the 'z' coordinate values of landmark #10 are plotted, also in a sitting posture.

Figure 6-13 plots the requested and actual output of the neural network for landmarks #10, #11, and #12 for 8 test subjects: (a) desired vs. ANN output (x,y) values of 3 landmarks on the shoulder in a sitting posture after transformation, with 90% landmarks in the 90% confidence interval; (b) 10^{th} landmark X values (desired vs. ANN output in sitting posture); (c) 10^{th} Y values (desired vs. ANN output in sitting posture); (d) 10^{th} landmark Z values (desired vs. ANN output in sitting posture).

In order to be able to compare these results with the results obtained for other landmark groups, a comparative experiment was conducted. The landmark cluster investigated, consisting of four landmarks, represented the back part of the human body. The results of teaching the neural network for this cluster are presented in Figure 6-14.

Tables 6-6 and Table 6-7 show the results obtained in transforming this cluster of landmarks in the case of 8 test subjects. It can be seen that the landmark cluster-based body-posture transformation is much more precise than whole body-oriented

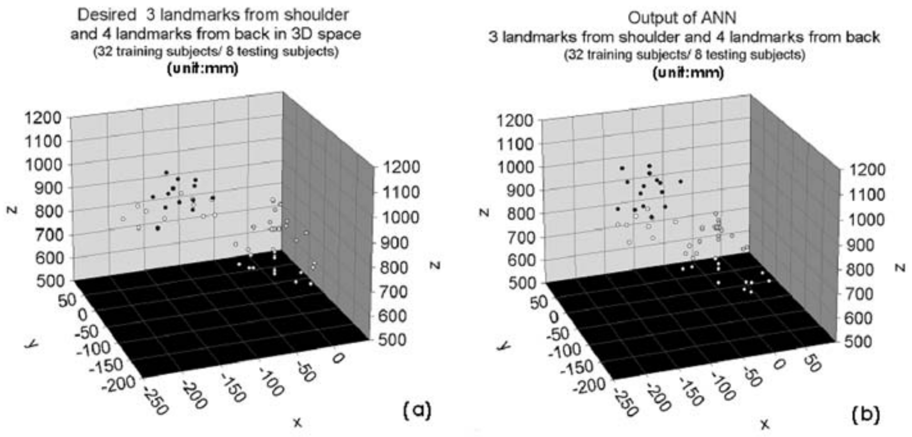


Figure 6-15 Visualization of the testing results of the cluster-based landmark transformation

landmark transformation. It is expressed by the higher value of the correlation index. In terms of figures, the value of r is higher than 50%. The concrete value was r = 0.581218. The most logical explanation for it is that the neural network has been taught with the coordinate values of landmarks behaving quasi-similarly in posture transformation.

This is in itself the explanation of the better performance of the cluster-oriented landmark transformation method as a whole. In the case of the whole body-oriented landmark transformation approach, the characteristics of the landmarks are mixed and, consequently, the ANN cannot learn the taught pattern with the same precision. This is expressed by the lower r values, obtained not only in the course of the teaching experiments, but also in the course of testing experiments.

Table 6-7 contains the coordinate values of landmarks #25, #26, #27 and #28 of the back part of the human body. Note that the asterisk (*) represents the 'x' and 'y' coordinate values of landmark #28, which are 0 both in standing and in sitting postures, since this is a reference landmark. For the purpose of comparison, the results of using the neural network to transform the standing postures of 8 subjects to sitting postures by cluster-oriented landmark transformation were visualized. This is shown in Figure 6-15. Figure 6-15a presents the requested output coordinates of the 3 landmarks on the shoulder (that is, landmarks #10, #11, and #12) and of the 4 landmarks on the back part of the human body (that is, landmarks #25, #26, #27, and #28). At the same time, Figure 6-15b shows the actual output coordinates produced by the neural network for the 3 landmarks of the shoulder and for the 4 landmarks of the back part of the human body. Reasonably good correspondence can be observed in the figures.

In general, landmark-based posture transformation by neural network is an effective method, but it has to be completed with the transformation of the non-landmark type general geometric points. Fortunately, a properly trained neural network can also be used for this purpose. This is a great advantage compared to other purely geometrical methods.

6.5 Comparison of genetic optimization algorithm and general optimization algorithm of multi-layer back-propagation neural networks

This section focuses on a comparison of two different algorithms of artificial neural networks in predicting human body posture. The purpose of a comparison research is to search for the better algorithm to minimize the neurons and the cost of ANNs for predicting the landmark coordinates of the whole human body in 3D space. This prediction technique will save a great deal of costs and time for ergonomists to help them acquire unknown 3D anthropometic data in their design.

6.5.1 Comparison of the two optimization algorithms on whole-body landmark prediction

In my latest research, the measured human body has been substituted by a proper set of landmarks, which is used as a basis for transforming the data, as they are needed to describe specific body postures. Artificial neural networks were used for the actual data conversion. The input variables are a set of demographic data and the coordinates of the landmarks characterizing a given posture, and the output is another set of landmarks characterizing the transformed posture.

Before designing the BP-ANN, the raw data need to be pre-processed. This pre-processing included an analysis of the landmarks and calibration based on a global coordinate system and a local coordinate system respectively. Meanwhile, because of the drawbacks of the scanning technique itself, some landmarks could not be acquired directly from the scanning data, because laser rays could not reach them. The missed landmarks have to be estimated in CAD software based on anatomical definition; the related 1D or 2D measurements also have to be estimated in CAD software. In the design of the BP-ANN, two multiple BP-ANNs architectures were experimented with and compared, specifically two-layer BP-MLPs. The experiments included not only different hidden layers and different numbers of neurons, but also different momentums and step intervals on different layers of MLPs.

The posture prediction was based on 25 landmarks, selected from a total of 73 landmarks identified on the measured data of the human body scanned by the laser scanning technique. The steps of posture prediction for whole body are as follows:

1. Obtain point cloud of the whole body in the source posture;
2. Find the landmarks on the source posture and on the target posture;
3. Generate a set of descriptive input variables;

4. Use the descriptive parameters and the source and target posture landmarks to teach the ANNs in general algorithm;
5. Regenerate the landmarks representing the target posture based on the transformed landmarks and proportionality.

We experiment with 40 subjects (20 male and 20 female) in total in 4 groups that were formed according to the ratio between the leg and height of the subjects. The input of the ANN was whole-body landmark coordinates of 32 subjects in a standing posture, with some demographic information, such as gender, weight, height, head width, shoulder width, and waist. The ANN is constructed of multi-layer perceptrons, which formed a layered feed-forward network, typically trained using static back-propagation with a general algorithm. The desired/target values were landmark coordinates of the whole body of 32 subjects in a sitting posture in 3D space. In the general algorithm method, the search for the optimal MLPs took place manually. It is important to find the network with the minimal number of free weights that can still learn the problem. The minimal network is likely to generalize well using new input data.

Genetic algorithms are general-purpose search algorithms based upon the principles of evolution observed in nature. Genetic algorithms combine selection, crossover, and mutation operators with the goal of finding the best solution to a problem. Crossover is a genetic operator that combines (mates) two chromosomes (parents) to produce a new chromosome (offspring). The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each of its parents. Mutation is a genetic operator that alters one or more gene values in a chromosome from its initial state. This can result in entirely new gene values being added to the gene pool. Genetic algorithms search for this optimal solution until a specified termination criterion is met.

The solution to a problem is called a chromosome. A chromosome is made up of a collection of genes that are simply the parameters to be optimized. A genetic algorithm creates an initial population (a collection of chromosomes), evaluates this population, then evolves the population through multiple generations in the search for a good solution for the problem. Therefore, genetic optimization can be beneficial any time the network designer is unsure of optimal parameter settings.

In the design of the genetic algorithm, some component configurations need to be set up, such as the maximum generations, which specifies the maximum number of generations that will be run until the simulation is stopped, and the population size, which is the number of chromosomes to use in a population. This determines the number of times that the network will be trained for each generation.

There are two types of genetic algorithm: generational and steady-state. A generational genetic algorithm replaces the entire population with each iteration. This is the traditional method of progression for a genetic algorithm and has been proven to work well for a wide variety of problems. It tends to be a little slower than steady-state progression, but it tends to do a better job of avoiding the local minima. A steady-state genetic algorithm only replaces the worst member of the population with each iteration. This method of progression tends to arrive at a good solution faster than generational progression. However, this increased performance also increases the chance of getting trapped in local minima. In the experiments, a generational genetic algorithm was chosen. In order to make the comparison in the similar situations, the experiments using a general algorithm were conducted with 40 subjects (20 male and 20 female) in total in 4 groups. The steps of posture prediction for the whole body are as follows:

1. Obtain point cloud of the whole body in the source posture;
2. Find the landmarks on the source posture and on the target posture;
3. Generate a set of descriptive input variables;
4. Configure the component of the genetic algorithm, use the source and target posture landmarks to train the ANNs;
5. Regenerate the landmarks representing the target posture based on the transformed landmarks.

6.5.2 *Results and discussion*

First the results obtained in using the general algorithm in whole-body landmark-based posture transformation are presented. After many experiments in training, it was determined that the best weights are based on minimum neurons on 2 hidden layers of MLPs. In Table 6-8, the MSE is the mean squared error of training progress with 32 training subjects. The best network has the minimum MSE, which is 0.006260938. In Table 2, the MSE is the mean squared error of testing progress with 8 test subjects. NMSE is the normalized mean squared error of testing, and r is the correlation coefficient between the desired values and actual output values of 8 test data. The size of the MSE can be used to determine how well the network output fits the desired output, but it does not necessarily reflect whether the two sets of data move in the same direction.

The correlation coefficient (r) between a network and a desired output solves this problem. A correlation

Table 6-8 General algorithm ANNs learning error.

All Runs	*Training Minimum*	*Training Standard Deviation*
Average of Minimum MSEs	0,007356934	0,000924267
Average of Final MSEs	0,007608058	0,000824541
Best Network	*Training*	
Run #	1	
Epoch #	781	
Minimum MSE	0,006260938	
Final MSE	0,00672186	

coefficient of 0.88 means that the fit of the model to the data is reasonably good. In this case, the training was stopped when MSE < %Error/2, which means that the configured MLPs had been trained well enough, although the total r of 25 landmarks from the whole body is only 0.469439. Figure 6-16 visualized the results of whole-body posture prediction with a general algorithm: (a) desired (x,y,z) value of 25 landmarks of 8 test subjects; (b) ANN output (x, y, z) value of 25 landmarks of 8 test subjects.

Table 6-9 General algorithm ANNs prediction error.

MSE	0.225633
NMAE	1.237537
r	0.469439
%Error	48.969887

Now we turn our attention to the results obtained by using the genetic algorithm in whole-body landmark-based posture prediction. The experiment which finds the best fitness (lowest cost) of a genetic algorithm was configured with the following specifications:

1. Number of epochs is 800;
2. Population size is 40;
3. Maximum generations are 50;
4. Maximum evolution time is 60 minutes;
5. The bound of step interval optimization is [0, 1];
6. The bound of momentum optimization is [0, 1];
7. The bound of processing element optimization is [15, 67] (Since the best network of general algorithm is based on 67 neurons, 67 processing elements were chosen

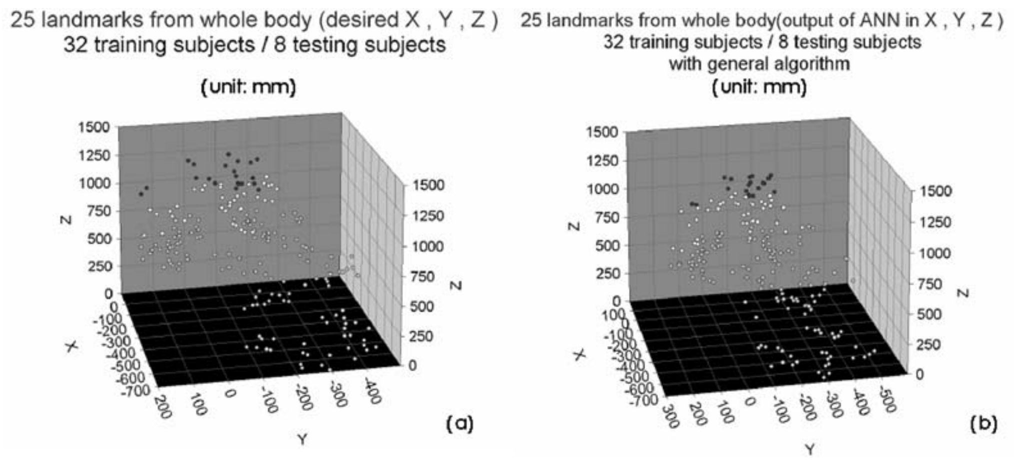


Figure 6-16 Visualizaion of the results of whole body posture prediction with general algorithm (a) Desired (x,y,z) value of 25 landmarks of 8 testing subjects; (b) ANNs output (x, y, z) value of 25 landmarks of 8 testing subjects. (Unit: mm)

as the maximum value in the genetic algorithm for the purpose of comparison.);

8. Crossover is set up as one point (which means it randomly selects a crossover point within a chromosome then interchanges the two parent chromosomes at this point to produce two new offspring.);
9. Mutation is set up as uniform.

The best fitness minimum MSE) is found at the first generation of chromosomes with the value of 0.00731 (Figure 6-17 and Table 6-10). Figure 6-18a and Figure 6-18b plot and visualize the desired output and actual network output in the genetic algorithm with 25 landmarks from the whole body. It shows that the prediction in the Z coordinate is much more precise than in X and Y coordinates. One possible reason is that the input variables related in height are efficient, but variables related in width and depth are not efficient. The testing MSE with 8 test subjects of genetic algorithm is 0.1951.

