Supporting machine vision system design for quality control in manufacturing

An automotive case study

Master Thesis

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TU Delft   VOLVO

Supporting machine vision system design for quality control in manufacturing

An automotive case study

by

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Preface

Dear reader,

In front of you, you have the report I wrote as part of my Master thesis at the Delft University of Technology. The report describes the thesis work I have been conducting the past seven months in collaboration with Volvo Car Corporation.

The report is aimed at readers who are interested in how one can decide on machine vision system design for a manufacturing environment. It is expected that the reader is familiar with machine vision systems and the associated terminology. The goal of my research was to study how the design for machine vision systems for quality control in manufacturing can be supported. My hope is that my work will be of guidance to many decision-makers that face the challenge of designing machine vision systems for quality control in the future.

Also, I would like to make use of this opportunity to express my gratitude to my supervisors at Volvo Car Corporation: Alf Andersson and Yvan Jacquet. I would like to thank them for their support during the entire project and the many meetings we had. It has been interesting to have industry perspectives throughout the research. Also, thank you very much for inviting and welcoming me to different facilities of Volvo Cars.

In addition, I would like to thank Bilge Atasoy for chairing my graduation committee and for the valuable feedback she provided me during the meetings we had with the committee. They helped me in steering the research to a better direction.

Furthermore, I would like to thank Rafael Leite Patrão for his guidance throughout the research and the many sparring sessions we had. I have appreciated the way in which we have worked together.

Moreover, I would like to thank Alessia Napoleone for providing me the opportunity to conduct my Master thesis under her supervision and the feedback she provided me throughout the entire research. I have learned a lot regarding academic writing and have appreciated the many talks we had about how to proceed with the research.

Finally, I would like to thank my family and friends, and in particular my parents, for supporting me throughout my entire study career.

I wish you an enjoyable read!

Lars W. van Keulen

Gothenburg (Sweden), December 2024

Abstract

Quality control is considered an important process in manufacturing to minimise waste related to the manufacturing process. A way of performing quality control is with help of machine vision. Understanding all decisions that are to be made when designing a machine vision system for quality control is essential, but challenging. This research presents a method that aids decision-makers in the process of designing these machine vision systems for quality control so the efficiency of the decision-making process can be increased. The method results in a knowledge base and a tool that can both be considered as useful to decision-makers. The method was designed by following a Design Science Research approach and the method was applied on a use case in the automotive industry to prove that it addresses its goal.

Keywords: Quality control; manufacturing; machine vision systems; decision-support systems; decision-making; Design Science Research; automotive.

Summary

There is a demand for increasing the efficiency of the decision-making process for the design of machine vision systems for quality control in the manufacturing industry. This efficiency can be increased by aiding the decision-makers during step two, three and four of the decision-making process for machine vision system design (see Figure 1).

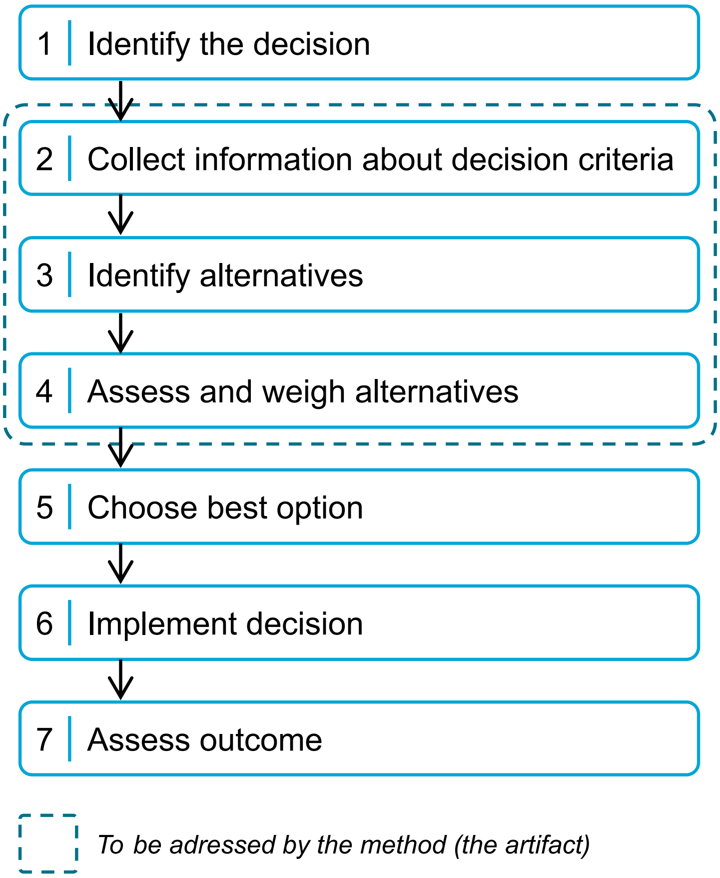

Figure 1: Decision-making process for MVS design

To support these steps, a method was developed with help of Design Science Research. From this research methodology, a method resulted that leads to a knowledge base and tool that assists decision-makers during step two, three and four of the decision making process (see Figure 2). The method consists of 7 phases: Understand, Identify, Map, Classify, Link, Build and Evaluate. The first five phases generate the so called knowledge base, which is a collection of information that already supports decision-makers during the decision-making process. The last two phases lead to the tool that allows decision-makers to more easily interact with the knowledge base. During the first phase (Understand), an understanding of machine vision systems should be developed by conducting a literature review following a pre-specified search strategy. During the second phase (Identify), industry specific influential environmental characteristics should be identified by interviewing practitioners, to understand what aspects of the manufacturing system are relevant to the design of machine vision systems considering a particular industry. For the third phase (Map), the identified environmental characteristics should be structured in a hierarchy to identify the space of possible decision-making choices and the internal relations it contains. For the fourth phase (Classify), the identified influential environmental characteristics should be classified based on the domain they belong to (to allow for root cause analyses) and based on their relevance to machine vision (to scope the method). In the fifth phase (Link), the links between the environmental characteristics and the specifications of machine vision equipment they influence should be described, so the effect of a change in the environmental characteristic on the equipment is understood. During the sixth phase (Build), all knowledge obtained in the previous steps should be processed into a tool that is accessible by decision-makers, so they only have to use this tool when willing to make decisions, and not the knowledge base. Finally, in the last and seventh phase (Evaluate), the obtained knowledge and created tool should be evaluated by practitioners to obtain feedback on whether all relevant linkages are made and whether the tool is complete. Based on the feedback that is gained, improvements should be made in the knowledge base after which the tool should be updated again. The seven phases are to be repeated until no new feedback is mentioned during discussions with practitioners.

As prescribed by Design Science Research, the developed method was demonstrated by applying it to a use case. For this research a use case was found in the automotive industry. The application led to a knowledge base and tool that were able to support decision-makers during the decision-making process for the design of a machine vision system. From the evaluation, it followed that decision-makers were supported and that the efficiency of the decision-making process was increased as the required time needed to fulfil a decision-making process was decreased while not changing other parameters than adding the support to step two, three and four.

For future work it is advised to see if the method can be expanded so it can assist even more with assessing and eventually even selecting different alternatives. Also, enlarging the scope of the method could be beneficial (e.g. also taking into account technologies like X-ray imaging or 3D imaging) as it will enhance the decision-making like expanding the method will do.