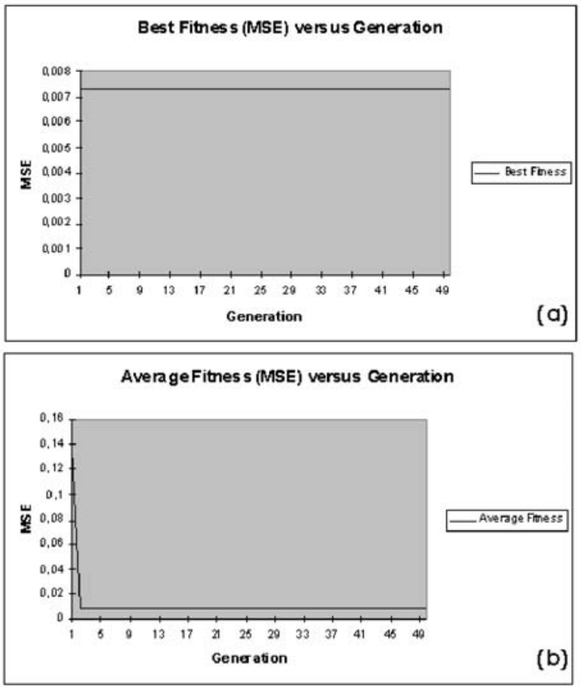


Figure 6-17 Performance of training: (a)Plots of best fitness versus generation in genetic algorithm and (b) lowest cost (MSE) versus generation in genetic algorithm

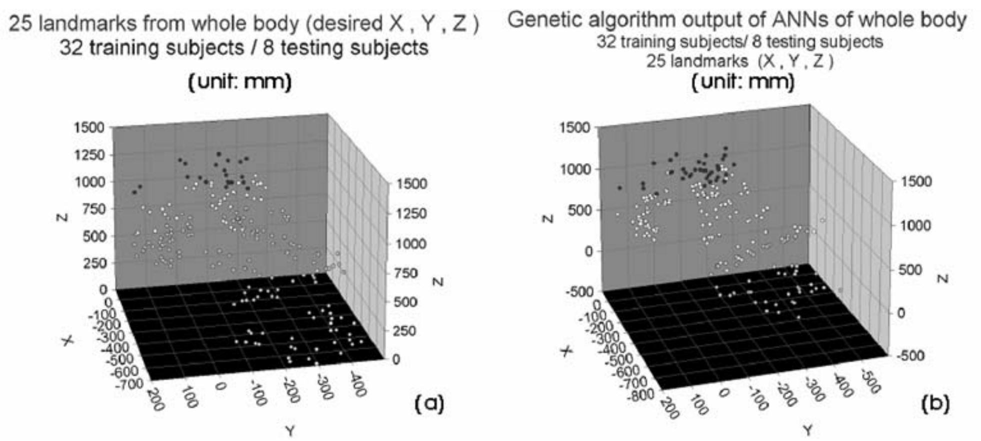


Figure 6-18 Visualization of 25 landmarks from whole body in 3D space: (a) desired landmarks in sitting posture; (b) actual genetic algorithm output in sitting posture. (Unit: mm)

The correlation coefficient (R) between desired and actual ANN outputs of the genetic algorithm is 0.479263, which is lower than the final experiment with the general algorithm (Table 6-10 and Table 6-11). However, the genetic algorithm is much more time-consuming than the general algorithm, which has an impact on the final prediction effectiveness (Table 6-11).

Table 6-10 Results of training with genetic algorithm and results of testing

Optimization Summary	**Best Fitness**	**Average Fitness**
Generation #	1	2
Minimum MSE	0,00731	0,00731
Final MSE	0,00731	0,00731

MSE of testing	0.1951
NMSE of testing	1.0701
R between desired and output	0.479263
% Test ERROR	37.1424

Table 6-11 Comparison of general algorithm and genetic algorithm in Sum, Mean of testing error of 25 landmarks of 8 testing subjects in 3D coordinates and testing correlation coefficient (R)

	General Algorithm (mm)			**Genetic Algorithm (mm)**			**Difference between General and Genetic Algorithm**		
	X	**Y**	**Z**	**X**	**Y**	**Z**	**X**	**Y**	**Z**
Sum of testing error	-1585,93	-797,48	-381,73	-305,88	-2343,68	934,18	-1497,49	1580,33	-1324,79
Mean of test error	-7,93	-3,99	-1,91	-1,53	-11,72	4,67	-7,49	7,90	-6,62
R	0.46944			0.47926			0.00982		
Time	50-120 minutes			5-15 minutes			45-115 minutes		

6.6 Conclusions

This chapter presented a neural network-based approach to transforming human-body postures based on 3D landmarks. In the research, the human body was measured by 3D laser scanning and the measured parts of the body were represented as point clouds. For the purpose of posture transformation, the human body was substituted by a proper set of landmarks, as they are needed to describe specific body postures. A multi-layered neural network was used for the actual conversion of data in the computer training and testing experiments. Two approaches were tested, namely the whole body-oriented and the landmark cluster-oriented approaches. The results of the whole body-oriented and the landmark cluster-oriented body-posture transformation were compared, analyzed, and evaluated. My conclusion is that the landmark cluster-oriented transformation method is computationally more efficient in regenerating human body postures, and the clustering of landmarks lends itself to a reliable method. The reason for the efficiency is that clustering produces quasi-similar behavior in landmark groups for teaching the neural network. In practice, it means that the changes in the positional coordinates of these groups of landmarks in the 3D space are similar, and these changes are easier for the neural network to learn.

Our other conclusions concerning the transformation of 3D landmarks of the human body are: (i) in order to get a more precise output result from the neural network, the input variables with sufficient information content should be provided (that is, in other words, the ANN should be taught with enough knowledge, such as demographic information and 1D and 2D anthropometric data); (ii) clustered landmarks are more expressive and help achieve shorter teaching times and more precise correlation coefficients in testing than that which the ANN can produce with landmarks of strongly varying characteristics (which is the case if we consider the cluster of all the landmarks that can be identified on the whole body); (iii) the precision of the landmark cluster-oriented method can nevertheless depend on the actual changes of the 'z' value of the coordinates of the landmarks, especially if the clusters are defined based on the traditional segmentation of the human body; (iv) using more neurons and more hidden layers in the neural network seems to be a solution to reduce MSE in teaching process, but it always results in a larger MSE in the testing process because of over-teaching. Therefore, this problem needs a compromise. Optimization of the architecture of the neural network is always important in order to achieve a smaller MSE in the testing process, but a minimum number of neurons and hidden layers leads to a more adaptive and practical neural network.

In general, landmark-based posture transformation by neural network is an effective method, but it has to be completed with the transformation of the non-landmark type general geometric points. Fortunately, a properly trained neural network can also be used for this purpose. This is a great advantage compared to other purely geometrical methods. The proposed methodology is a relatively general one. It provides us with the ability to predict any postures of human bodies and body parts once 3D anthropometric data are available. The type and number of postures has no limitations, with the exception of the required computation capacity and power. Therefore, this posture transformation approach will help ergonomic experts save a great deal of time and costs to acquire 3D information about human bodies in 3D space. The further research will focus on the regeneration of human body postures based on a small number of landmarks for the design of DHMs of CAED.

According to the comparison experiments between a general algorithm and a genetic algorithm of posture prediction of 25 landmarks from the whole body, my conclusion is that a genetic algorithm can help networks search automatically for an optimal design at a low cost, but it is highly time consuming and requires a great deal of computer processing power compared with a general algorithm. Because of the optimal search periods, the genetic algorithm not only trains the good networks but also has to train the bad networks in order to get rid of them. The general algorithm produced a lower r result in the testing procedure than the genetic algorithm, but it saves a lot of time of training and manually optimal searching if the designer has had good experience in training and in data pre-processing.

Our conclusion in this research is that the cluster-oriented transformation method is computationally more efficient in regenerating human body postures and that the clustering of landmarks lends itself to a reliable method. In the second research, a general algorithm and a genetic algorithm of multi-layer BP-ANNs were compared. The conclusion is that a genetic algorithm can help networks search automatically for an optimal design at a low cost, but it is highly time consuming and requires a great deal of computer processing power compared with a general algorithm.

Chapter 7

Validation of posture prediction technology with application case studies

7.1 Introduction

The objective of this chapter is to validate the posture prediction technology described above for concrete design problems, by investigating the advantages it provides for designers, and by exploring unsolved issues of application that beg further research. From the point of view of application in product design, the efforts needed to prepare the data for computation and the concrete processing time are the most important aspects. However, since I intend to apply the ANN-based posture prediction technology in the ergonomics-inclusive conceptual design of consumer products, the geometric accuracy of posture prediction is also an important aspect. Three design applications (which will be called “case studies” in the next part of the paper) were selected, which represent three different levels of requirements from a design point of view.

What this chapter tries to discover is the extent to which the requirements related to the posture prediction in these application case studies will be met. In other words, I study the appropriateness of the results of posture transformation with a view to the concrete requirements of the design tasks. The three case studies are as follows: (i) designing an office chair, (ii) designing the workspace of furniture, and (iii) designing driving space in an automobile interior. The first and second application case studies address not only different requirements, but also different complexities. The third application case was selected with the intent of exploring the limitations of the ASNN-based technology in application. From the point of view of the interaction of the human body with the designed product in various postures, these three case studies can be considered as representative of an under-constrained, fully constrained, and over-constrained application case respectively.

Thus, the primary research questions have been: (i) how the ANN and landmark-based posture prediction technology performs in various application cases; (ii) what advantages it provides for the designers; and (iii) what limitations it poses. In order to be able to express the applicability of the proposed PPT quantitatively, first the requirements of the three applications will be analyzed, and then criteria will be formulated. To enumerate the fulfillment of the criteria, quantitative measures (indices) will be introduced. The applicability in the design application cases and the usefulness of the technology for the designers will be expressed in terms of these measures.

7.2 Establishing validation criteria for posture prediction technology

When defining a valid design, some basic requirements of this design must be met. However, in terms of anthropometry, the most crucial aspect is that the design must fit the target user population in any functional postures of using. Consequently, three validation criteria in terms of information provision for the anthropometric requirements can be established for validating research. First of all, the predicted posture should provide sufficient anthropometric information for design, which should be representative for the target user population and should provide the required anthropometric data, as well as providing minimum and correct functional postures for design. Secondly, the accuracy should be met in terms of information. Finally, the sensitivity of the system is another important criterion for designers using the predicted model. In other words, the tolerated range of variation should be an assessment in terms of providing correct information to designers. As for assessment of collision between modeling and the workplace, it is outside the scope of the topic of this paper, since the current results of posture prediction are in point clouds without connections between the predicted landmarks.

Sufficiency

The sufficiency is defined by an index created in the assessment procedure with an application study based on the required design parameters and predicted design parameters. In designing workspace, office furniture, and so on, it is the task of the designer to accommodate and fit large numbers of an amazingly diverse population. Therefore, posture prediction technology should be able to provide enough design parameters for the designer. At the same time, the database of anthropometry used in the training procedure must offer a representation of the target user population. Additionally, the posture prediction technology should provide minimum functional postures for diverse design. In the previous research, all the samples were scanned in two functional postures, one standing and the other sitting comfortably, instead of the traditional upright seated posture.

Accuracy

The definition of PPT accuracy should be based on the comparison between scanned landmarks and predicted landmarks. The anatomical landmark and ANN-based posture prediction is a completely new 3D solution to the 3D anthropometric problem. The 3D coordinates of anatomical landmarks provide a more complete archive of form than de univariate 1D or 2D traditional anthropometric data. However, this paper compared this 3D solution with 1D traditional anthropometric data because the transformation from 1D data to 3D data is difficult but 3D data can always be transferred into 1D data easily.

Sensitivity

In order to understand the robustness of the PPT, it was decided to explore the sensitivity of the PPT. The concept of sensitivity was defined, which provides a measure of the relative importance among the inputs of the neural model and illustrates how the model output varies in response to the variation of an input. The first input is varied between its mean +/- a defined number of standard deviations, while all other inputs are fixed at their respective means. The network output is computed for the defined number of steps above and below the mean. This process is repeated for each input.

The above-mentioned three criteria are a small subset of the characteristics which define the total biofidelity of a digital human model. These three, however, directly affect the evaluation of chair accommodation, workspace design, and automobile interior design. The intention was to quantify the posture prediction system using 1) traditional anthropometry, 2) literature survey data, and 3) an overlay, within the CAD model, of the 3D landmarks of the subjects in both desired and ANN output data.

We also developed measures for the criteria of posture prediction. In order to measure the sufficiency, accuracy and sensitivity of the landmark and ANN- based prediction models in the target population, a statistic comparison will be conducted in the experiments between traditional anthropometric data and predicted models which are based on 3D scanning. By comparing the ANN output and traditional anthropometric data from the literature, the prediction accuracy will be validated. Additionally, by varying the input variables to the posture prediction network, the sensitivity of the network can be known based on the differences of the corresponding outputs. Whether these validations will be proved by the posture prediction technology is a major question in this paper. All will be presented in the cases that follow; the answer is not simply stated. In general, the cases indicate that some positive value was realized by using this technology in specific design, but the type and magnitude of the contribution varies.

7.3 Introducing the samples used in the practical assessment of posture prediction

In this posture prediction technology, the 32 trained samples and 8 test samples are selected from 5000 scanned Dutch subjects according to the ratio of the leg length

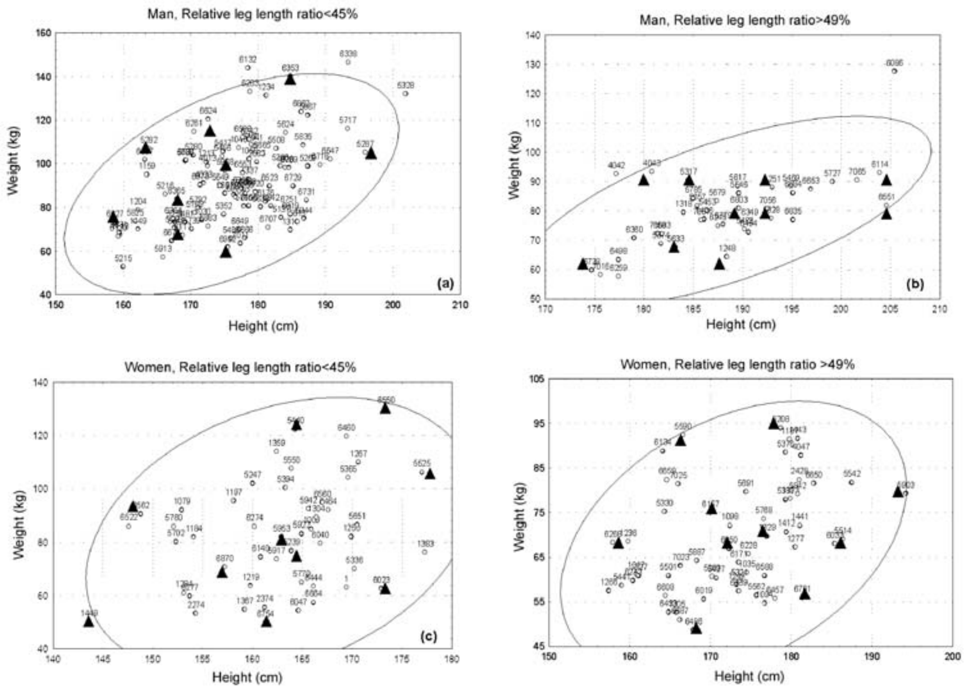


Figure 7-1 32 training samples and 8 testing samples (20 males and 20 females) in 4 groups according to the ratio of leg length and height

and height (20 males and 20 females) (Daanen, 2001). Those 40 subjects are selected from four groups. The samples are marked in black triangles in the following figures (Figure 7-1). Figure 7-1 illustrates 32 training samples and 8 testing samples (20 males and 20 females) in 4 groups according to the ratio of leg length and height: (a) 10 male samples with a ratio of leg length versus height < 45%; (b) 10 male samples with a ratio of leg length versus height > 49%; (c) 10 female samples with a ratio of leg length versus height < 45%; (d) 10 female samples

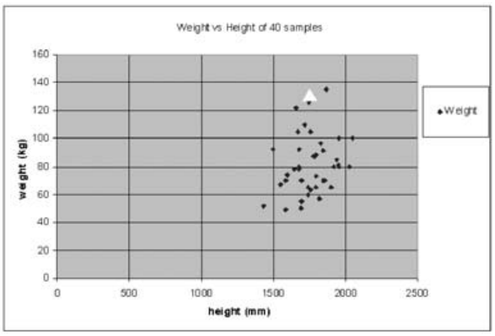


Figure 7-2 Distribution between weight and height of 40 samples used in ANN posture prediction technology where cross-section is the selected individual sample (number 6550)

with a ratio of leg length versus height > 49%. Seven of the ten are extreme boundary samples and three of ten are medium samples in all four of the groups.