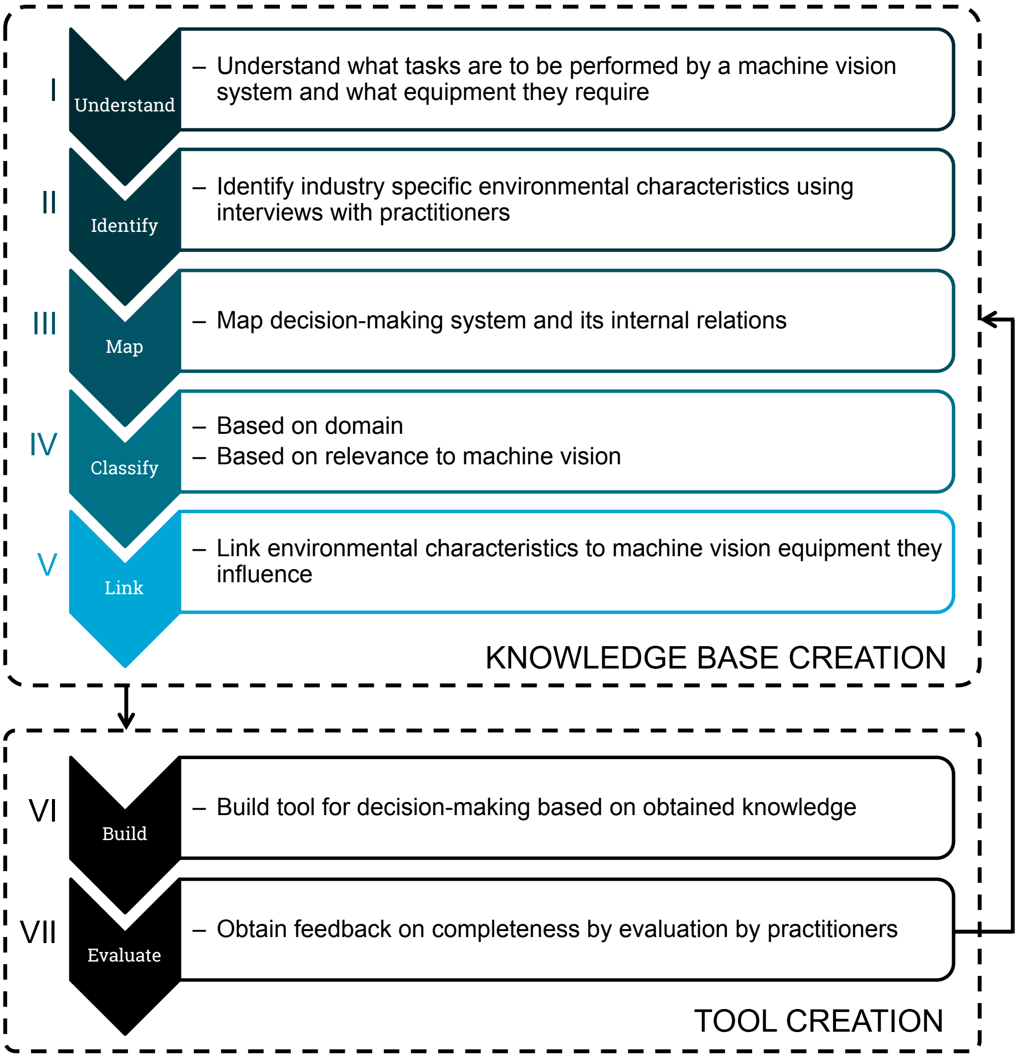

Figure 2: Method for developing a knowledge base and a tool that supports decision-makers in the decision-making process of MVS design

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List of abbreviations

Abbreviation	Definition
DMN	Decision Model and Notation
DSR	Design Science Research
DSS	Decision support system(s)
IP	Ingress protection
FOV	Field of view
ML	Machine learning
MV	Machine vision
MVS	Machine vision system(s)
RFID	Radio-frequency identification
VBA	Visual Basic for Applications

1 Introduction

Quality control is considered an important process in manufacturing to minimise disturbances, rework, material consumption and other waste. Hereby, the value adding processes can be optimised to reach an efficient production. Almost all manufacturing processes contain some form of quality control. Ways in which quality control takes place are, amongst others, off-line sample control or inline continuous verification. Among others, a characteristic of quality control is that it can be based on human inputs (Brosnan & Sun, 2004). If one of these human inputs is vision, one can attempt to support the human aspect by machine vision to allow for automation of the quality control process.

Machine vision can be defined as the ability of a machine to obtain information about its environment by sensing and thereafter processing the sensed information which can then be used for further analysis (López et al., 2008). Another definition of machine vision is that it studies the hardware, software and image acquisition techniques necessary in real applications (Davies, 2012). Machine vision consists of five tasks: image acquisition, image preprocessing, image segmentation, feature extraction and classification (Bhargava & Bansal, 2021; Goutam & Sailaja, 2015; Patel et al., 2023) all with their own influential environmental characteristics. Computer vision is said to be the technology that extracts information form the acquired images (Zebra Technologies Corp., n.d.), or the software for the design of vision (Davies, 2012). Computer vision, does not need technology to capture an image, it can use data that is acquired by another system (Zebra Technologies Corp., n.d.). Due to the advancements of the technologies used for both machine and computer vision, the terms machine vision and computer vision get used interchangeably more and more (Davies, 2012). Computer vision will (solely) be considered as the science of extracting useful information of the acquired image. In this research, focus will be paid to machine vision systems only.

The design of a machine vision system is challenging and involves multiple decisions, such as selection of the right equipment based on the environment the system is to be placed in. Machine vision systems can namely be very different due to the conditions under which they have to perform.

For example, the light required to have a well performing system can vary significantly (Brosnan & Sun, 2004), from back lighting to front lighting and all other types of lighting as described by (Anand & Priya, 2020). Also, one might require special imaging pre-processing techniques if their system is to function in a machining environment (Banda et al., 2022) or special lenses when one wants to study dimensions (Williamson, 2018). It is important that the designer of a machine vision system is aware of all environmental characteristics and thereby understands all decisions that are to be made in order to design a proper functioning machine vision system.

This is where challenges arise. Understanding all decisions that are to be made is essential, but achieving this requires extensive study and expertise in machine vision. In industry, time constraints and a high demand for machine vision systems make it challenging to develop in-depth expertise. Therefore, an effective solution would be to consolidate knowledge on decisions that are to be made when designing a machine vision system and present it in a way that enables decision makers to effectively make these decisions. A review of the literature reveals numerous papers on machine vision systems, including those focused general component descriptions (Golnabi & Asadpour, 2007; Pajares et al., 2016). However, there appears to be a lack of comprehensive resources that integrate this knowledge into a cohesive design guideline for practical application by industry professionals.

To develop such a solution and thus quicker improve process efficiency in manufacturing, this research's aim is to answer the following research question:

How to guide decision-makers (on the design of machine vision systems) in the process of designing a machine vision system for quality control?

To answer this question, the remainder of this thesis is organized as follows: Chapter 2 presents the methodology used in this thesis to address the research question and it will highlight what contributions will be made. Chapter 3 describes a literature review on decision support systems from which principles were used in the creation of the results of this research. Chapter 4 presents the developed method that supports decision-makers in this decision making process for the design of a machine vision system. Chapter 5 presents the results from the application of the developed method on a use case from the automotive industry. The result of the use case is both a knowledge base and a tool that can be used by decision-makers. Chapter 6 describes how the method was validated by applying it to two use cases from the automotive industry again. Finally, chapter 7 and 8, discusses and concludes this research, respectively.

2 Research methodology

The Design Science Research (DSR) methodology was selected to answer the research question for its capacity of tackling complex problems and to address the need for actionable solutions. This research paradigm is used to design a methodology, or artifact according to the DSR terminology, that meets the needs of one specific industry, or environment, while also ensuring the provision of knowledge that can be valuable for other industries and thus for society (vom Brocke et al., 2020). The implementation of the DSR methodology followed six activities, as follows. In the first activity, problem identification and motivation, the challenge of supporting the design of machine vision systems for quality control so to increase manufacturing efficiency was identified, as is also highlighted in chapter 1.

In the second activity, definition of objectives for a solution, the generic requirements for a solution were determined by studying the decision-making process for machine vision system design and determining during which of the steps of the decision-making process support could and should be given. The decision-making process for machine vision system design was said to consists of seven steps (see Figure 2.1). First, the decision-maker should acknowledge that decisions are to be made (i.e. recognise that a machine vision system is to be designed). Thereafter, in step two, information on the decision criteria is to be collected. After information on the decision criteria has been collected, the alternatives (i.e. possible designs of machine vision systems) should be identified. Following, in step four, these alternatives should be assessed and weighed. Thereafter, the best option should be chosen, the decision should be implemented and finally, the outcome is to be assessed. To support decision-makers in the design of machine vision systems, it was decided to develop a method that when executed aids the decision-maker during step two, three and four of the decision-making process (marked by the dashed box in Figure 2.1).