The method of selecting the individual sample is randomized. Number 6550 is a woman with a weight of 126 kg, height of 1750 mm, waist of 1296.69 mm and sitting height of 897.85 mm. According to the statistical analysis (Figure 7-2 and Figure 7-3), it represents a large-sized woman. Figure 7-4 visualized the 27 anatomical landmarks from this sample: (a) standing posture with connection between selected anatomical landmarks from the whole body; (b) top view of desired sitting posture (middle) and ANN-predicted sitting posture (left); (c) perceptive view of desired sitting posture (middle) and ANN-predicted sitting posture (left); (d) back view of desired sitting posture (middle) and ANN-predicted sitting posture (right).

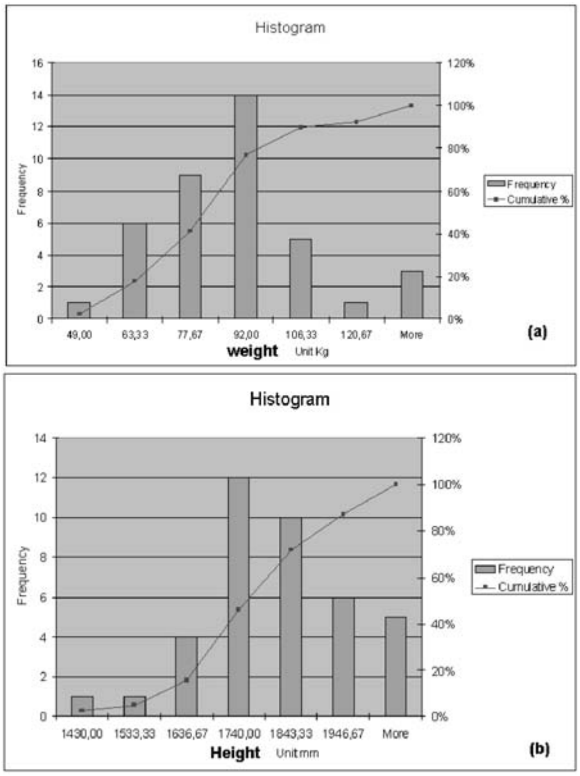


Figure 7-3 Basic statistics on sample weight and height: (a) Histogram of weight of 40 samples; (b) Histogram of height of 40 samples.

The following experiments with three case studies will validate three aspects of the predicted model: (1) sufficiency of the information provided; (2) accuracy of the model in terms of anthropometric data for design requirements; and (3) sensitivity of the model in terms of variation tolerance.

Figure 7-4 visualizes the 27 anatomical landmarks from 3D scanned human body (selected individual sample-number 6550): (a) standing posture with connection between selected anatomical landmarks from whole body; (b) top view of desired sitting posture (middle) and ANN predicted sitting posture (left); (c) perceptive view of desired sitting posture (middle) and ANN predicted sitting posture (left); (d) back view of desired sitting posture (middle) and ANN predicted sitting posture (right).

7.4 Description of the case studies

In Table 7-1, there are thirteen 1D anthropometric items which are required individually in the following three design application case studies in order to fit the

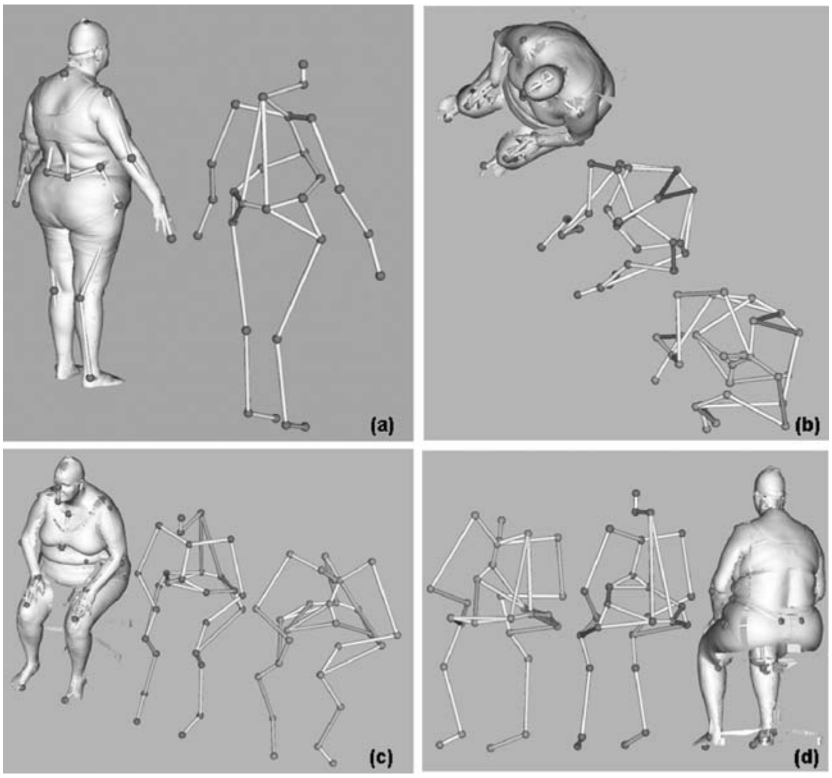


Figure 7-4 Visualization of 27 anatomical landmarks from 3D scanned human body (selected individual sample-number 6550). (Explanation is provided in the text.)

user population.

7.4.1 *Case study 1: design requirements of an office chair*

The office chair design should meet six requirements, which includes anthropometric considerations in order to fit the body shape of the target user population, and at least one functional posture (sitting posture) should be provided in the design evaluation stage (Table 7-2). The stability of the pelvis while seated is very important for working, so the position of the seat back should be provided in a related sitting posture (Bridge, 1991; Brodeur, 1995). As for the texture of the seat surface, it is one factor which influences the comfortableness and work effective that will not be discussed in this research.

7.4.2 *Case study 2: design requirements of furniture for computer workstation*

The design of computer workstations is among the most recent topics to be studied by human factors specialists, but it only touched by a few publications dealing with anthropometrics. It is possible to find many recommendations in recent human factors publications regarding standards for anthropometric data and the methods for their use in the design of computer workstations (HFES 300, 2004). The American National Standards Institute (ANSI) provided both general solutions and specific solutions for design problems.

Table7-1 Thirteen 1D anthropometrics measurements needed in design of office chair/ computer workstation/ driving space in car interior

Number	Distance Measured (Design parameters)	Landmarks Used
1	Acromion height sitting	Arcomion, functional butt block
2	Functional leg length	Functional butt block, heel point lateral
3	Eye height sitting	Sellion, functional butt block
4	Knee height sitting	Femoral epicondyle lateral, digit II
5	Knee crease height sitting	Knee crease, digit II
6	Thumbtip or fingertip reach	Acromion, dactylion
7	Hip breadth sitting	Right and left trochanters
8	Elbow rest height sitting	Functional butt block, humeral medial epicn
9	Sitting height	Functional butt block vertex (crown)
10	Buttock crease length	Functional buttblock, knee crease
11	Buttock knee length	Functional butt block, femoral epicondyle lateral
12	Foot length	Pternion, digitII
13	Elbow width	Right and left Radiale

The anthropometric Values for Furniture Design Standards are all based on percentages, either 1st or 99th percentage or 5th–95th percentage. Height is important in the design of a computer workstation, but more consideration should be given to the interactions of height with the orientations of armrests, keyboards, and seat backs. Chair height is not a simple variable; rather, it depends on the type of work, length of tasks, and presence or absence of footrests (Table 7-3). Observations of operators of computer workstations show that they adopt a remarkably wide range of postures, well outside those typically displayed in recommendations for ”correct” posture. Frequent changes of posture are highly recommended for sedentary work (Roebuck, 1995).

7.4.3 Case study 3: design requirements for designing driving space of car interior

The design of personal, commercial, and military automobiles involves many of the same anthropometric considerations that are involved in the design of passenger seating space and computer workstation space (Bush et al., 1998) (Zhang et al., 2000). However, there are differences in the type and range of the population accommodated, the fixed points selected for geometric reference, and the approaches to protection of the user from environmental conditions. Automobiles continue to evolve as the car links to the information age by becoming a mobile communication center. There are several requirements and concerns for a successful automotive interior design, such as definition and description of the user population, body posture selection, feet location, package origin point, seat reference points, the H-point (hip joint center), the machine and drafting template, eye position standards, reach and envelopes.

Table 7-2 Six 1D anthropometric measurements needed for office chair design

Number	Design parameters required for office chair design	Number of posture
1	Acromion height sitting	1 (correct sitting posture)
5	Knee crease height sitting	
7	Hip breadth sitting	
8	Elbow rest height sitting	
10	Buttock crease length	
13	Elbow width	

Table 7-3 Eight anthropometrics measurements needed for computer workstation design

Number	Design parameters required for computer workstation design	Number of posture
1	Acromion height sitting	2 (Correct work posture and reach posture)
5	Knee crease height sitting	
7	Hip breadth sitting	
8	Elbow rest height sitting	
10	Buttock crease length	
11	Buttock knee length	
12	Foot length	
13	Elbow width	

Basic features should be considered in vehicle driving space design, for example, average heel location, adjusted heel location, steering wheel height, heel adjustment spacer, accelerator heel point height, floor spacer, steering wheel angle, center of steering wheel and location, seat H-point, front seat track spacer, and rear seat track spacer (Robbins et al., 1984). For preliminary design, one 2D articulated drafting mannequin representation of the H-point machine is used to establish approximate leg clearances using 90^{th} or 95^{th}-percentile leg segments. In concept (50^{th} percentile male) and realization, both 2D and 3D H-point mannequins have limitations as representations of human beings, but it is useful for gross evaluation of the leg clearances of the operator or passenger. The dimensions of large people determine many of the overall space dimensions of automobile interiors, particularly overall height and length of the space (Table 7-4).

Table 7-4 shows thirteen measurements required for car driving space design. Those measurements are just fit the static posture which makes sure the driver has comfortable space and clearance to drive. The dynamic anthropometric requirements are overlooked in this research. However, the dimensions of small people cannot be ignored, because they are related to reach and location of the steering wheel. Allowances for entry and exit, vibration, road-induced jostling, impacts, clothing, and hair styling must be added to the static, nude dimensions for the driver and passenger. In almost all cases, these allowances require that an increase in the volume be allocated to the persons in the vehicles.

7.5 Practical assessment of posture prediction technology with experiments

7.5.1 Creating the index of model sufficiency in case studies

As discussed, there are many factors that influence the final accuracy of the ANN prediction. One of the most important impacts is the limitation of the input subjects. This research project only trained 32 subjects who were in 4 different groups with different leg and height ratios. In order to get a relatively effective result, the training (input) subject number was expanded to 256 by multiplying 32 with 8 and then randomizing. However, even then, the ANN could learn the representative samples completely. When a new test subject is not completely learned by the ANN, the output accuracy is low. This part seems not to be aligned with the focus of this research.

Table 7-4 Thirteen anthropometrics measurements needed for driving space design in car interior

Number	Design parameters required for car interior design	Number of posture
1	Acromion height sitting	1 static posture and several dynamic postures
2	Functional leg length	
3	Eye height sitting	
4	Knee height sitting	
5	Knee crease height sitting	
6	Thumbtip or fingertip reach	
7	Hip breadth sitting	
8	Elbow rest height sitting	
9	Sitting height	
10	Buttock crease length	
11	Buttock knee length	
12	Foot length	
13	Elbow width	

Figure 7-5, Figure 7-6, and Figure 7-7 illustrate respectively the case studies involving experiments in designing an office chair/computer workstation/driving space in car interior using posture prediction technology. In Figure 7-5, the number of design parameters required for an office chair is 6, which means N_{DP1}=6. In Figure 7-6, the number of design parameters required for a computer workstation is 8, which means N_{DP2}=8. In the last case, Figure 7-7, the number of design parameters in a static posture required for driving space is 13, which means N_{DP3}^{1} =13. In practice, the number of design parameters for driving space includes not only static parameters but also dynamic parameters (N_{DDP}). Those dynamic design parameters are angles of the torso moving forward and backward, and also include the feet clearances, the reach envelope

Figure7- 5 Experiment in office chair design using posture prediction technology

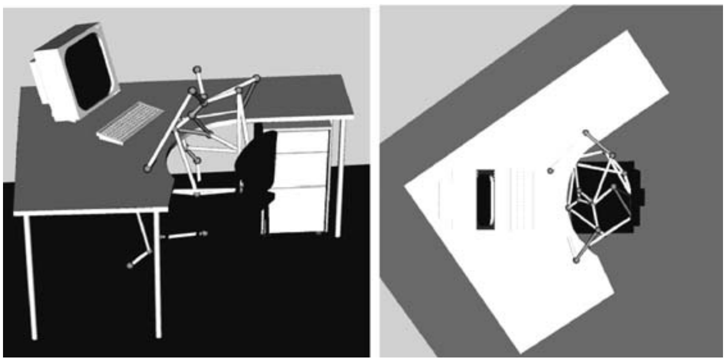


Figure 7-6 Experiment in computer workstation design using posture prediction technology

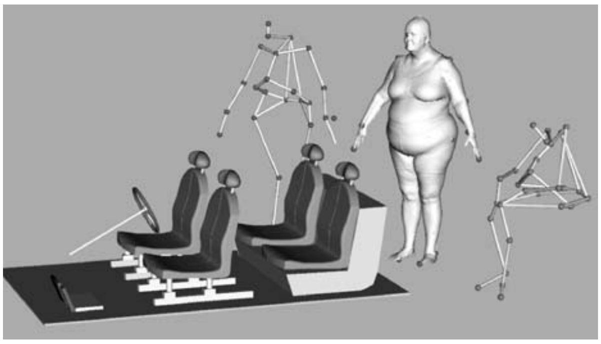


Figure 7-7 Experiments in automotive interior design using posture prediction technology

during moving the torso, and so on. In other words, the real $N_{DP3}=N_{DP3}^{1}+N_{DDP}=13+N_{DDP}$. Therefore, the sufficiency index of the model can be set as

$I_s=N_T / N_{DP}$, where N_T is the number of design parameters which the tested model can provide directly or indirectly based on estimation on known landmarks by ergonomic index, and N_{DP} is the number of the required design parameters.