Continuing with the DSR methodology, during activity three, design and development, a method (the artifact) that supports the decision-maker during step two, three and four of the decision-making process for the design of a machine vision system was designed by acquiring knowledge on the design

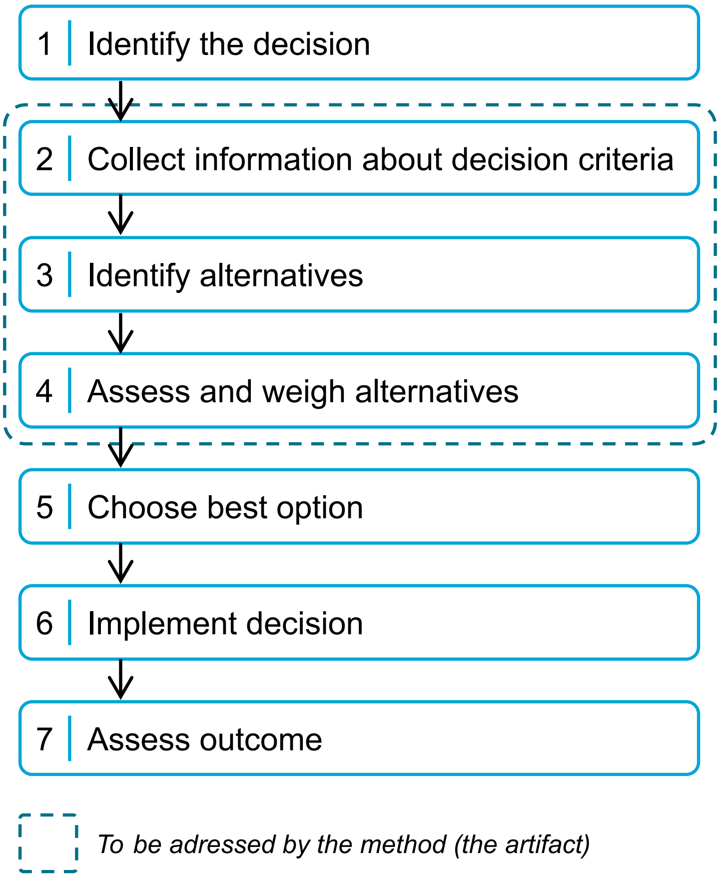


Figure 2.1: Decision-making process for machine vision system design

of machine vision systems by conducting literature research and expert interviews. In the fourth activity, demonstration, the designed method was applied on a use case in the automotive industry (at Volvo Cars) to demonstrate that it is capable of supporting the decision-making process. Its usefulness was proved by validating the results of the created artifact when it was applied to a use case. For the fifth activity, evaluation, the demonstration was validated by comparing its results with machine vision systems that are already in place. The method should propose these systems as a solution as well, since they are already in place and therefore have proven to work. The system in place might not be the most optimal solution, but that does not make it infeasible and thus the method should still suggest it as a solution. When the method was validated it was also evaluated if the efficiency of the decision-making process by using the method was increased. In the last activity, communication, the designed method was documented and presented in form of a report and the created tool to support decision-makers was presented to the stakeholders from industry.

The methodology results in three different contributions of this research: a method for developing a knowledge base and a tool that supports decision-makers in the decision-making process of machine vision system design (see chapter 4), a knowledge base for supporting decision-makers in the decision-making process of machine vision system design (see section 5.1) and a tool for supporting decision-makers in the decision-making process of machine vision system design design (see section 5.2).

3 Decision support systems

In order to understand how decision-makers can be supported in decision-making, a literature review on decision support systems (DSS) was performed. To find relevant literature, the queries as presented in Table 3.1 were fed to the Google Scholar database. From the results, 18 papers were studied in more detail.

Multiple sources describing DSS (Aerts et al., 2022; Bouabid & Louis, 2021; Raigar et al., 2020), show that all DSS perform the following general steps: identifying important decision criteria, processing user input, decision making and collecting feedback. From the literature research it can be concluded that these general steps can be performed in different ways. In the coming sections these different ways will be explained, when possible contrasted and comments will be made on how they can be useful for DSS for machine vision systems. Section 3.1 will do this for step 1 (Identifying important decision criteria), section 3.2 will do this for step 2 (Processing user input), section 3.3 will do this for step 3 (Decision making) and section 3.4 will do this for step 4 (Collecting feedback). Finally, section 3.5 will highlight the gaps in literature.

Table 3.1: Search queries literature research on decision support systems

QUERY	DESCRIPTION
1	”Systems engineering”
2	Systems AND engineering AND methods
3	”Product design”
4	Decision AND support AND component AND selection
5	Decision AND support AND systems AND engineering
6	Component AND machine AND vision AND selection

3.1. Step 1: Identifying important decision criteria

The first step in designing a DSS is to determine what decision criteria are considered to be important as is illustrated by Raigar et al. (2020), Booker et al. (2022), Aerts et al. (2022) and Farshidi et al. (2020). Raigar et al. (2020) suggests to use literature for determining what decision criteria should be important to the DSS. This literature-driven approach can also be used for the creation of a DSS for machine vision systems due to the high availability of literature on machine vision systems. Booker et al. (2022) suggests to determine the important decision criteria with help of statistics and historic data. The issue with this approach in combination with the creation of a DSS for machine vision systems is the low availability on datasets encompassing use cases of machine vision systems. The approach could be used, but that would require a big amount of literature research to be conducted first. Farshidi et al. (2020) and Aerts et al. (2022) describe the use of expert knowledge to determine the important decision criteria. In addition, Aerts et al. (2022) use the Decision Model and Notation (DMN) to capture this knowledge. Since machine vision systems often seem not to be an as exact science as one might think, it is expected that expert knowledge (partly based on experience) benefits a DSS for machine vision systems to a great extent. The use of DMN can be beneficial for the creation of a DSS for machine vision systems as well.

3.2. Step 2: Processing user input

The second step in designing a DSS is to determine if the DSS has to preprocess the user input and if so, how this should be done. Bouabid and Louis (2021) translate user input to a score that is then used by the DSS (like fuzzy logic). This can be of use when human judgement is to be captured. Raigar et al. (2020) do something similar. This translation of human judgement into a score can be of use for the design of a DSS for machine vision systems in case characteristics of a solution or an environment are difficult to objectively measure.

No preprocessing is needed if an input from the user can directly be used in the decision making. For example if a physical quantity is to be used or when there is a binary yes-no question excluding or including certain solutions. An example of this can be found in Yurdakul et al. (2020).

3.3. Step 3: Decision making

The third step in designing a DSS is to select a way in which the decision is going to be made. (Díaz & Soares, 2023) and (Raigar et al., 2020) suggest the use of the multi-criteria decision methodology. The multi-criteria decision methodology scores different solutions based on the defined decision criteria. With the help of weights, certain criteria can be given more importance then others. In theory, the solution with the highest score is the best solution to the problem. A boundary condition for this methodology is that the solutions must be known since they need to be scored. When one wants to design a DSS that encompasses endless solutions (like the case for machine vision systems where a lot of different equipment types can be combined), the problem might become uncontrollably big.

Another method for decision making is the filtering of a database based on the inputs as defined by the user (Bouabid & Louis, 2021). Again, with this methodology, one is forced to have an overview or database of all possible solutions. If there is a small amount of solutions, this might be a nice solution. If the number of solutions is high, it might however be a less efficient method.

3.4. Step 4: Collecting feedback

The fourth and final step in creating a DSS is to make sure feedback on the DSS is collected to assure a proper DSS design. Both, Aerts et al. (2022) and Farshidi et al. (2020) suggest to get this feedback by taking the DSS back to the experts and discuss the performance of the DSS with them. The way in which feedback is retrieved can be both structured and non-structured. As long as all feedback is properly reflected.

3.5. Discoveries and gap in literature

For DSS it was found that the design of a DSS consists of four steps: identifying important decision criteria, processing user input, decision making, collecting feedback. For each steps, different alternatives were reported. A DSS for machine vision systems was not found in literature. A result describing research that was the closest to discussing this combination was a paper written by Golnabi and Asadpour (2007). In this paper a general machine vision solution is proposed. However, little information on how this general solution was retrieved was reported. With help of the alternatives for all the steps, a DSS for machine vision systems can however be created. For the step 'decision making' there was however not yet found a methodology suitable for DSS for machine vision systems due to the endless possibilities of machine vision systems.

Furthermore, the author wants to highlight that many papers only seem to focus on the DSS itself (the product) and not on how this DSS was created (the process). Focusing on the process might cause a methodology to be found that is robust for many different scenarios maybe not only limited to machine vision. This methodology should then aim at aiding decision-makers during the decision-making process for the design of machine vision systems for quality control.