7.5.2 Index of model accuracy

In these experiments, thirteen anthropometric data are measured, both on scanned subjects and on corresponding ANN-predicted subjects. Table 7-5 is the location of 10 landmarks used in the experiments, both in scanned data (desired) and in ANN-predicted data. In total, 8 subjects were measured (4 males and 4 females). Table 7-6 is the measured values from scanned subjects and ANN-predicted subjects. The following Table 7-7 shows the statistic summary (Mean/SD) of error measures describing the accuracy archived in fitting the anthropometric data for designing an office chair/computer workstation/driving space of a car interior (unit: mm). The missed measurements were estimated to provide complete data for comparison, since the current prediction is based on 27 landmarks of the whole body (where * marks the estimations). For example, the sitting height is eye height plus 4.5 *25.4 (mm),

Table 7-5 Location of ten landmarks both in scanned data and in ANN-predicted data in the experiments

Scanned											
Sellion			*Rt. Acromion*			Rt. Radiale			*Rt. Dactylion*		
X1	**Y1**	**Z1**	**X29**	**Y29**	**Z29**	**X36**	**Y36**	**Z36**	**X38**	**Y38**	**Z38**
-306,27	-182,44	1243,3	-310,67	58,09	1048,13	-434,31	87,35	740,54	-572,75	-243,91	551,96
-245,89	-172,96	1249,18	-216,48	93,42	1033,17	-261,11	120,3	718,96	-489,1	-179,46	531,13
-210,1	-128,26	1254,45	-214,08	109,8	1041,73	-299,59	113,61	719,39	-527,69	-238,6	577,57
-219,77	-113,58	1390,11	-204,2	173,77	1153,27	-259,47	184,09	749,25	-570,94	-183,43	659,46
-197,23	-152,81	1174,85	-242,36	82,34	985,48	-332,39	153,37	700,74	-492,76	-148,04	541,1
-222,52	-107,87	1263,46	-238,54	152,25	1042,32	-297,78	162,35	719,17	-560,78	-103,29	539,56
-223,04	-166,95	1370,54	-220,77	130,36	1157,44	-250,95	190,05	776,55	-553,74	-153,86	659,68
-202,22	-147,54	1251,67	-212,35	86,71	1036,3	-218,21	164,25	720,94	-481,94	-138,47	581,88
ANN predicted											
Sellion			*Rt. Acromion*			*Rt. Radiale*			*Rt. Dactylion*		
X1 Output	**Y1 Output**	**Z1 Output**	**X29 Output**	**Y29 Output**	**Z29 Output**	**X36 Output**	**Y36 Output**	**Z36 Output**	**X38 Output**	**Y38 Output**	**Z38 Output**
-305,31	-136,03	1111,68	-303,60	161,67	1027,14	-521,45	150,03	741,09	-545,78	-132,72	563,56
-221,23	-154,73	1253,40	-209,92	73,05	1070,93	-167,53	172,33	723,54	-460,99	-119,19	572,04
-227,96	-109,56	1286,94	-194,79	128,32	1102,48	-288,43	154,36	751,79	-455,44	-135,75	600,76
-256,07	-151,97	1352,62	-226,68	109,70	1064,68	-257,12	209,53	769,10	-579,67	-128,63	632,16
-288,48	-128,23	1125,74	-262,50	167,45	962,53	-235,19	220,11	668,64	-481,19	-89,72	509,41
-298,23	-163,84	1267,50	-232,98	123,09	1110,09	-280,66	161,06	768,12	-645,10	-139,21	592,37
-240,91	-141,63	1374,29	-218,96	110,65	1089,30	-247,59	207,14	778,97	-551,16	-137,93	628,09
-256,04	-146,48	1309,91	-202,01	114,16	1119,18	-239,64	181,35	783,97	-510,5	-145,92	598,58
Scanned											
Rt.Knee Crease			*Rt.Metatarsal-phal. I*			*Rt.Trochanterion*			*Lt.Trochanterion*		
X53	**Y53**	**Z53**	**X60**	**Y60**	**Z60**	**X21**	**Y21**	**Z21**	**X23**	**Y23**	**Z23**
-491	-217,03	390	-669,14	-301,53	15,79	-300,34	86,35	601,86	6,81	-329,97	590,02
-468,55	-164,63	397,2	-550,02	-261,58	10,39	-196,19	89,8	593,81	-17,82	-219,74	582,45
-456,6	-215,79	416,2	-599,59	-356,07	12,36	-221,38	130,23	591,1	29,07	-243,59	582,09
-574,42	-182,54	505,5	-691,31	-294,3	7,12	-220,09	99,43	658,93	-4,89	-227,1	639,31
-448,3	-103,37	341,5	-581,05	-273,06	3,97	-265,73	91,07	512,47	-14,66	-279,62	503,62
-507,48	-80,01	390,5	-657,93	-221	9,67	-247,39	94,82	572,3	-19,45	-231,42	554,38
-565,67	-169,86	497,6	-653,93	-311,1	8,06	-224,16	98,39	638,05	31,05	-231,53	609,05
-492,81	-177,4	444,5	-614,54	-293,82	9,81	-219,77	48,74	592,93	-44,36	-244,67	570,62
ANN predicted											
Rt.Knee Crease			*Rt.Metatarsal-phal. I*			*Rt.Trochanterion*			*Lt.Trochanterion*		
X53 Output	**Y53 Output**	**Z53 Output**	**X60 Output**	**Y60 Output**	**Z60 Output**	**X21 Output**	**Y21 Output**	**Z21 Output**	**X23 Output**	**Y23 Output**	**Z23 Output**
-620,66	-48,50	435,59	-627,43	-247,32	21,26	-355,64	150,59	595,39	-28,52	-355,74	634,94
-434,55	-200,01	445,89	-571,61	-275,37	4,21	-183,58	79,18	582,23	-2,54	-198,64	597,55

-461,07	-107,00	435,90	-649,45	-288,33	14,73	-233,84	91,95	629,67	3,97	-215,31	624,41
-543,96	-184,40	475,00	-646,42	-243,53	10,25	-227,82	84,39	618,50	-25,29	-248,41	624,25
-475,20	5,75	307,68	-530,02	-164,88	9,78	-233,38	113,79	511,76	-0,98	-234,36	511,97
-602,93	-241,61	457,90	-557,02	-261,80	9,88	-222,65	81,79	560,93	-13,91	-204,23	577,78
-516,01	-189,10	476,43	-656,93	-243,83	8,26	-215,80	93,27	632,54	-21,25	-244,47	637,19
-479,30	-270,44	473,87	-591,32	-285,29	3,53	-195,14	94,00	605,60	-2,15	-205,82	616,99
Scanned											
Rt. PSIS			*Lt.Radiale*								
X26	**Y26**	**Z26**	**X48**	**Y48**	**Z48**						
-34,25	56,06	618,94	-46,68	-410,03	765,81						
-25,27	36,03	604,82	7,72	-271,32	710,16						
-13,64	58,36	639,21	-23,65	-321,49	717,09						
-40,33	51,17	689,99	57,66	-271,3	779,77						
-9,08	51,22	597,92	-4,49	-383,85	695,9						
-22,28	34,42	602,02	-17,76	-327,63	725,48						
-31,87	36,34	683,91	116,08	-309,19	785,4						
-26,6	32,7	627,78	66,47	-286,76	712,79						
ANN predicted											
Rt. PSIS			*Lt.Radiale*								
X26 Output	**Y26 Output**	**Z26 Output**	**X48 Output**	**Y48 Output**	**Z48 Output**						
-40,730	63,059	653,714	-15,284	-460,572	776,862						
-23,569	36,065	617,983	5,224	-263,633	708,249						
-12,542	40,630	688,540	16,582	-270,998	749,566						
-19,408	39,678	689,340	-11,589	-313,632	787,880						
8,183	32,604	544,690	-119,205	-300,354	721,501						
-27,636	41,229	701,264	-51,297	-362,863	772,721						
-18,236	38,833	701,081	10,590	-290,718	800,447						
-25,100	41,273	708,217	-8,880	-283,325	784,399						

where 4.5 is the index in inches (Roebuck, 1975). Additionally, because of the lack of a complete Dutch anthropometric database, some measurements used a German database which would result in a bias (where ** marks the German database). Table 7-5 shows the location of ten landmarks used in those experiments, both in scanned (desired) data and in ANN-predicted data.

In the assessment of model accuracy, M_{d_i} was set up as the measured value based on scanned landmarks (desired) from 8 subjects who were test samples in the experiments, and M_{t_i} as the measured value based on predicted landmarks from ANN. Then, the error between desired values and the predicted values is $\varepsilon_{error} = \frac{\sum_{i=1}^{n}(M_{d_i} - M_{t_i})}{N}$, where N is the number of subjects, which is 4 for male and 4 for female respectively.

Table 7-6 Measured values from scanned subjects and ANN-predicted subjects (Unit: mm)

Measured values from scanned subjects (desired)												
	Male (n=4)				Mean	SD	Female (n=4)				Mean	SD
Subject	6738	5649	6114	6551			6550	6023	5208	5440		
acromion height sitting	557,636	620,84	645,375	643,726	616,894	41,061	597,07	537,306	593,045	601,37	582,197	30,12
functional leg length	991,382	904,72	1070,5	1057,205	1005,95	75,836	947,516	971,532	1018,024	991,343	982,103	29,909
eye height sitting	807,17	833,35	872,94	884,61	849,517	35,752	853,3	851,98	838,25	833,35	844,22	9,94
knee height sitting	556,222	563,276	652,151	646,731	604,595	51,910	566,496	517,746	507,797	523,656	528,923	25,888
knee crease height sitting	439,064	380,83	487,93	434,69	435,628	43,783	374,21	386,81	403,84	341,5	376,59	26,356
sitting reach (re-check)	749,601	743,411	859,597	897,961	812,642	77,998	738,336	739,351	776,449	683,862	734,499	38,132
hp readth sitting	338,5	396,533	403,553	390,005	382,147	29,619	462,713	381,879	451,043	471,263	441,724	40,748
elbow hight	226,44	278,46	228,95	193,75	231,9	34,936	300,54	261,76	253,19	309,24	281,182	27,825
sitting height	921,17	947,35	986,94	998,61	963,517	35,752	967,3	965,98	957,25	947,35	959,47	9,228
feet length	252,316	261,026	296,582	278,672	272,149	19,634	247,752	221,871	240,091	231,865	235,394	11,107
crease buttock lenghth	502,318	473,89	532,57	572,515	520,323	42,246	523,306	474,071	537,871	483,948	504,799	30,633
knee uttock length	629,837	623,552	669,215	697,796	655,1	34,907	661,778	603,188	671,55	622,074	639,647	32,381
elbow width	445,197	513,567	561,695	524,184	511,16	48,580	534,243	418,425	516,278	590,327	514,818	71,583
Measured values from ANN output and estimated based on scanned landmarks												
Subject	6738	5649	6114	6551	mean	SD	6550	6023	5208	5440	mean	SD
acromion height sitting	646	653	613,3	589,7	625,5	29,478	591,54	624,1	628,6	654,8	624,76	25,956
functional leg length*(+50)	1069,806	932,08	1063,52	1091,164	1039,14	72,349	1054,91	1007,15	948	832,045	960,526	96,170
eye height sitting	836	810	898	877,622	855,40	39,774	676,7	807	850,1	818	787,95	76,387
knee height sitting	594,5	519	618,1	621,94	588,38	47,821	547,3	567,9	584,37	499,6	549,792	36,737
knee crease height sitting	469,5	384	466,1	464,74	446,08	41,438	414,3	441,7	428,62	297,92	395,635	66,097
sitting reach *establised	807,164	851,62	809,923	800,464	817,292	23,226	694,349	802,74	703,989	725,42	731,624	49,156
hp readth sitting	355,879	353,42	389,793	389,576	372,167	20,253	602,87	331,63	388,549	418,643	435,423	117,31
elbow hight* (to crease-50)	260	261	252,97	244,1	254,517	7,810	255,4	227,2	259,04	261	250,66	15,811
sitting height	950	924	1012	991,622	969,405	39,774	790,7	921	964,1	932	901,95	76,387
feet length*(+50)	212,2	148,5	233,493	224,26	204,613	38,411	238,32	210,84	253,6	83,743	196,625	77,306
crease buttock lenghth	550,306	498,08	547,42	570,424	541,557	30,738	590,61	515,45	469,38	484,125	514,891	54,01
knee uttock length* (+100)	650,306	598,08	647,42	670,424	641,557	30,738	690,61	615,45	569,38	584,125	614,891	54,01
elbow width	517,965	570,937	560,88	577,88	556,915	26,888	793,108	468,833	522,303	532,78	579,256	145,29

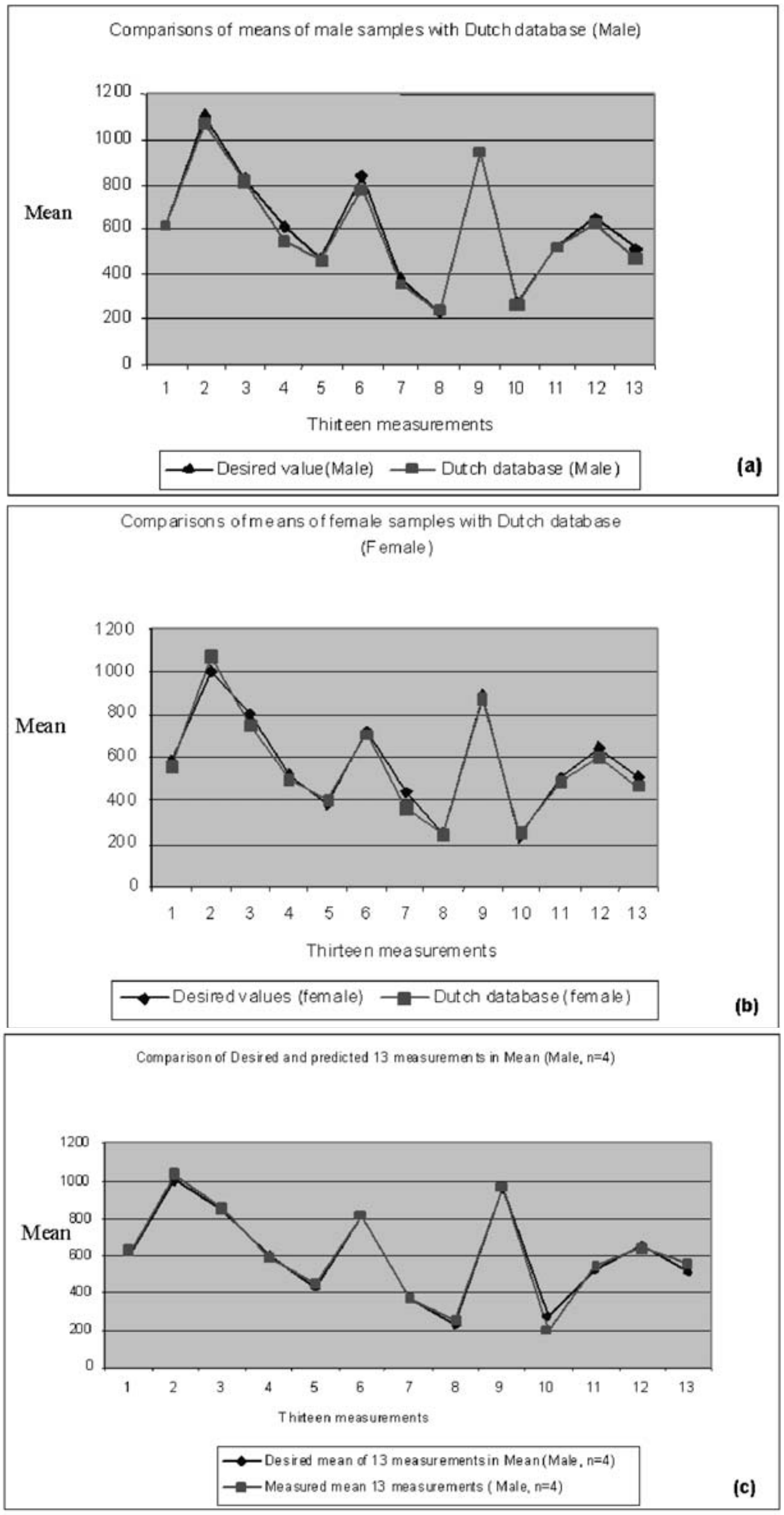
7.5.3 Index of model sensitivity

This assessment process provides a measure of the relative importance among the inputs of the neural model and illustrates how the model output varies in response to variation of an input. The first input is varied between its mean +/- a user-defined number of standard deviations, while all other inputs are fixed at their respective means. The network output is computed for a user-defined number of steps above and below the mean. This process is repeated for each input. A report is generated which summarizes the variation of each output with respect to the variation in each input. The generated report should contain the following information: a) a 3D column plot of the table in b; b) a table reporting the standard deviation of each output divided by the standard deviation of the input which was varied to create the output; c) a plot created for each input showing the network output(s) over the range of the varied input.