4

Method for developing a knowledge base and tool that support decision-makers in the design of a machine vision system

The method for developing a tool that supports decision-makers in the design of a machine vision system as presented in Figure 4.1 consists of two consecutive parts: knowledge base creation and tool creation. The goal of the first part, knowledge base creation, is to create a knowledge base that contains all relevant information to already aid the decision-maker during step two, three and four of the decision-making process as presented in Figure 2.1. The first part (creation of the knowledge base) consists of the first five phases of the method: Understand, Identify, Map, Classify and Link. The goal of the second part of the method (tool creation), is to create a tool that allows a decision-maker to interact with the knowledge base to increase the efficiency of the decision-making process. This second part contains the last two phases of the method: Build and Evaluate. The reason for dividing the method into two parts is to emphasize the fact that only the structured way of creating the knowledge base as done in the first part of the method could already aid decision-makers in the decision-making process as described by Figure 2.1. To however increase the efficiency of the process, it is highly advised to also execute the second part of the method, the generation of a tool, that allows the decision-makers to more easily interact with the knowledge base. Without the tool, the decision-maker has to understand the knowledge base by studying all information that is in there. The tool has this knowledge embedded and therefore allows the user to passively use this knowledge by providing the tool with inputs and then using the outputs of the tool for the decision-making which increases the efficiency of the decision making process even more.

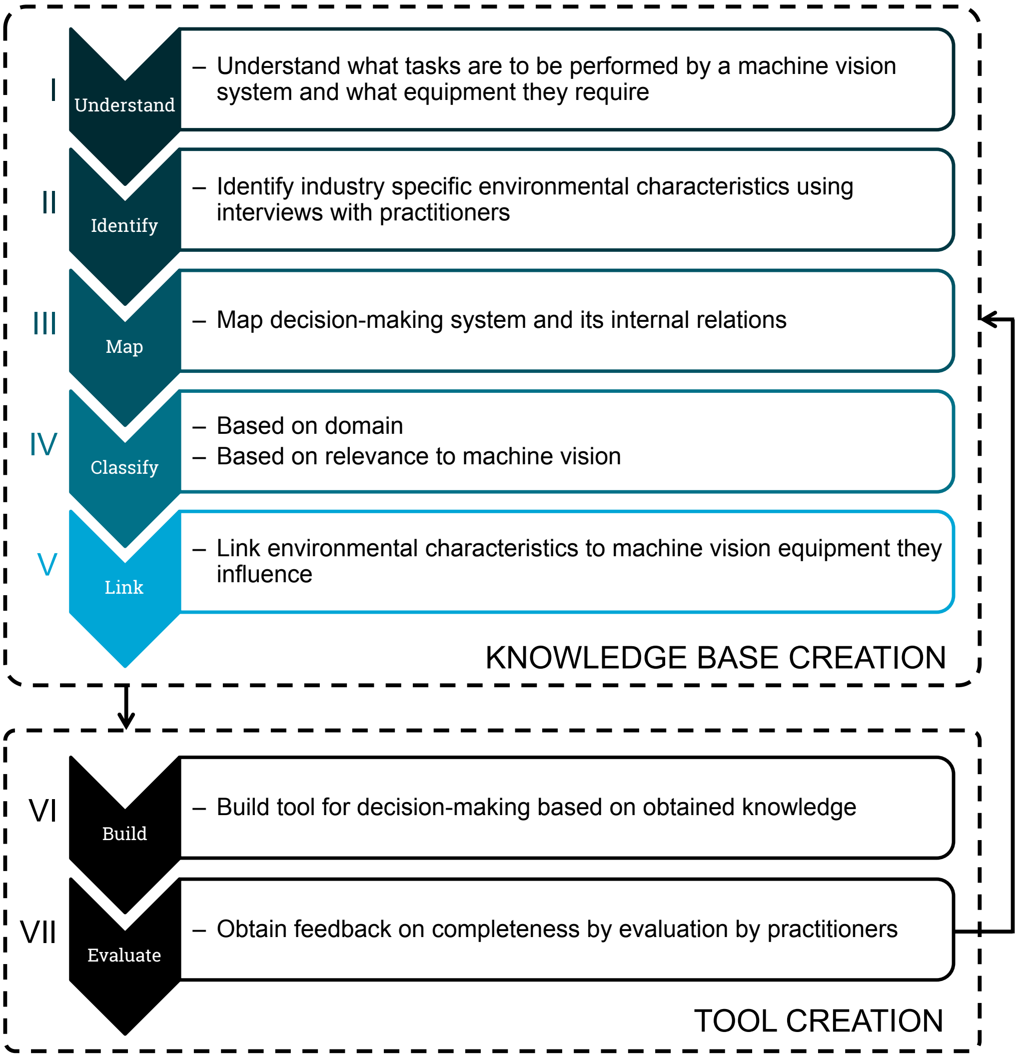


Figure 4.1: Method for developing a knowledge base and a tool that supports decision-makers in the decision-making process of machine vision system design

In the remainder of this chapter, first the assumptions that were made when designing the discussed method will be introduced in section 4.1. Thereafter, in section 4.2, 4.3, 4.4, 4.5, 4.6, 4.7 and 4.8 the phases Understand, Identify, Map, Classify, Link, Build and Evaluate will be explained, respectively. Finally, in section 4.9, the designed method will be discussed.

4.1. Underlying assumptions to the method

The first assumption on which the method is based is that the decision-making process as presented in Figure 2.1 properly reflects the true decision-making process a decision-maker has to go through when designing a machine vision system. The presented decision-making was based on observations from industry.

The second assumption is that the knowledge base and the tool that are the result of the method are to be used by a human decision-maker. This implies that knowledge in the knowledge base and the tool should be interpretable by a human, but also that parts of the knowledge base and the tool might be interpreted in a different way by different humans. Also, different humans might have different initial understanding of machine vision which might lead to them using the knowledge base and the tool in different ways. The method was designed in such a way that the knowledge base and the tool it results in, provide support to a decision-maker with no initial understanding of machine vision.

4.2. Phase I: Understand

During phase I (Understand), an understanding of machine vision systems should be developed. It is critical to know what tasks they have to perform and how these tasks can be performed (what equipment is necessary) to understand what parts of the system can be influenced by decisions that are to be made. The development of an understanding of machine vision systems can be achieved by performing a literature review based on the method as presented by Figure 4.2. The result of this literature review should be a framework for machine vision system design explaining the tasks of machine vision and the equipment needed to perform these tasks. The framework will also highlight some initial characteristics of the environment that influence the specifications of the equipment needed. These initial characteristics of the environment will be referred to as initial environmental characteristics. Decision-makers have to identify if there are more environmental characteristics than mentioned in the framework that are specific to their industry to know all decisions that are to be made in their decision-making process. This will be done in the next phase II of the method (see section 4.3).

The reason for using the strategy as presented in Figure 4.2, is that it, next to highlighting tasks that are to be performed and equipment that is therefore needed, also highlights similar technologies in different environments which might tell something about the specifications of the technology and its relation to the environment.

4.3. Phase II: Identify

During phase II (Identify), industry specific influential environmental characteristics should be identified by interviewing practitioners, to understand what aspects of the manufacturing system are relevant to the design of machine vision systems considering a particular industry. This identification of industry specific influential characteristics should be based on the framework for machine vision system design that is created during phase I (Understand). To ensure one gets an as complete as possible overview from the influential environmental characteristics, one should select interviewees according to the following guidelines:

i) Different facilities: If you are studying an industry of which you know many companies in that industry have different facilities (global or national), you should interview practitioners form the different facilities to increase the chance practitioners have different experiences with machine vision systems.

ii) Different manufacturing stages: If you are studying an industry of which you know its manufacturing process clearly contains several stages (e.g. in automotive there is the body-shop, paint-shop and final assembly), you should interview practitioners from all of these stages for the same reason as mentioned above. Depending on the industry, these stages might be similar or very different which might cause different environmental characteristic to be relevant for different industries. If you find

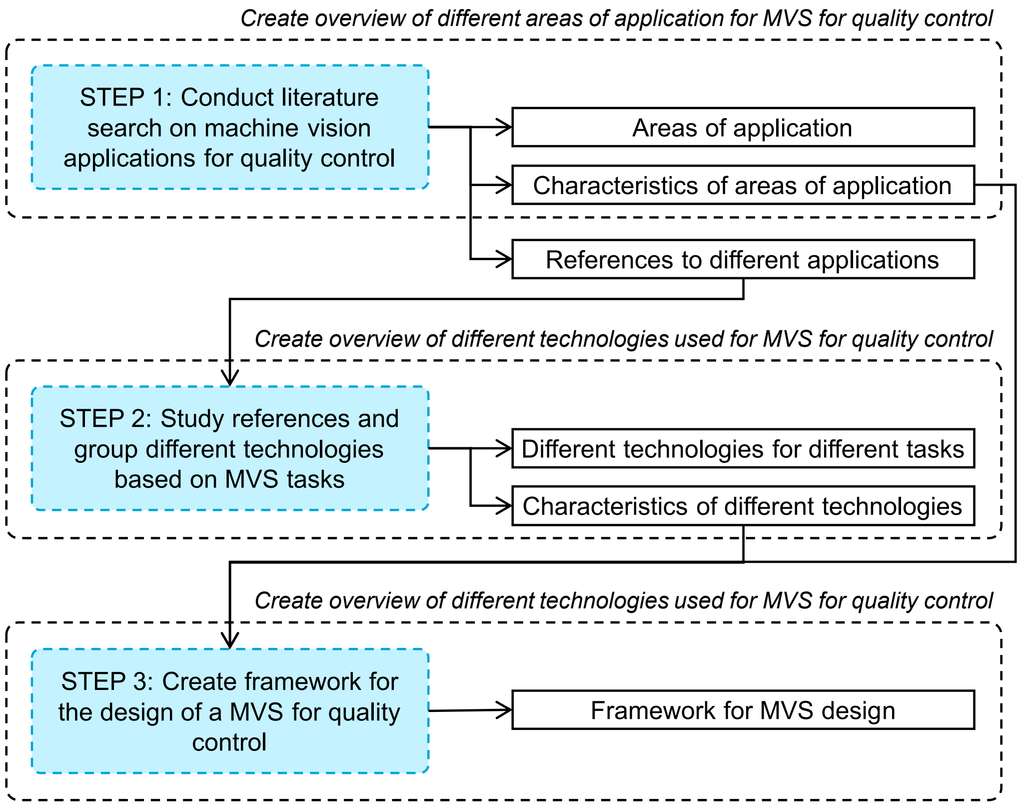


Figure 4.2: Strategy for literature search

many environmental characteristics that are relevant to a specific stage only, you might want to take this into account in the method you develop by asking the decision-maker what stage it is to operate in. A separate knowledge base and tool might then be designed.

iii) Different roles: Interview different roles within the organisation as they might pose different requirements to machine vision systems. Examples of different roles that can be interviewed are Technical Experts, Shop engineering managers, Equipment engineers and Strategy engineers.

In addition to the selection of interviewees, the interview questions should also be carefully prepared in order to not guide interviewees towards earlier identified characteristics which limits the free thinking of the interviewee. An advised setup is the following:

1. For which processes in the plant is machine vision used as a method to perform quality control?
   (a) What environmental factors were taken into account during the design of the machine vision system?
   (b) What issues were encountered during the design/implementation of the machine vision system?
2. For which processes in the plant is machine vision wanted as a method to perform quality control?
   (a) What environmental factors should be taken into account for these processes?
3. What research on machine vision for quality control has already been performed within Volvo?
   (a) What are the results of this research and what can I learn from them?

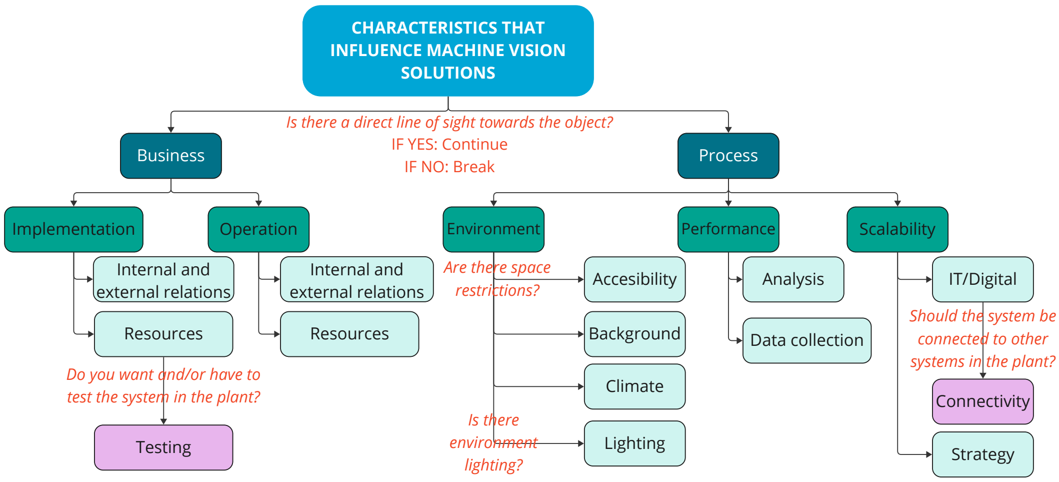


Figure 4.3: Example of a hierarchy to understand the decision-making system

4.4. Phase III: Map

For phase III (Map), the identified environmental characteristics should be structured in a hierarchy to understand the decision-making system and the internal relations it contains. There might be situations in which a lower level decision is made automatically as soon as a higher level decision is made. By mapping these relations, decisions can be presented to the decision-maker in such a way that only decisions that still matter are made. This will potentially decrease the amount of decisions that are to be made by the decision-maker. The mapping of these relations can be done by creating a hierarchy of the environmental characteristics. An example of how such a hierarchy could look like is presented in Figure 4.3.

4.5. Phase IV: Classify

During phase IV (Classify) the identified environmental characteristics are classified in two different ways in order to (i) allow for root-cause analysis in case no feasible alternatives are identified in the decision-making process, and (ii) scope the machine vision design problem. The classifications are independent and therefore the order in which the classifying is performed does not affect the outcome of the method. The classifications are to be performed in the same phase to make the phases more insightful.

i) Classification in domains: will help in understanding what decisions led to the situation for which there are no alternatives available that might be the outcome for step four later in the decision-making process (see Figure 2.1). It is also referred to as decision traceability. Suggested is to define the domains 'Physics', 'Engineering' and 'Commercial', but more domains may be introduced. The Physics-domain should contain all environmental characteristics that have their origin in physics, meaning that no-matter who you ask, everyone will treat that environmental characteristic the same. An example is the environmental characteristic *Object-camera speed*, no matter who you ask the interaction between the speed of an object compared to the camera and the frame rate will always be the same. If you get no feasible alternatives because of this characteristic, the situation is not well described or machine vision cannot provide you with a solution. The engineering-domain contains all characteristics that require some form of engineering to obtain an alternative in the decision-making process. An example of an environmental characteristic that belongs to the engineering domain is *Environment humidity*. If your equipment is to be placed in a humid environment, but you cannot find a suitable camera that is waterproof, you can build (engineer) a waterproof case around the camera and then your solution becomes a valid alternative. The commercial-domain contains all environmental characteristics that are influenced by requirements posed by the business and/or legal department of an organisation. An example is *Available budget*. If no alternatives are found because of a commercial environmental characteristic, the business and/or legal department can be asked for more flexibility in the budget.

ii) Classification in relevance to machine vision: will help in determining the scope of the knowledge base and the tool. The knowledge base and the tool envy to support an engineering problem and those problems are often extremely complex. Most of the time, many experts and engineers are involved and different prototypes have to be tested before a suitable solution is found. Since this method focusses on providing a knowledge base and tool that aid decision-makers during the design of a machine vision system, it is advised to focus more on environmental characteristics related to machine vision systems. This increased focus can be put into practice by only processing the environmental characteristics that are unique to machine vision systems. Processing environmental characteristics means that the inputs describing these environmental characteristics are used to create output that is not equal to the input anymore (i.e. links are made for these environmental characteristics in phase V). One could also say that knowledge is used to convert observations into system requirements, which is work that is normally done by an engineer. Inputs to environmental characteristics that are less specific to machine vision systems, are forwarded to the output. For those environmental characteristics the output will be equal to the input, allowing them to be interpreted by an expert on the topic they are related to. This expert can then advise on system requirements.

4.6. Phase V: Link

In phase V (Link), the linkages between the environmental characteristics and the machine vision equipment they influence should be described, so the effect of a change in the environmental characteristic on the equipment is understood. To understand what equipment is needed, inspiration should be taken from the framework that will be the result of phase I (Understand), but also by looking at the environmental characteristics that were classified as influential to machine vision systems and the types of equipment they influence. The linkages between environmental characteristics and equipment can be described by formulas or databases, both based on the theory describing the interactions.