In the research into the robustness, I defined standard deviations of input variation as +/-1 and the number of steps above and below the mean as 100. Sensitivity analysis is a method for extracting the cause and effect relationship between the inputs and outputs of the network. The network learning is disabled during this operation in such a way that the network weights are not affected. The basic idea is that the input to the network is shifted slightly and the corresponding change in the output is reported either as a percentage or a raw difference.

Table 7-7 Statistic summary (Mean/SD) of error measures describing the accuracy achieved in fitting the anthropometric data for designing an office chair/computer workstation /driving space of car interior (Unit: mm)

	Anthropometric items required for office chair design/ computer workstation design/ driving space design in car interior	Value in Dutch anthropometry database (Male)		Value in Dutch anthropometry database (Female)		Scanned value (n=4) (Male) M_{d_i}		Scanned value (n=4) (Female) M_{d_i}		Predicted value (n=4) (Male) M_{t_i}		Predicted value (n=4) (Female) M_{t_i}	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	Acromion height sitting**	615.2	29.2	561.9	27.6	616.9	41.1	582.2	30.1	625.5	29.47	624.76	25.95
2	Functional leg length *	1071	49	1065	52	1005.95	75.84	982.1	29.9	1039.14	72.35	960.53	96.18
3	Eye height sitting	818	32	750	32	849.52	35.75	844.2	9.94	855.4	39.8	787.95	76.39
4	Knee height sitting**	550.4	25.3	498	28	604.6	51.9	528.9	25.9	588.4	47.82	549.8	36.7
5	Knee crease height sitting	457	25	403	25	435.63	43.78	376.6	26.36	446.085	41.44	395.94	66.1
6	Reach sitting *,**	775.5	38.4	707.5	27.9	812.64	78	734.5	38.13	817.3	23.22	731.6	49.15
7	Hip breadth sitting	356	18	365	28	382.15	29.62	441.7	40.7	372.2	20.25	435.4	117.3
8	Elbow rest height sitting **	238	26	238	26	231.9	34.94	281.18	27.825	254.5	7.8	250.7	15.81
9	Sitting height*	939	34	874	33	936.52	35.75	959.5	9.23	969.5	39.7	901.9	76.38
10	Buttock crease length	518	30	494	32	520.3	42.2	504.8	30.6	541.6	30.74	514.9	54.01
11	Buttock knee length*	620	28	599	31	655.1	34.9	639.7	32.4	641.6	30.8	614.9	54.01
12	Foot length*,**	264.2	12.2	247	11.5	272.2	19.6	235.4	11.2	204.6	38.41	196.6	77.31
13	Elbow width*	467	34	465	53	511.2	48.6	514.8	71.6	556.9	26.9	579.3	145.3


Comparisons of means of male samples with Dutch database (Male)
1200
1000
800
600
400
200
0
Mean
1 2 3 4 5 6 7 8 9 10 11 12 13
Thirteen measurements
Desired value(Male)
Dutch database (Male)
(a)
Comparisons of means of female samples with Dutch database (Female)
1200
1000
800
600
400
200
0
Mean
1 2 3 4 5 6 7 8 9 10 11 12 13
Thirteen measurements
Desired values (female)
Dutch database (female)
(b)
Comparison of Desired and predicted 13 measurements in Mean (Male, n=4)
1200
1000
800
600
400
200
0
Mean
1 2 3 4 5 6 7 8 9 10 11 12 13
Thirteen measurements
Desired mean of 13 measurements in Mean (Male, n=4)
Measured mean 13 measurements (Male, n=4)
(c)

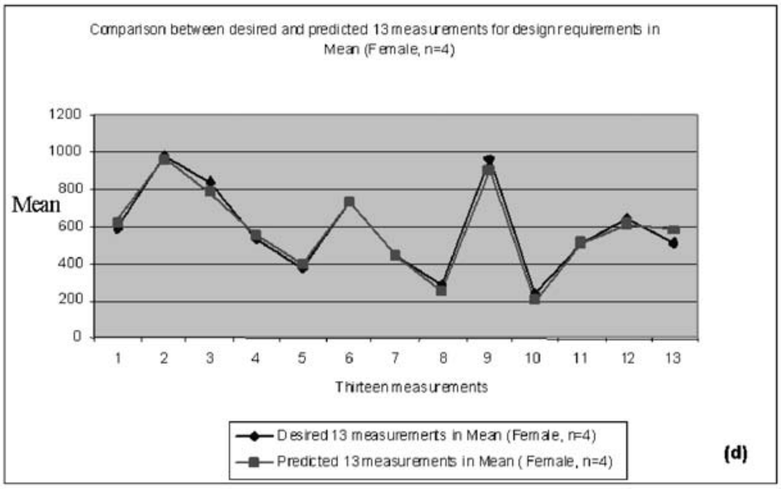


Figure 7-8 Results of PPT assessments in terms of accuracy in application cases study:(a) Means of required measurements for 3 case studies with a Dutch anthropometric database (male, n=4); (b) Means of required measurements for 3 case studies with a Dutch anthropometric database (female, n=4); (c) comparison of desired and ANN-predicted measurements in mean (male, n=4); (d) comparison of desired and ANN-predicted measurements in mean (female, n=4)

7.6 Results and discussion of validation with the case studies

7.6.1 *Validation of sufficiency*

Since $I_s=N_T/N_{DP,}$ in the case of office chair design, $I_{s1}=N_T/N_{DP1}=13/6=2.167>1$. Figure 7-5 illustrated that the predicted posture of one individual model aided the office chair design with one posture. All anthropometric information for office chair design can be acquired from the predicted model. The same predicted model was used in the computer workstation design aid.In this case, even though the reach posture is not predicted it can be estimated based on some related predicted landmarks coordinates (Figure 7-6). Therefore, $I_{s2}=N_T/N_{DP2}=13/8=1.625>1$. Figure 7-7 shows that for designing car driving space in a car interior, the current predicted model has insufficient postures for aiding design in both static and dynamic postures since more postures should be predicted. The design needs more posture information in this case. In other words, for car driving space design, the current model is limited. Consequently, $I_{s3}=N_T/N_{DP3}=13/(13+N_{DDP})<1$. As a result, the current posture prediction technology is sufficient in static design aid cases with all known predicted landmarks, but is not sufficient in design that needs dynamic design parameters.

7.6.2 *Validation of accuracy*

The validation of accuracy is based on the comparison between desired values and predicted values of thirteen anthropometric data parameters. Figure 7-8 illustrates the results of PPT assessments in terms of accuracy in the case studies: (a)

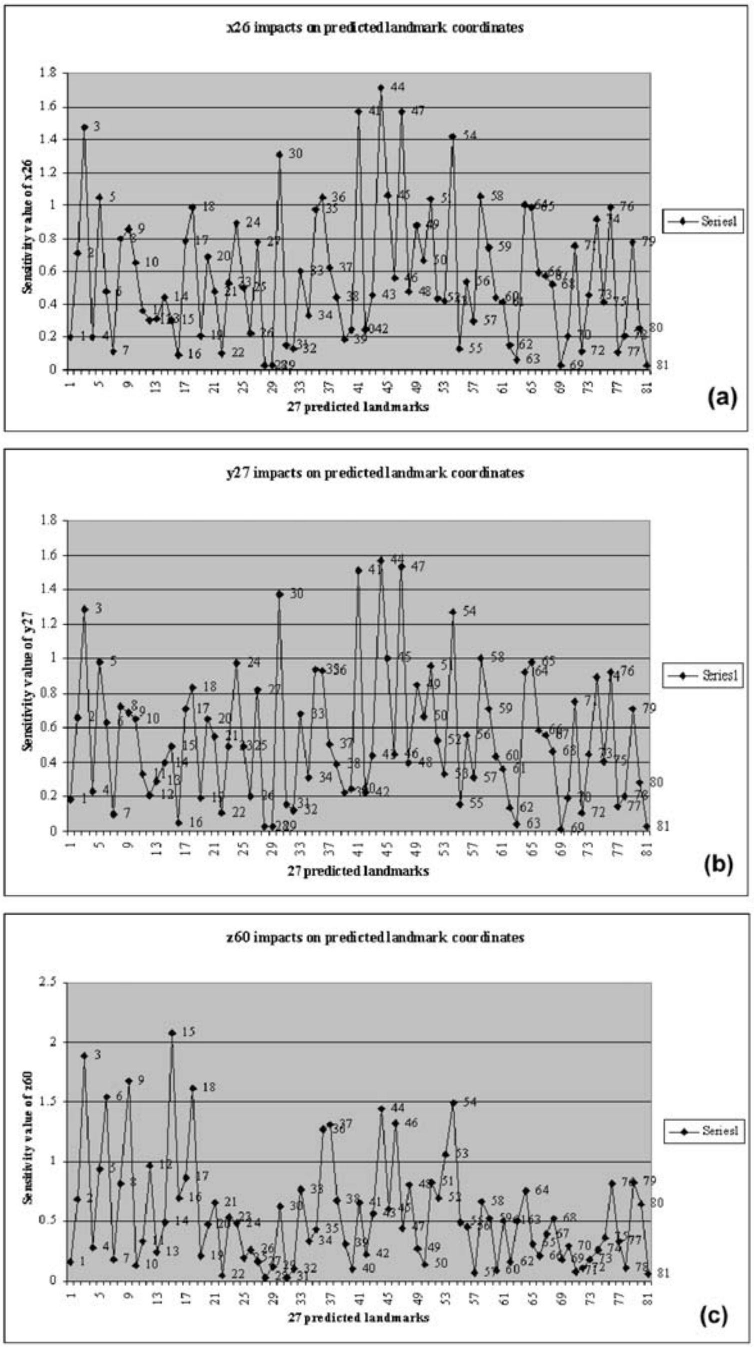


Figure 7-9 Plots of three main impact input factors on posture prediction model: (a) x26 impacts on 27 predicted landmarks in a sitting posture; (b) z60 impacts on 27 predicted landmarks in sitting posture; (c) y27 impacts on 27 predicted landmarks in a sitting posture

Table 7-8 Results of validating accuracy of posture prediction technology

(a)

	Anthropometric items required for office chair design/ computer workstation design/ driving space design in car interior	Mean errors between desired value and predicted vale (mm)	
		Male (n=4) ε_{error}	Female (n=4) ε_{error}
1	Acromion height sitting	-8.61	-42.6
2	Functional leg length	-33.2	21.6
3	Eye height sitting	-5.89	56.27
4	Knee height sitting	16.21	-20.87
5	Knee crease height sitting	-10.46	-19.05
6	Reach sitting	-4.65	2.86
7	Hip breadth sitting	9.98	6.3
8	Elbow rest height sitting	-22.62	30.52
9	Sitting height	-5.9	57.52
10	Buttock crease length	-21.23	-10.09
11	Buttock knee length	13.54	24.76
12	Foot length	67.54	38.77
13	Elbow width	-45.76	-64.44

(b)

		Mean	SD
R_m	Male(n=4)	0,995	0,389
R_{fm}	Female (n=4)	0,988	0,467

comparisons of means of thirteen required measurements (desired) for 3 case studies with a Dutch anthropometric database (male, n=4); (b) comparisons of the means of 13 required measurements (desired) for 3 case studies with a Dutch anthropometric database (female, n=4); (c) comparison of 13 desired and ANN-predicted measurements in mean (male, n=4); (d) comparison of 13 desired and ANN-predicted measurements in mean (female, n=4). Table 7-8 is the results of validating the accuracy of posture prediction technology. Table 7-8a depicts the mean errors between desired values and predicted values of 13 anthropometric data required to design an office chair/computer workstation/driving space in a car interior (Unit: mm). In Table 7-8a, the foot length has bigger errors compared with other measurements. The reason is probably that two landmarks were used (right first metatarsalphalangeal protrusion and right later malleolus) which could not decide the foot length correctly. Additionally, the foot length was simply estimated by plus 50 mm to the distance between these two landmarks, which probably leads to this error.

Table 7-8b shows the correlation coefficience (R) between desired measurements and ANN-predicted measurements in mean and standard deviation of male and female. The R_m between the desired measurements and ANN-predicted measurements is 0.995, and R_{fm} between the desired measurements and ANN-predicted measurements is 0.988. The accuracy of PPT is considerably higher.