4.7. Phase VI: Build

During phase VI (Build), all knowledge obtained in the previous steps should be processed into a tool that is accessible by decision-makers, so they only have to use this tool when willing to make decisions. Since the tool has to process a lot of information, it is advised to build the tool in a digital way using software that can perform calculations, allow users to enter input and show output in an insightful way.

The tool should guide the decision-maker, to make decisions regarding all environmental characteristics and then show them what kind of specifications for machine vision systems this results in.

Also, the tool should be able to deal with uncertainty regarding values for some environmental characteristics as sometimes some situations might not yet be known in advance. Decision-makers can be aided in this by marking the outputs that are affected by the uncertainty in the inputs. The decision-makers are then noted what specifications might change or where there was uncertainty about so they can take this into consideration when making decisions regarding the equipment. If they do not feel comfortable predicting the consequences of the uncertainty themselves, they can take the output to machine vision experts or suppliers and discuss the uncertainty. In addition, decision-makers can be advised on the most robust value for a certain environmental characteristic. The most robust value is then defined as the value for which the solution will for sure fulfill the requirements, but maybe not in the most optimal way. For example, if a decision-maker is unsure about the available space, it is advised to enter the smallest expected value, the result is that a smaller camera and lens are advised which may be more expenisive, but may for sure fit. Also, if the space seems to be bigger in the end.

4.8. Phase VII: Evaluate

Finally, in phase VII (Evaluate), the obtained knowledge base and created tool should be evaluated by practitioners to obtain feedback on whether all relevant linkages are made and whether the tool (and thus the knowledge base) is complete. Based on the feedback that is gained, improvements should be made. The seven phases are to be repeated until no new feedback is mentioned during discussions with practitioners.

4.9. Discussion

When studying the designed method, one could argue that the same method can also be used to develop a tool that supports decision-makers during the design of systems containing other technologies than machine vision. In more general terms, one could say that the method develops a tool that supports decision-makers during the design of systems that need to acquire data of their surroundings and thereafter process this data. For machine vision the data that is to be acquired are images and this is done by means of the camera as the sensor. Examples for other systems could be Radio-frequency identification (RFID) tags that are to be scanned by RFID readers (Kour et al., 2014) or the detection of vibrations by using accelerometers (Soto-Ocampo et al., 2020). In all cases it is about designing a data acquisition system. This generality of the method also supports that the method can be used for other purposes than designing a system for quality control.

5

Knowledge base and tool for supporting decision-makers in the design of a machine vision system: A use case at Volvo Cars

To demonstrate the effectiveness of the designed method as discussed in the previous chapter and represented by Figure 4.1, the method was applied to a use case. The use case selected was the vision system design for quality control purposes in a manufacturing environment at Volvo Cars. Volvo Cars is a major global car manufacturer headquartered in Gothenburg (Sweden) that sold over 700,000 cars in 2023 and has production locations in different countries on different continents (Volvo Car Corporation, 2024). Like many companies in the automotive industry, Volvo Cars strives towards, among others, efficient manufacturing processes. To achieve this, it is necessary to reduce waste in all parts of the processes. In many processes, quality assurance is done manually or by sample control. In order to decrease waste, new technology using vision systems and AI can be used to do the quality inspection more efficient and both avoid uncertainties with manual inspection as well as increase the quantity of inspected parts. The design of these vision systems can be done in-house.

Section 5.1 will describe the creation of the knowledge base needed to support decision-makers in the design of machine vision systems. An interesting finding, is that this knowledge base can be considered as independent to the use case. It can be useful to other automotive companies and maybe any other industries (when minor adjustments are made) as well (more details to be provided in the specific section). Section 5.2 will describe the creation of the tool that is based on the knowledge base.

5.1. Creation of the knowledge base

For the creation of the knowledge base, phase I, II, III, IV and V were executed at Volvo Cars. It is not unthinkable that the resulting knowledge base is generalizable to other manufacturing environments.

5.1.1. Execution phase I: Understand

During the execution of phase I (Understand), the literature search strategy as presented in section 4.2 (see Figure 4.2) was executed. Details on this execution can be found in a separate report (see appendix A). The resulting framework for machine vision system design is presented in Figure 5.1. From this framework it can be understood that there is machine vision equipment related to every task of machine vision systems (e.g. lighting equipment is related to image acquisition and classification algorithms to classification) and that different environmental characteristics determine what technology is needed to perform the specific task. E.g. when an object is moving at a high speed, a higher frame rate is required to obtain an image without motion blur if all other settings remain the same.

5.1.2. Execution phase II: Identify

During the execution of phase II (Identify), 20 different experts employed at Volvo Cars were interviewed on their experiences with machine vision systems. The interviewees were selected according to the guidelines as presented in section 4.2. Some job titles of the interviewees were Technical expert, Shop engineering manager, Process strategy engineer, Equipment engineer. Also, the interviewees were spread over multiple locations of Volvo Cars (Belgium, China and Sweden) and they were all involved in different processes of the manufacturing stage (body shop, paint shop and final assembly). The questions the interviewees were asked were equal to the ones as presented in section 4.2.

After processing the interviews, the 57 environmental characteristics as presented in the list underneath were defined and they are considered to be part of the knowledge base. Please find more details on the environmental characteristics in appendix B.

- Ability to test
- Ability to test (money)
- Ability to test (time)
- Acquisition time
- Availability of training images
- Availability of training parts
- Available height
- Available length
- Available width
- Classification type
- Connectivity
- Connectivity (hardware)
- Connectivity (wireless)
- Contrast
- Contrast consistency
- Cybersecurity
- Data processing
- Data storage
- Decision time
- Dependency on supplier during implementation
- Dependency on supplier during operation
- Environment dust
- Environment explosiveness
- Environment humidity
- Environment temperature max