7.6.3 Sensitivity of posture prediction model

The results of sensitivity research show that x26, z60, and y27, with the sum sensitivity value of 45.922, 45.24, and 43.987 respectively, are three important input variables (Table 7-9). In this sensitivity research, there are a total of 85 input variables

Table 7-9 The sum of sensitivity of all input variables to the posture prediction model

Sensitivity	sum	Sensitivity	sum	Sensitivity	sum	Sensitivity	sum
		z29	1.745	x31	4.414	y23	13.005
Waist	5.187	x41	16.117	y31	1.608	z23	1.892
Height	1.847	y41	11.302	z31	0.950	x53	8.657
Weight	20.610	z41	1.943	x36	2.669	y53	10.752
sitting height	2.692	x20	7.617	y36	8.095	z53	5.715
x1	4.574	y20	13.618	z36	1.343	x57	5.813
y1	2.464	z20	1.156	x38	5.118	y57	9.310
z1	1.711	x22	11.677	y38	1.551	z57	21.017
x4	11.763	y22	5.567	z38	3.064	x60	8.621
y4	16.214	z22	1.729	x43	2.479	y60	8.584
z4	0.697	x26	45.923	y43	0.745	z60	45.240
x11	10.947	y26	28.674	z43	1.511	x63	8.773
y11	18.137	z26	1.139	x48	2.587	y63	9.016
z11	2.134	x27	21.673	y48	2.511	z63	8.062
x15	2.834	y27	43.987	z48	0.993	x67	5.446
y15	22.040	z27	2.473	x50	1.275	y67	17.407
z15	1.462	x16	4.140	y50	1.398	z67	12.488
x24	8.639	y16	7.078	z50	4.014	x70	14.952
y24	7.419	z16	0.457	x21	4.640	y70	12.745
z24	1.339	x18	2.708	y21	34.642	z70	21.956
x29	9.407	y18	8.325	z21	2.425		
y29	12.811	z18	2.271	x23	5.735		

(waist, height, sitting height, weight, 27 landmark coordinates (x, y, z) in a standing posture) to the network.

Figure 7-9 illustrates the three main impact input factors on the posture prediction model: (a) x26 has an impact on 27 predicted landmarks in a sitting posture; (b) z60 has an impact on 27 predicted landmarks in a sitting posture; (c) y27 has an impact on 27 predicted landmarks in a sitting posture. The labeled numbers are the number of landmark coordinates; for example, number 1, 2 and 3 represent X1, Y1 and Z1. Because a total of 27 landmarks are predicted, the numbers labeled run from 1 to 81 (3 times 27 is 81).

Table 7-9 displays a column of values, each corresponding to the percentage effect that a particular input variable has on the output vector as a whole (the sum of all output channels). As mentioned above, the three input variables x26, y27, and z60 have the most significant impact on the networks. In fact, x26 is the x coordinate of landmark (# 26) Rt. PSIS, y27 is the y coordinates of landmark (#27) Lt. PSIS, and z60 is the z coordinate of landmark (#60) Rt.Metatarsal-phal. Rt.PSIS and Lt.PSIS are close to the calibration landmark in this posture prediction research, which is the #28 landmark of waist in preferred posture. Landmark Metatarsal-phl is on the feet of subjects who decide what the sitting and standing plane of all the trained and tested subjects are. Consequently, since these four input variables have a significant impact on the network, the current network could be simplified by training based only on these four input variables in order to shorten the computer time and cost. This hypothesis needs to be studied in further research.

In this research, because ANNs are being employed instead of traditional statistics, the problem of percentiles is avoided, since the use of percentiles of anthropometrics in current computer workstation design has produced incorrect design results if multi-variables need to be considered in the design. The predicted model is an individual model based on input variables, which are demographic information and the 3D coordinates of 27 landmarks in a standing posture.

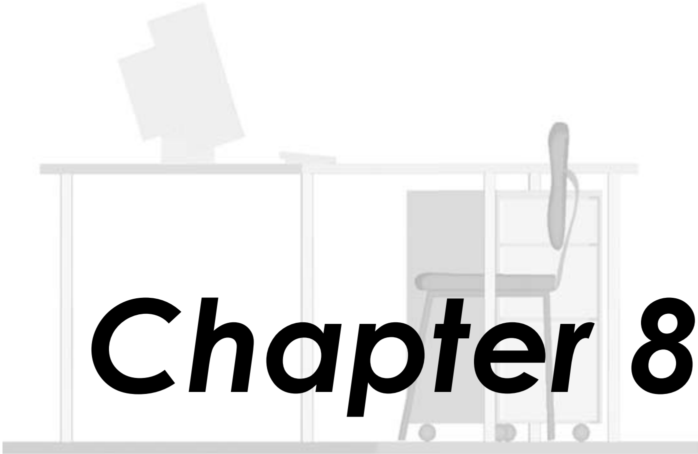
One important factor which should be mentioned in this validation research is that all scanned subjects are almost completely unclothed, wearing only tight underwear for the men and underwear and an extra bra for the women during the scanning procedure. The posture prediction results therefore overlooked the influence of personal garments in the real working situation. Additionally, the surface of legs and seat cushions, for instance, have been modeled as solid objects in all case studies, while in reality both display compressibility.

7.7 Conclusions

This chapter assessed the developed posture prediction technology based on three design application case studies. In order to quantify the performance characteristics of this technology, three criteria have been developed, which are sufficiency, accuracy and sensitivity. Thirteen design parameters were considered in three application case studies. Using these criteria and the related measures, it would be possible to express sufficiency, accuracy and sensitivity as values of numeric indices. Based on the computed indices, the conclusions are that the PPT provides sufficient information for the design parameters in static cases, which means that it predicted the target postures with a high degree of accuracy. Additionally, it was determined that gender is the most influential input variable from the point of view of sensitivity of the network.

This posture prediction technology takes advantage of the availability of 3D human anthropometric data sets. However, some technical issues were also important for the correct application of the ANN-based PPT. For instance, in the current work 27 landmarks were employed to represent the anatomic landmarks of the whole body; however, they are not sufficient for the reconstruction of a vivid human geometric model in 3D space. This was considered as a limitation, although the posture prediction technology can be used to support ergonomic design. Whether using more training subjects warrants better prediction accuracy or not remains an unknown issue, which needs further research. Nevertheless, it is possible to argue that using the scanned 3D landmarks makes it possible to achieve a reasonably high-quality prediction of the human postures for design purposes.

This posture prediction technology is extendable. It means that when more input postures are scanned and used in training, more output postures can be predicted. The goal of the follow-up research in ANN and landmark-based posture prediction technology is to explore new applications in the field of 3D anthropometry and CAED, as well as in clothing design and anthropometric visualization.



Chapter 8

Conclusions and further research

8.1 Findings

A comprehensive review of the literature with regards to 3D anthropometry, anthropometric digital human modeling, and artificial neural networks has been carried out to investigate the opportunity of working out an effective computational posture prediction technology as part of a digital human modeling system. In the doctoral research, I concentrated on the combination of landmark-based representation of the human body with neural network-based coordinate transformation. A pilot system has been developed which made it possible for me to further investigate the process of the neural network-based posture transformation and in particular the performance of the applied neural network. Most of my findings have been discussed at the end of the respective chapters. In this final chapter, I bring all the findings together and draw some final conclusions related to the main research questions studied in this dissertation.

On 3D anthropometry

Anthropometry plays a predominant role in CAED, since the dimensions and the shape of DHM are defined by measured anthropometric data. On the one hand, 3D anthropometry methods have a lot of advantages compared to traditional anthropometry. On the other hand, they also have limitations and disadvantages. One of the recognized problems with 3D anthropometry is that the modern scanning technologies provide such a large amount of data that it is difficult to process it efficiently in real time by computer. For this reason, various simplification techniques are needed which preserve only the so-called feature data about the geometry of the human body and, at the same time, filter out the less significant data in order to simplify the computation. It proved to be meaningful and beneficial to apply landmark-oriented data processing in this research. In the proposed approach, landmarks are extracted from the scanned body surface and used as a basis of posture transformation. The accessibility of landmarks by the measuring equipment was studied and a corrective technique was developed. The conclusion is that anthropometric landmarks lend themselves to an effective posture prediction and, at the same time, facilitate the reconstruction of a geometric model of the human body. After completing the transformation of the landmarks between the source posture and the target posture, the changed body shapes can be reconstructed based on the landmarks using geometric techniques.

On computational posture prediction in digital human modeling

Current approaches of computer-aided ergonomics tools to facilitate digital human modeling start out from body measurements and make use of the anthropometric correlations of the data. These approaches typically rely on traditional anthropometric databases, which were developed based on data about anatomical landmarks. The known traditional posture prediction techniques estimate the center of joints from the anatomical landmarks measured on the surface of the human body. The accompanying data processing is time-consuming, error-prone, and difficult to automate, since human interpretation and decision are both needed. The proposed posture prediction technology, which is based on the processing of scanned landmarks by a dedicated ANN, can achieve a much higher level of automation, while still offering significant flexibility in application. In fact, it transforms the landmarks from one posture to a different posture directly, based on the transfer rule that was taught to the neural network. Even the process of teaching the ANN by constructed samples can be computerized. For these characteristics of the proposed posture prediction technology, my conclusion has been that it can enhance DHM in CAED systems and provide many advantages in industrial design applications.

It is known from practical experience that conventional posture prediction is very time-consuming and error-prone, due to the manual measurement of 1D/2D anthropometric data and the manual identification of anatomical landmarks. However, by using a set of landmarks belonging to a validated set of scanned 3D body data, the posture prediction problem can be simplified. Because different genders, different races, different ages, and different occupations have an impact on the body shape and the postures, including demographic data makes it possible to make the relationship between postures explicit. It is thus possible to create a correlation between the descriptive anthropometric data and the posture data, as relationships between the input and output of the ANN. The properly conditioned ANN can learn the rules of the posture transformation. A combination of geometric data and selective demographic data has provided a sufficient basis for teaching the appropriately chosen artificial neural network system for posture prediction.

On the application of artificial neural networks in posture prediction

The primary hypothesis of my doctoral research was that artificial neural networks offer new opportunities to solve the computational posture transformation problem and can be incorporated in a methodology and a system that can conveniently be used by industrial designers. Based on the results of other researchers, it could be forecast that ANNs could perform better than, or at least as well as, the conventional methods in terms of modeling multi-dimensional non-linear relationships. By and large, ANNs are based on data alone, and can be taught transfer rules by showing the input-output data pairs to the network in a structured way. The network itself determines the transfer rule and the parameters of the learned model by means of its learning capability. Moreover, ANNs can always be updated to obtain better results by presenting them with new training examples whenever new data become available.

It is well known from past experience that ANNs behave differently with different sets of input data. For each neural network architecture and learning method, there are optimal data sets which will provide optimal results in application. According to the experiences with various ANNs, they function correctly only if the input data is sufficient and if the learning mechanism is efficient enough. Radial basis function-based ANN (RB-ANN) and back-propagation-based ANN (BP-ANN) have been two competing candidates based on the preliminary literature study. From the development and application reports, I concluded that BP-ANN is more suitable for small samples, because it learns from all of the input data. RB-ANN learns better in the case of large samples, since it is a kind of reductive mechanism. It is clear that the ease and simplicity of input data preparation is a cardinal issue in using an ANN-based system for posture prediction in product design. Back-propagation ANN (BP-ANN) has been proven to work better for small training samples and provide efficiency in posture prediction. If the input data are close to each other and homologous, learning is faster and more accurate than with strongly dissimilar discrete input data. I therefore investigated the option of clustering the landmarks. I concluded that the input data need to be purposefully clustered to achieve optimum performance. A method oriented to a limited set (a cluster) of landmarks achieved better efficiency in posture prediction than a method oriented to the simultaneous processing of all the landmarks of the whole human body.

All applications are case-dependent. In other words, the relationship between the input and output data is different in each application case, as well as the data themselves. My research reconfirmed that back-propagation multi-layer perceptron artificial neural networks (BP-MLP-ANN) can process multi-dimensional variables (such as 3D coordinates of landmarks, demographic characteristics, and posture data) in an integral way. There is an optimum number of layers, and an optimum number of neurons on the layers, for an optimum BP-MLP-ANN architecture. In spite of the fact that there is in principle a general rule for finding an optimum architecture of a BP-MLP-ANN, in practice it has to be found by trial and error and experimentation in each case. Experimentation means changing the learning parameters, for example the number of neurons on the layers, and also the number of hidden layers. Experiences with such types of neural networks can support the process. Due to the phenomenon of over-training, a larger number of training epochs and a larger number of neurons will result in an over-fitted generalization in terms of the learned prediction rule. This will spoil the performance of the neural network.

ANNs actually implement an approximation method. It means that they have no determined learning results, and the performance depends heavily on several interacting factors. In other words, the operation, efficiency and reliability of ANNs are influenced not only by the input and output data sets, but also by the learning rules and learning epochs. Due to the non-explicit nature of the interactions and influences, the performance characteristics have to be verified by making computer experiments. Based on the doctoral research, my conclusion was that the cluster-oriented transformation method is computationally more efficient in regenerating human body postures, and the clustering of landmarks lends itself to a reliable method. Additionally, another conclusion was that using a genetic algorithm can help the BP-MPL-ANN to search for an optimal design automatically, but it needs a lot of time and computer capacity in posture prediction compared to the general algorithm. The operation, efficiency, and reliability of the ANNs were verified by various training experiments.

For designers, the most important issue related to a design support tool is how helpful (useful, dexterous, and obvious) it is. However, the support offered may vary from application to application. The designers want to know in advance what they can expect from a given tool in various design processes and applications. However, it is not easy to predict the performance of ANN-based posture transformation in diverse applications. However, general utility indicators can be constructed that inform and guide the designers how a particular set-up performed in various past applications. A characterization of the applications with indices was therefore introduced. Three indices were defined to validate the utility, which can be calculated or estimated. The utility of the ANNs and landmark-based posture prediction technology in application cases was expressed in terms of sufficiency, efficiency, and sensitivity.

The proposed posture prediction technology is able to: (1) represent the target population or individual user of a product or workspace; (2) describe the geometry (shape) of the human body in 3D space in different postures based on manipulation anatomical landmarks; (3) allow designers to acquire and predict unknown postures by presenting demographic information and known coordinates of landmarks to the trained ANNs; (4) make it possible to compute unknown postures based on scanned landmarks; (5) shorten the time needed for predicting postures; and (6) save computing capacity by reducing the amount of data to be processed.

8.2 Some limitations and opportunities for further research

On the one hand, ANN and landmark-based posture prediction offers many advantages. On the other hand, it has some limitations, since the landmark data alone do not provide sufficient information about the transformed geometric shape of the human body. For example, the curvature of the surfaces between landmarks could be important in certain applications. However, a method that capitalizes on the simplification offered by landmarks from the point of view of computation cannot incorporate all geometric information simultaneously. Nevertheless, with repeated application of the taught neural network, the coordinates on non-landmark points can also be transformed. However, the repeated application is time-consuming and requires the designers to have a reasonable level of familiarity with the ANN-based posture transformation technology. Otherwise, specific geometric techniques can be used. Further research and development seems to be necessary in this field.

Despite its good performance in regular applications, ANNs suffer from a number of shortcomings, notably from a lack of theory to help their development. It is also a fact that success in finding a good solution is not always guaranteed. Unfortunately, ANNS have only a limited capability for explaining the way they use the available information to arrive at a solution. Consequently, there is a need to develop guidelines which can help in the process of designing ANNs. In addition, there is also a need for more research on how to provide more information about how ANNs can arrive at a reliable and robust prediction.