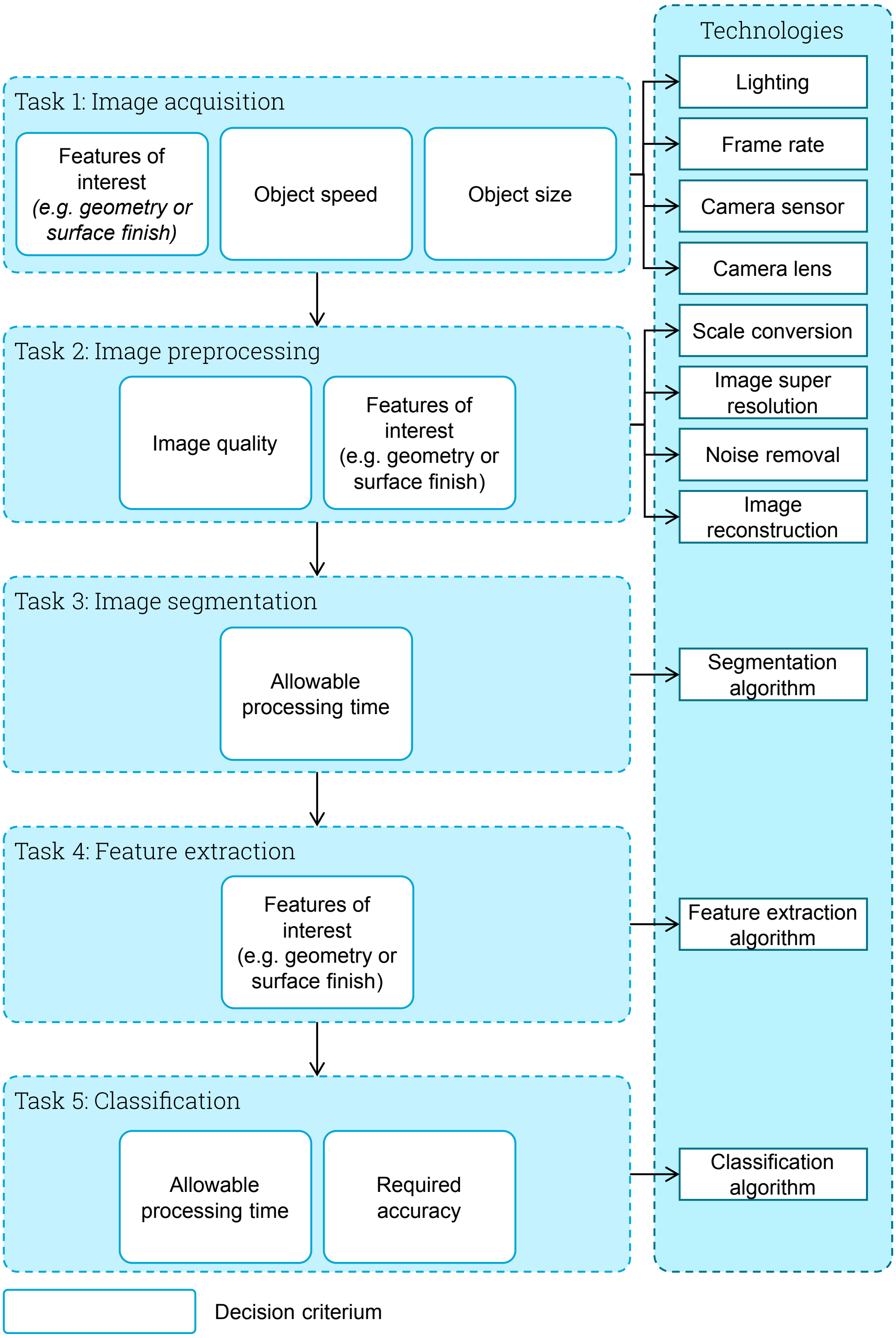


Figure 5.1: Initial framework for machine vision system design

- Environment temperature min
- Environmental light
- Environmental light direction
- Environmental light stability
- Feature size
- Features of interest
- FOV height
- FOV width
- Frequency power grid
- Implementation costs of the solution
- Implementation time
- Installation hours required
- Line of sight
- Machining environment
- Maintenance requirements
- Maximum distance to object
- Method of report generation
- Minimum distance to object
- Object position
- Object-camera speed
- Operational costs of the solution
- Personal safety
- Product variety
- Receive info via XPS
- Required accuracy
- Send info via XPS
- Signaling method
- Space restrictions
- Surface finish
- Sustainability
- System flexibility
- Worldwide implementation

5.1.3. Execution phase III: Map

For phase III (Map) the 57 identified characteristics were mapped into the structure as presented by Figure 5.2. Please see appendix C for an overview of which characteristics belong to which level of the hierarchy. By asking the decision-maker the questions written in red across the branches, it can be determined if the environmental characteristics in that branch are still relevant to the situation the decision-maker is facing. If not, decisions regarding those criteria do not have to be made any more.

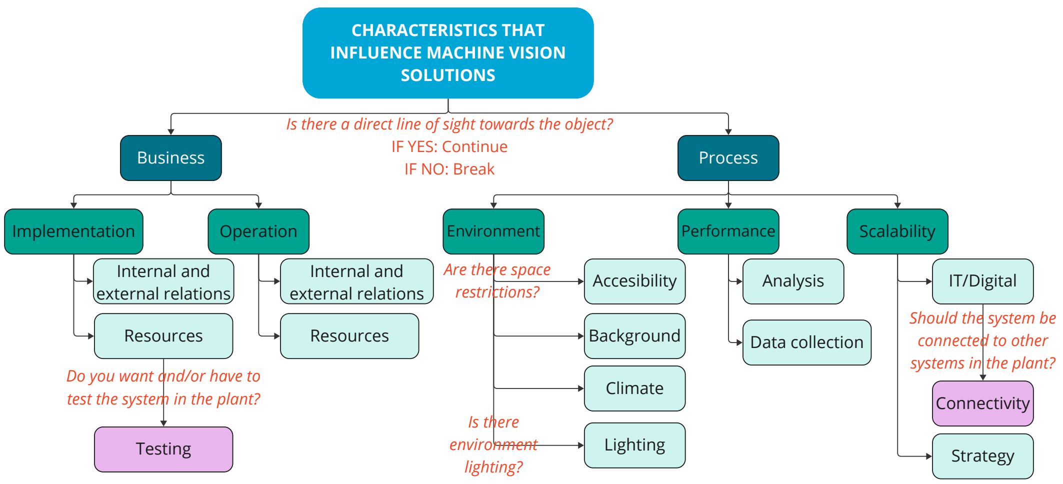


Figure 5.2: Hierarchy of identified characteristics

Table 5.1: Classification of environmental characteristics in domains

PHYSICS	ENGINEERING	COMMERCIAL
Available height	Acquisition time	Ability to test
Available length	Connectivity	Ability to test (money)
Available width	Connectivity (hardware)	Ability to test (time)
Classification type	Connectivity (wireless)	Availability of training images
Contrast	Cybersecurity	Availability of training parts
Contrast consistency	Data processing	Dependency on supplier during implementation
Environmental light	Data storage	Dependency on supplier during operation
Environmental light direction	Decision time	Implementation costs of the solution
Environmental light stability	Environment dust	Implementation time
Feature size	Environment explosiveness	Installation hours required
Features of interest	Environment humidity	Maintenance requirements
FOV height	Environment temperature max	Operational costs of the solution
FOV width	Environment temperature min	Sustainability
Frequency power grid	Method of report generation	System flexibility
Machining environment	Personal safety	Worldwide implementation
Maximum distance to object	Receive info via XPS	
Minimum distance to object	Send info via XPS	
Object position	Signaling method	
Object-camera speed		
Product variety		
Required accuracy		
Space restrictions		
Surface finish		

5.1.4. Execution phase IV: Classify

During phase IV (Classify), the 56 characteristics that remain after removing the requirement characteristic (*Line of sight*) were classified according to the classification method as proposed in section 4.4.

For the first method of classification, classification in domains, the 56 characteristics were defined into the three categories as suggested. 23 characteristics were appointed to the physics domain, 18 characteristics to the engineering domain and 15 to the commercial domain.Table 5.1 shows the three domains and the environmental characteristics they contain after the classification.

For the second method of classification, classification in relevance to machine vision, 27 characteristics were classified as specifically relevant to machine vision systems: *Availability of training images*, *Available height*, *Available length*, *Available width*, *Contrast*, *Contrast consistency*, *Environment dust*, *Environment humidity*, *Environment temperature max*, *Environment temperature min*, *Environmental light*, *Environmental light direction*, *Environmental light stability*, *Feature size*, *Features of interest*, *FOV height*, *FOV width*, *Frequency power grid*, *Line of sight*, *Machining environment*, *Maximum distance to object*, *Minimum distance to object*, *Object position*, *Object-camera speed*, *Product variety*, *Space restrictions* and *Surface finish*. The reason for this classification is the scoping of the knowledge base.

Environmental characteristics that are only relevant to machine vision equipment will be studied in more detail on their influence to the necessary equipment. Performing an in-depth study for all environmental characteristics was infeasible due to time limitations. The characteristics that are only relevant to machine vision were chosen as machine vision is the main topic of this research. When there is more time available, also links regarding environmental characteristics that are not specific to machine vision can be investigated.

5.1.5. Execution phase V: Link

In phase V (Link), links for environmental characteristics that are specific to machine vision that were classified as such in the previous phase are created. A link is the connection between an environmental characteristic and the relevant machine vision equipment specification. Links are based on knowledge captured in literature, formulas, databases and experiences. The different links formed can be grouped by type of equipment they influence. In the knowledge base as introduced in this report, four groups are defined: links to the camera and lens specifications, links to the lighting specifications, links to the algorithm specifications and links to all equipment.

Links to the camera and lens specifications

The links between machine vision specific environmental characteristics and specifications of cameras and lenses are displayed by Figure 5.3.

The first link that can be identified is the link between the dimensions of the camera and lens and the available height, length, and width and whether there are space restrictions or not. If there are no space restrictions, the decision-maker does not have to decide on the available height, length and width. If there are space restrictions, the combined outer dimensions of the camera and lens must be smaller than the height, length and width of the location where the camera is to be placed. Only dimensions of the camera and lens are targeted since it is assumed that other equipment needed for machine vision can be placed on any location and be connected using cables and/or using wireless communication.

A second link between the environmental characteristics and specifications of the camera and lens is the relation between the power grid frequency, the relative speed between the object and the camera and the frame rate of the camera. In order to make sure a moving object is properly captured, the camera should be taking images at a proper frame rate. The minimum required frame rate can be determined based on the research of (Bartosinski et al., 2012). The authors in (Bartosinski et al., 2012) have determined what frame rates are appropriate for acquiring images of objects at different speeds. When interpolating between these values, one can construct a table with the minimum required frame rate for a specific speed (see Table D.1 in appendix D). After the minimum frame rate is determined, it is important to take the frequency of the power grid into account. The frequency of the power grid is not visible to the naked eye, but might appear on camera footage if the frame rate is not chosen appropriately. The images will then display differences in illumination, called flickering. To prevent flickering a rule of thumb can be used which is: the number of light fluctuations should be a multiple of the frame rate (FLIR Systems Inc., 2024).