The proposed posture prediction technology takes advantage of the availability of 3D human anthropometry data sets. However, there are some technical issues that are important for the correct application of the ANN-based posture prediction technology. For instance, in the current work 27 landmarks were employed to represent the geometry of the whole body. Obviously, that is not enough for reconstruction of a high-fidelity geometric model of the human body in 3D space. It was sufficient to test the ideas developed in the doctoral research and to investigate the performance, but the comprehensiveness can be further enhanced. The current situation can be considered as a limitation, though it is a significant advancement in computational posture prediction and in the computer support of ergonomics design. Whether or not using more training subjects warrants better prediction accuracy remains an unknown factor, which needs further research. Nevertheless, it is possible to argue that by using scanned 3D landmarks, from the aspect of using the results in product design, we could achieve a reasonably high quality in prediction of the human postures.

The proposed posture prediction technology is extendable. It means that when more input postures are scanned and used in training, more output postures can be predicted. The goal of the follow-up research in landmark and ANN-based posture prediction technology is to explore new applications in the field of 3D anthropometry and CAED, as well as in clothes design and anthropometric visualization. Consequently, the further research should be focused on: (i) training ANNs with comprehensive and representative subjects in terms of demographic variables and anthropometric variables for increasing generalization in the final posture prediction; (ii) transforming enough non-landmarks points using cluster-oriented methods in order to reconstruct more vivid digital human models; (iii) training ANNs with various functional human-body postures based on 3D landmarks, which originate not only from a 3D scanning technique, but from other 3D measuring techniques, such as photogrammetry and contact measuring.

Summary

My research is a combination of physical ergonomics and computer science. The trend in anthropometry has been shifted from traditional manual anthropometry to modern 3D anthropometry and involves using laser or stereo-photogrammetry. The increased power of computer workstations has permitted more sophisticated statistical analysis than those of the past and made it possible to complete such analyses in a timely manner. Computer aided ergonomic design (CAED) is a currently forming multi-disciplinary subfield of science that combines the knowledge and resources of (i) physical and information ergonomics, (ii) customer oriented product design, and (iii) advanced computational technologies. There is a strong demand for digital modeling of humans for design applications. Since, the existing computer-mediated methods show limitations, a new approach of digital human body modeling has been put in the focus of this promotion research. The known models frame data into meaningful interrelationships, but does not provide support for the processing of dynamically changing data structures such as concomitant to posture transformation. A major drawback is that, there is no robust bridge between 3D data and the design process. This is why designers are always confused about using anthropometric methods to guide designing of products. Frequently discussed limitations of using digital human models are (i) the difficulty with obtaining the necessary input data for a complete analysis, and (ii) I embedding the digital human model into existing CAD systems, which could used in ergonomics controlled product design.

One of the most interesting, but challenging function of digital human modeling is posture prediction. Posture prediction is a demanding task since there is no conventional technology to support generating postures for (i) large populations, and (ii) all postures in multiple actions. As it was hypothesized, a proper solution could only be expected from a combination of advanced anthropometric methods and high-end computer technologies. One of the major questions is how to connect 3D anthropometric data with a processing algorithm, which provides optimal efficiency even in the case of extreme large sets of descriptive geometric data. This efficiency

is indispensable when we consider quasi-real time transformation of the data sets of various postures of human body. Finding an answer to this efficiency problem needs the consideration of effective computational methods which are also able to reduce the procedural and computational complexities.

In order to rationalize the processing of bulky 3D anthropometric data, many researchers proposed to use landmarks. Actually the landmark-based approaches proved to be extremely useful in various anthropometric and morphological manipulations of the shape of human body. Landmarks not only rationalize the way of processing anthropometric information, but also facilitate the application of non-conventional geometry transformation methods. In other words, landmarks can be considered natural means to reduce the representational complexity of the human body, without destroying the interpretability of the data. Relying on landmarks in posture transformation can also contribute to reduction of the computational efforts and time. ANNs have been proposed as an alternative to statistical methods, in particular, to modeling non-linear functional relationships. The differences between ANNs and statistics are that ANNs is based on determining and adjusting weights in the computational mechanisms. For this adaptive nature, we used artificial neural network as the basis mechanism of processing posture and demographic data.

The knowledge synthesis part of the promotion research involved four major activities with different purposes. These activities have been completed in the following subsequent phases:

. Development of a comprehensive concept that provided a foundational theory and guided the implementation of a pilot system for proving the ideas

The concept was developed by using various explorative and constructive research methods. For instance, body shape measurement were made by a 3D Microscribe device and a 3D data recording software, and human body models were reconstructed by using various graphical and design software packages. In the measuring experiments, we selected samples from students of our Faculty, and located and marked the anatomical landmarks on the pelvis and belly region of the body of the subjects. With 3D Microscriber device and the 3D software packages, the data were recorded and reconstructed for further statistic analyses. In the forerunning experiments with ANNs, various sets of input data were first sampled, then RB-ANNs were trained and tested.

. Implementation of an ANN for posture prediction

This work involved building and testing alternative architectures for ANN. In the teaching process, 3D coordinates of landmarks in a specified posture were presented together with demographic information and 1D/2D anthropometric variables. As design of ANN back-propagation multi-layer perceptron (BP-MLP) type of ANN was used. It contained one input layer, one hidden layer, and one output layer. For the performance analysis a simplified case was used, that is, the 3D coordinates of the landmarks of head as input and target data set in training and testing of ANN. For the actual posture transformation and prediction, the anthropometric data were received from TNO. The coordinates of data points and landmarks were produced by laser scanning. The total number of scans that have been considered in the promotion research was 32, from which 28 scans were used to train the neural network, and 4 scans were used to test the performance of the neural network

. Verification of the posture prediction technology

BP-MLP-ANN has been used to transform input data and predict output data. Both the common algorithm and the genetic algorithm of BP-MLP-ANN were considered. In the research the scanned human body was substituted by a proper set of landmarks, which was used as a basis of transforming the data, as they were needed to describe specific body postures. The testing concentrated not only on the proper transfer, but also on the comparison of the performance of the ANN in two cases, when it was used to transform the landmarks coordinates of the whole body, and when it was used to transform clustered landmarks. In the extensive verification process large amount of teaching experiments and comparative tests have been made.

. Validation of the posture prediction technology by application case studies

The goal was to validate the usefulness of ANN-based posture prediction technology in design processes from an information provision and processing point of view. Because we intend to apply the ANN-based posture prediction technology in ergonomics-inclusive conceptual design of consumer products, three related criteria have been defined, which are sufficiency of information for designing, accuracy of the anthropometric landmarks- neural network-based posture transformation procedure, and sensitivity of the taught transformation model for biases in the samples. The fulfillment of these design criteria has been expressed qualitatively and quantitatively by measures and indices, respectively. We selected three design cases that represented three different levels of requirements from an application point of view.

The developed posture prediction technology has many advantages but also introduce some limitations. The further research work should be focused on: (i) training ANNs with comprehensive and representative subjects in terms of demography variables and anthropometric variables for increasing the generalization in final posture prediction; (ii) transforming large number of non-landmarks points with cluster oriented methods in order to reconstruct more vivid digital human models; (iii) training ANNs with various human body postures and functional postures based on 3D landmarks, which originate not only from scanning technique but also from other 3D measuring techniques, for example, from photogrammetry, contact measuring machines and hand motion based shape input.

Samenvatting

Het onderzoeksgebied van dit proefschrift betreft een combinatie van de fysieke ergonomie en de informatica. De ontwikkelingen in de antropometrie hebben zich verplaatst van de traditionele handmatige antropometrie naar moderne 3Dantropometrie en omvatten het gebruik van laser- en stereofotogrammetrie. De toegenomen rekenkracht van computers staat verdergaande statistische analyse toe dan in het verleden het geval was en maakt het mogelijk om deze analyses in korte tijd te maken. Computer Aided Ergonomic Design (CAED) is een opkomend multidisciplinair onderdeel van de wetenschap, dat de kennis en bronnen combineert van (i) de fysieke en informationele ergonomie, (ii) klantgericht productontwerp en (iii) hoogontwikkelde computertechnologieën. Er is een sterke behoefte aan digitale mensmodellen voor toepassing bij het ontwerpen. Omdat de bestaande computerondersteunde methoden beperkingen vertonen, is het onderwerp van dit promotieonderzoek een nieuwe benadering van het digitaal modelleren van het menselijk lichaam. De bekende modellen vormen data tot betekenisvolle samenhangen, maar verschaffen geen ondersteuning voor het verwerken van dynamisch veranderende data-structuren, zoals welke samengaan met houdingsverandering. Een grote beperking is dat er geen goede vertaalmogelijkheid bestaat tussen de 3Ddata en het ontwerpproces. Ontwerpers worden daardoor ontmoedigd om antropometrische methoden te gebruiken ter ondersteuning van het productontwerpproces. De beperkingen die vaak genoemd worden bij het gebruik van digitale mensmodellen zijn (i) de moeilijkheid om de benodigde inputdata te verkijgen voor een complete analyse, en (ii) het importeren van het digitale mensmodel in bestaande CAD-systemen, wat toegepast zou kunnen worden in het door de ergonomie geleide productontwerpen.

Een van de meest interessante, maar moeilijk te realiseren functies van het modelleren van mensfiguren is het voorspellen van de lichaamshouding. Het voorspellen van de lichaamshouding is een veeleisende taak, omdat er geen conventionele techniek bestaat om het genereren van houdingen te ondersteunen voor (i) grote populaties en (ii) alle houdingen in verschillende activiteiten. Zoals voorspeld kan een goede oplossing alleen verwacht worden van een combinatie van hoogontwikkelde antropometrische methoden en zware computer-technologie. De belangrijkste vraag is hoe 3D antropometrische data uitgewisseld kan worden met een dataverwerkend algoritme, dat optimale efficiëntie verschaft bij extreem grote sets van descriptieve geometrische data. Deze efficiëntie is onmisbaar wanneer quasi-realtime transformatie van de datasets van verschillende lichaamshoudingen overwogen wordt. Het zoeken naar een oplossing voor het efficiëntieprobleem vereist efficiënte calculatiemethoden, die eveneens in staat zijn om de complexiteit van procedures en berekeningen te reduceren.

Om grote hoeveelheden antropometrische data geschikt te maken voor verwerking hebben veel wetenschappers het gebruik van markers aanbevolen. De methoden die gebruik maken van markers bleken in de praktijk zeer bruikbaar te zijn bij verschillende antropometrische en morfologische manipulaties van de bouw van het menselijk lichaam. Markers vereenvoudigen niet alleen de manier waarop antropometrische informatie verwerkt wordt, maar vergemakkelijken ook de toepassing van onconventionele methoden voor het omzetten van geometrische gegevens. Met andere woorden, markers kunnen beschouwd worden als een eenvoudig middel om de kenmerkende complexiteit van het menselijk lichaam te reduceren, terwijl de interpreteerbaarheid van de data behouden blijft. Het afgaan op markers bij het veranderen van houdingen kan ook bijdragen tot reductie van de benodigde rekenkracht en tijd. Als een alternatief voor statistische methoden is daarnaast het gebruik van ANN's (Artificial Neural Network) voorgesteld, vooral bij het modelleren van niet-lineaire transformaties. Het verschil tussen ANN's en statistiek is dat ANN's gebaseerd zijn op het bepalen en aanpassen van weegfactoren in de rekenprocessen. Vanwege dit aanpassend vermogen is gekozen voor het gebruik van het ANN als basistechniek voor het verwerken van data met betrekking tot houdingen en demografie.

De fase van kennissynthese van het promotieonderzoek bestond uit vier hoofdactiviteiten. Deze activiteiten kenden verschillende doelen en zijn uitgevoerd in respectievelijk de volgende fasen:

- De ontwikkeling van een breed concept, dat een basistheorie verschafte en leidraad was voor de ontwikkeling van een pilotsysteem om de ideeën te verifiëren.

Voor de ontwikkeling van het concept werden verschillende exploratieve en constructieve onderzoeksmethoden gebruikt. Metingen aan lichaamsbouw werden bijvoorbeeld gemaakt door een 3D Microscribe-apparaat en 3D data recording software. Modellen van het menselijk lichaam werden gereconstrueerd met behulp van verschillende grafische en designsoftwarepakketten. Bij het verkrijgen van meetgegevens werd gebruik gemaakt van studenten van de faculteit. Anatomische markers werden op het bekken en de buik van de proefpersonen geplaatst. Met het 3D Microscribe-apparaat en de software-pakketten werden de datasets opgenomen en gereconstrueerd voor statistische analyse. In voorgaande experimenten met ANN's werden eerst verschillende sets van data ingevoerd, waarna RB-ANN's getraind en getest werden.

- De implementatie van een ANN voor houdingsvoorspelling

Bij dit werk werden verschillende architecturen voor het ANN gebouwd en getest. In het leerproces van het systeem werden 3D coördinaten van markers bij een bepaalde houding aangeboden, samen met demografische informatie en 1D/2D antropometrische variabelen. Als ontwerp werd een zogenaamd "back-propagation multi-layer perceptron" (BP-MLP)-type ANN gebruikt. Dit bevat één invoerlaag, één verborgen laag en één uitvoerlaag. Voor de analyse van de prestaties werd een versimpeld voorbeeld gebruikt.De 3D coördinaten van de markers op het hoofd dienden namelijk als set van uitgangs- en doeldata voor het trainen en testen van de ANN. Voor de werkelijke transformatie en voorspelling van de houding werd antropometrische data geleverd door TNO. De coördinaten van datapunten en markers werden vastgesteld door laserscanning. Het totale aantal scans dat geanalyseerd is tijdens het promotieonderzoek bedraagt 32, waarvan 28 scans gebruikt zijn om het ANN te trainen en 4 om de prestaties te testen.

- De verificatie van de techniek van houdingsvoorspelling

BP-MLP-ANN werd hierbij gebruikt voor het omzetten van inputdata en het voorspellen van outputdata. Zowel het gebruikelijke algoritme als het genetische algoritme van het BP-MLP-ANN werd bekeken. Het menselijk lichaam werd voor het onderzoek vervangen door een voldoende groot aantal markers. Deze markers waren nodig voor het beschrijven van specifieke lichaamshoudingen en werden gebruikt als basis voor het omzetten van de data. De test was niet alleen gericht op het juist uitvoeren van de transformatie, maar ook op het vergelijken van de prestaties van het ANN in twee gevallen: wanneer het gebruikt werd om de coördinaten van de markers voor het gehele lichaam om te zetten en wanneer het gebruikt werd om clusters van markers om te zetten. Om het uitgebreide verificatieproces te kunnen uitvoeren zijn grote aantallen experimenten gedaan voor het leerproces en grote aantallen vergelijkende tests uitgevoerd.

- Het beoordelen van de technologie voor houdingsvoorspelling door de bestudering van de toepassing ervan in voorbeeldsituaties

Het doel van deze stap was het beoordelen van het nut van de op ANN gebaseerde technologie voor houdingsvoorspelling in ontwerpprocessen in het opzicht van informatievoorziening en -verwerking. Het doel is om de op ANN gebaseerde technologie voor houdingsvoorspelling toe te passen bij het ontwerpen van concepten voor consumentenproducten waarbij ergonomische aspecten betrokken worden., Daarom zijn er drie criteria opgesteld. Deze betreffen de toereikendheid zijn van de informatie voor het ontwerpen, de accuratesse van de houdingstransformatie zoals geproduceerd door de ANN op basis van de markers, en de gevoeligheid van het geleerde transformatiemodel voor afwijkingen in de data. Het voldoen aan deze ontwerpcriteria is kwalitatief en kwantitatief uitgedrukt door respectievelijk waarden en indices. Er zijn hiertoe drie ontwerpsituaties geselecteerd met drie verschillende niveaus van eisen met betrekking tot de toepassing.

De ontwikkelde technologie voor houdingsvoorspelling heef veel voordelen, maar introduceert ook enige beperkingen. Het verdere onderzoek zal gericht moeten zijn op de volgende punten. (i) Het trainen van de ANN's met representatieve proefpersonen die geen extremen vertonen op het gebied van demografische en antropometrische variabelen, om de kwaliteit van de generalisatie in houdingsvoorspellingen te vergroten. (ii) Het omzetten van grote aantallen punten tussen de markers met de methoden voor clusteromzetting, om de mensmodellen meer levensecht te maken. (iii) Het trainen van ANN's met verschillende posturen van het menselijk lichaam en functionele houdingen gebaseerd op de 3D-markers, welke niet alleen voortkomen uit de scantechniek, maar ook uit andere 3D-meettechnieken, bijvoorbeeld fotogrammetrie, contactmeetapparatuur en houdingsgegevens gebaseerd op handbeweging.

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Appendix 1

Landmarks sample from one subject—Standing

AUX_LAND = 73

AUX =

1	0	1	47.24	-47.18	-9.32	800.05	Sellion
2	0	2	59.83	-50.08	32.74	777.75	Rt. Infraorbitale
3	0	3	30.90	-10.62	-27.85	775.93	Lt. Infraorbitale
4	0	4	43.95	-45.65	-6.79	712.39	Supramenton
5	0	5	108.77	-2.79	112.16	787.18	Rt. Tragion
6	3	294	725.62	-5.86	97.86	719.44	Rt. Gonion
7	0	7	81.54	75.29	-22.17	789.76	Lt. Tragion
8	0	8	71.05	64.24	-12.95	725.51	Lt. Gonion
9	0	9	150.80	117.92	93.55	794.23	Nuchale
10	0	10	51.93	-0.38	55.06	584.26	Rt. Clavicale
11	0	11	35.11	13.86	33.30	578.33	Suprasternale
12	0	12	38.07	33.95	10.71	584.72	Lt. Clavicale
13	0	13	126.05	-88.62	92.42	399.01	Rt. Thelion/Bustpoint
14	0	14	113.11	38.90	-106.21	407.95	Lt. Thelion/Bustpoint
15	0	15	32.48	-32.45	-1.28	404.09	Substernale
16	0	16	110.19	-53.15	98.78	280.41	Rt. 10th Rib
17	0	17	146.81	-78.36	124.15	135.77	Rt. ASIS
18	0	18	71.17	32.49	-63.32	288.32	Lt. 10th Rib
19	0	19	116.88	59.26	-100.74	139.36	Lt. ASIS
20	0	20	180.07	-38.31	175.95	189.49	Rt. Iliocristale
21	0	21	223.23	-26.02	222.74	20.12	Rt. Trochanterion
22	0	22	153.59	121.73	-93.66	193.99	Lt. Iliocristale
23	0	23	189.61	155.91	-104.97	23.77	Lt. Trochanterion

24	0	24	140.23	113.83	82.01	651.18	Cervicale
25	0	25	146.81	121.51	82.58	282.53	10th Rib Midspine
26	0	0	195.58	107.58	141.47	163.34	Rt. PSIS
27	0	27	164.60	151.92	66.22	165.78	Lt. PSIS
28	1	11732	213.18	129.51	100.60	168.25	Waist, Preferred, Post.
29	0	29	247.25	-17.31	247.75	586.07	Rt. Acromion
30	0	30	217.17	-83.82	205.09	464.73	Rt. Axilla, Ant
31	0	0	262.19	-262.19	332.14	0.13	Rt. Radial Styloid
32	0	32	265.07	9.41	261.02	428.57	Rt. Axilla, Post.
33	0	35	295.68	-68.97	282.81	243.80	Rt. Olecranon
34	0	33	328.97	-96.98	310.13	250.59	Rt. Humeral Lateral Epicn
35	0	35	259.06	-82.25	245.66	250.84	Rt. Humeral Medial Epicn
36	0	36	339.60	-106.59	318.10	235.27	Rt. Radiale
37	0	0	322.29	-310.88	360.95	-84.98	Rt. Metacarpal Phal. II
38	0	0	352.63	-305.07	433.64	-170.69	Rt. Dactylion
39	0	0	223.14	-218.79	370.82	-8.20	Rt. Ulnar Styloid
40	6	13550	235.25	-226.07	402.85	-65.08	Rt. Metacarpal-Phal. V
41	1	4895	610.85	183.81	-82.09	597.62	Lt. Acromion
42	0	0	489.63	141.91	-125.84	468.24	Lt. Axilla, Ant
43	3	8170	215.17	213.94	-351.87	-0.39	Lt. Radial Styloid
44	0	1244	485.90	227.55	-71.53	435.93	Lt. Axilla, Post.
45	0	45	289.78	242.44	-162.17	247.22	Lt. Olecranon
46	0	45	308.21	251.59	-186.40	271.50	Lt. Humeral Lateral Epicn
47	0	47	248.58	199.05	-153.69	248.51	Lt. Humeral Medial Epicn
48	0	46	322.61	255.12	-202.19	253.69	Lt. Radiale
49	0	0	235.78	225.11	-385.26	-70.14	Lt. Metacarpal-Phal. II
50	6	15013	312.21	283.60	-408.08	-150.55	Lt. Dactylion
51	0	0	269.83	269.52	-319.20	12.94	Lt. Ulnar Styloid
52	6	7618	299.02	292.25	-328.58	-63.24	Lt. Metacarpal-Phal. V
53	0	54	201.50	96.07	173.82	-451.26	Rt. Knee Crease
54	4	15858	455.08	9.94	185.19	-454.44	Rt. Femoral Lateral Epicn
55	0	53	120.65	73.46	90.75	-469.84	Rt. Femoral Medial Epicn
56	6	596	977.85	-60.61	183.30	-975.97	Rt. Metatarsal-Phal. V
57	0	0	929.73	84.73	207.79	-929.15	Rt. Lateral Malleolus
58	0	58	154.35	80.54	127.29	-913.72	Rt. Medial Malleolus
59	6	14830	942.72	66.96	121.94	-939.90	Rt. Sphyrion
60	6	14533	972.18	-45.38	84.12	-971.12	Rt. Metatarsal-Phal. I
61	6	11359	972.88	143.56	187.43	-962.14	Rt. Calcaneous, Post.
62	6	13798	993.37	-109.28	106.60	-984.65	Rt. Digit II
63	0	63	199.09	199.02	31.06	-458.72	Lt. Knee Crease
64	0	63	176.35	166.98	-46.35	-439.80	Lt. Femoral Lateral Epicn

65	0	65	130.30	115.86	59.63	-468.40	Lt. Femoral Medial Epicn
66	6	8218	989.48	146.45	-105.92	-978.58	Lt. Metatarsal-Phal. V
67	0	67	214.11	211.65	4.02	-924.99	Lt. Lateral Malleolus
68	0	68	165.24	155.23	54.77	-916.51	Lt. Medial Malleolus
69	0	0	963.30	158.73	50.97	-947.79	Lt. Sphyrion#
70	6	13811	981.28	58.31	-55.09	-979.54	Lt. Metatarsal-Phal. I
71	0	71	246.07	235.80	70.35	-969.05	Lt. Calcaneous, Post.
72	6	13854	980.75	63.32	-111.08	-987.11	Lt. Digit II
73	0	0	0.0	64.945	58.885	-47.1	Crotch

Appendix 2

Landmarks sample from one subject—Sitting

AUX_LAND = 74

AUX =

1	0	1	27.72	-18.55	-19.01	406.08	Sellion
2	0	2	27.81	-23.01	21.88	377.77	Rt. Infraorbitale
3	0	3	41.12	16.15	-34.60	378.34	Lt. Infraorbitale
4	0	4	24.83	-16.17	-17.52	312.55	Supramenton
5	0	5	105.32	26.95	105.82	386.65	Rt. Tragion
6	0	9815	317.03	29.96	80.09	317.83	Rt. Gonion
7	0	7	114.24	106.68	-31.47	389.10	Lt. Tragion
8	0	569	327.82	90.32	-23.42	316.44	Lt. Gonion
9	0	9	170.43	151.03	80.83	383.82	Nuchale
10	0	10	58.87	31.59	50.85	178.35	Rt. Clavicale
11	0	11	53.97	42.79	32.48	168.44	Suprasternale
12	0	12	64.51	61.46	5.29	174.14	Lt. Clavicale
13	0	13	96.68	-43.20	88.68	-12.32	Rt. Thelion/Bustpoint
14	0	14	129.52	76.19	-95.95	-2.82	Lt. Thelion/Bustpoint
15	0	15	14.36	12.97	3.82	-0.05	Substernale
16	0	16	99.37	-7.17	101.61	-113.94	Rt. 10th Rib
17	-999	-999	0.00	0.00	0.00	0.00	Rt. ASIS
18	0	18	107.05	88.90	-57.29	-110.15	Lt. 10th Rib
19	-999	-999	0.00	0.00	0.00	0.00	Lt. ASIS
20	0	20	189.29	31.89	186.58	-194.26	Rt. Iliocristale
21	0	21	214.40	-22.24	215.33	-316.18	Rt. Trochanterion
22	0	0	287.10	203.58	-70.38	-202.44	Lt. Iliocristale

23	0	23	230.57	193.85	-124.84	-330.47	Lt. Trochanterion
24	0	24	161.08	142.51	75.09	255.68	Cervicale
25	0	25	207.43	183.20	98.84	-107.88	10th Rib Midspine
26	1	16205	323.74	172.30	155.37	-274.08	Rt. PSIS
27	1	16197	352.24	221.26	82.25	-274.08	Lt. PSIS
28	2	147	313.49	193.82	107.17	-246.40	Waist, Preferred, Post.
29	0	29	229.29	-15.89	228.74	189.11	Rt. Acromion
30	1	6719	70.98	-38.88	173.66	44.01	Rt. Axilla, Ant
31	4	13350	325.59	-198.30	37.07	-258.24	Rt. Radial Styloid
32	0	32	269.75	34.91	263.17	35.09	Rt. Axilla, Post.
33	0	33	273.90	-14.63	269.36	-204.15	Rt. Olecranon
34	4	1537	176.57	-52.59	273.81	-168.31	Rt. Humeral Lateral Epicn
35	-999	-999	0.00	0.00	0.00	0.00	Rt. Humeral Medial Epicn
36	0	0	189.64	-63.87	264.74	-178.56	Rt. Radiale
37	5	4863	396.61	-276.43	-28.33	-285.01	Rt. Metacarpal Phal. II
38	0	38	373.08	-370.14	-46.72	-333.30	Rt. Dactylion
39	0	39	231.62	-216.85	72.95	-292.96	Rt. Ulnar Styloid
40	0	40	273.29	-265.31	53.50	-314.17	Rt. Metacarpal-Phal. V
41	0	41	244.74	214.22	-115.77	195.49	Lt. Acromion
42	0	15657	169.74	158.48	-117.00	60.80	Lt. Axilla, Ant
43	0	43	190.61	-18.74	-189.69	-265.54	Lt. Radial Styloid
44	0	44	295.39	279.88	-104.56	31.42	Lt. Axilla, Post.
45	0	45	293.37	267.80	-130.34	-194.21	Lt. Olecranon
46	0	45	292.14	256.56	-160.95	-159.51	Lt. Humeral Lateral Epicn
47	-999	-999	0.00	0.00	0.00	0.00	Lt. Humeral Medial Epicn
48	0	45	302.87	235.36	-173.07	-178.64	Lt. Radiale
49	0	0	320.13	-110.01	-230.93	-300.63	Lt. Metacarpal-Phal. II
50	3	7370	373.86	-171.22	-323.96	-332.35	Lt. Dactylion
51	0	51	238.22	6.64	-240.46	-290.35	Lt. Ulnar Styloid
52	0	52	288.28	-45.43	-286.88	-328.46	Lt. Metacarpal-Phal. V
53	-999	-999	0.00	0.00	0.00	0.00	Rt. Knee Crease
54	5	4680	609.87	-424.64	-48.97	-446.78	Rt. Femoral Lateral Epicn
55	3	4575	591.86	-368.14	-129.40	-467.31	Rt. Femoral Medial Epicn
56	5	6299	1063.41	-467.41	-97.94	-955.18	Rt. Metatarsal-Phal. V
57	0	0	951.23	-336.87	-63.83	-891.07	Rt. Lateral Malleolus
58	3	9655	939.40	-343.24	-140.68	-883.42	Rt. Medial Malleolus
59	4	10068	976.59	-350.99	-145.60	-909.41	Rt. Sphyrion
60	4	9456	1064.23	-475.19	-205.37	-952.25	Rt. Metatarsal-Phal. I
61	-999	-999	0.00	0.00	0.00	0.00	Rt. Calcaneous, Post.
62	5	6416	1086.39	-520.28	-178.80	-955.70	Rt. Digit II
63	-999	-999	0.00	0.00	0.00	0.00	Lt. Knee Crease

64	3	7094	482.99	-177.11	-375.39	-446.08	Lt. Femoral Lateral Epicn
65	0	65	382.62	-233.71	-296.81	-471.35	Lt. Femoral Medial Epicn
66	4	9491	994.37	-291.79	-448.13	-948.99	Lt. Metatarsal-Phal. V
67	0	0	914.09	-176.55	-335.60	-896.88	Lt. Lateral Malleolus
68	0	0	914.45	-233.55	-284.33	-887.44	Lt. Medial Malleolus
69	4	6424	941.53	-239.04	-291.07	-915.28	Lt. Sphyrion
70	0	0	1004.92	-337.40	-356.93	-944.88	Lt. Metatarsal-Phal. I
71	-999	-999	0.00	0.00	0.00	0.00	Lt. Calcaneous, Post.
72	4	9384	1027.43	-364.50	-427.93	-956.90	Lt. Digit II
73	-999	-999	0.00	0.00	0.00	0.00	Crotch
74	0	74	268.03	239.17	122.16	-426.46	Butt Block