A third link between the environmental characteristics and specifications of camera and lens equipment is the relation between the features of interest, object-camera speed and the shutter type. A rolling shutter is a shutter that causes different rows or columns of the camera sensor to be exposed in sequence (Szeliski, 2022). This way of image capturing might cause distortions in the image when the object-camera speed is not equal to zero (Albl et al., 2020). For a global shutter, an entire image frame is captured at the same time (Fan et al., 2022). An advantage of rolling shutters are their low costs (Wang et al., 2024). Based on their characteristics, global shutters are advised for situations where the object-camera speed is not zero or when dimensions are to be measured. Rolling shutters are advised for static applications. Exceptions are to be made when sensors are available that use algorithms that correct for the distortions that are the effect of rolling shutters.

Fourth, a link between the object-camera speed and the sensor type can be determined. There are two types of sensors known: line scan sensors and area scan sensors. Line scan cameras capture a line of pixels (Szeliski, 2022). These lines are to be stitched together to achieve a 2D image. Area scan cameras capture a matrix of pixels (Szeliski, 2022). Line scan cameras can only be used if the object under study is moving (unless a line of pixels is wanted as an image). Area scan sensors can be used for both moving and non-moving objects.

A fifth link between environmental characteristics and specifications of the camera and lens is the feature type that is linked to the type of lens. There are different types of lenses available namely standard lenses, zoom lenses, wide-angle lenses, telecentric lenses, super zoom lenses and macro lenses (Szeliski, 2022). Telecentric lenses are advised when geometry as a feature is to be determined because of the constant magnification telecentric lenses provide (Szeliski, 2022; Williamson, 2018). The other lenses are suitable for other types of features. Telecentric lenses can of course be used for other feature types as well, however, telecentric lenses are mostly more expensive than standard lenses (Anand & Priya, 2020) and their unique ability is only useful for measuring.

A sixth link between characteristics and specifications of the camera and lens is the link between the maximum distance to the object, minimum distance to the object, the features of interest, the height of the field of view (FOV), the width of the FOV and the specifications of the camera lens. It is important that the entire FOV shows up on the camera sensor. A camera lens can make sure this happens if it has the right specifications for the situation. The first thing the lens should be able to do, is to magnify the real-world object to a size that fits the camera sensor. The extent to which a lens magnifies can be expressed by its magnification, which is defined as the size of the object in the image plane divided by the size of the real-world object (Anand & Priya, 2020). The magnification should be determined for all lenses. Then in case features other then dimensions are to be studied, the required lens focal length (for entocentric lenses) should be determined. The lens focal length is a specification of a lens and can be determined using the Gaussian Lens Formula when the usage of a thin lens is assumed (Hecht, 2017) (see section D.2 from appendix D for more details). If the focal length is calculated with help of the minimum distance the lens can have to the object, it is the minimum focal length. If the focal length is calculated with help of the maximum distance the lens can be away from the object, the maximum focal length will be calculated. For the machine vision system, the focal length can be between the minimum and maximum. It is important that the correct distance between the lens and the object is chosen for a specific focal length in order to have the highest magnification. This will namely benefit the resolution of the FOV.

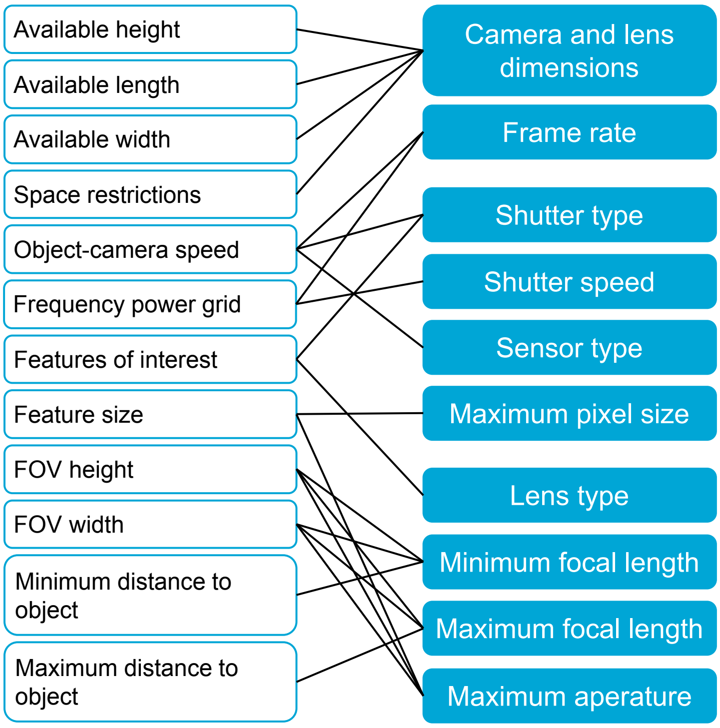


Figure 5.3: Links between environmental characteristics and camera and lens specifications

Seventh, a link between the feature size and the sensor pixel size of the camera can be identified. In order to be able to make sure a feature is well captured on the sensor, it should at least span three pixels on the sensor (Anand & Priya, 2020; West & Dechow, 2020). Otherwise there is the chance that a feature is missed.

Finally, the last link where the feature size is important is the link between the feature size and the camera lens aperture. In case the feature is very small, diffraction of the lens might start to play a role, causing the feature not to be visible in the image. The feature cannot be smaller than the Airy disk. According to Equation (5.1) the Airy disk is dependent on the lens aperture, and hence the link between feature size and the camera lens aperture. In this equation d_s is the Airy disk diameter, $f_{\#}$ the f-stop of the lens, λ the wave length of the light and M the magnification of the lens.

$$d_s = 2.44 f_{\#} \lambda \left(1 + M\right) \tag{5.1}$$

Next to the relations between the environmental characteristics and the specifications for camera equipment, there are also relations between the equipment specifications themselves. For machine vision systems it is important to understand that there is something called the 'exposure triangle'. The exposure triangle explains the relation between the ISO (equivalent to gain (Chin et al., 2003; Szeliski, 2022)), aperture and shutter speed settings of a camera (Gibson, 2014). Tuning those settings influences the amount of flickering on an image, but also the amount of motion blur on an image, the depth of field and the brightness of an image. The following guidelines explain the behaviour of the triangle and can be used by decision-makers designing an machine vision system:

- The higher the shutter speed, the less motion blur, but the darker the image and the higher the

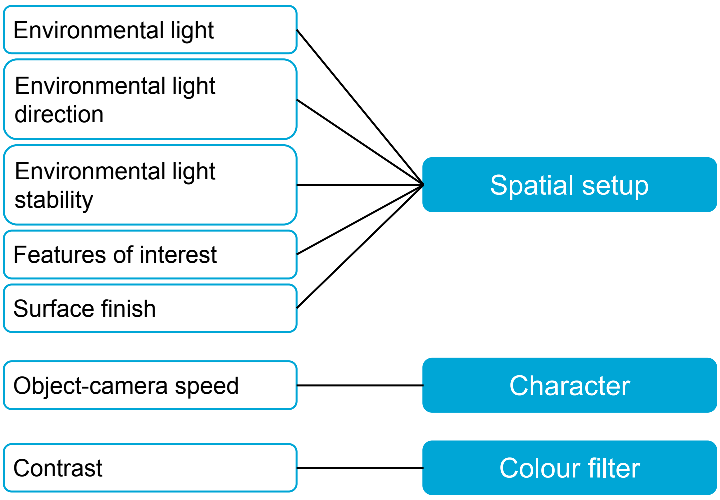


Figure 5.4: Links between environmental characteristics and lighting specifications

chance of flickering;

- The lower the aperture (the bigger the opening), the brighter the image, but the shallower the depth of field.

Links with the light

Links between the environmental characteristics and the specifications of the lighting equipment can be found in Figure 5.4. A first visible link is the link between the environmental light, environmental light direction, environmental light stability, features of interest and surface finish and the spatial setup. Due to the complexity of lighting and the dependency on experience, a database was created in which an advise on the spatial setup was linked to a certain combination of influential characteristics, as no single source providing advise for all situations was found. The advises in the database are based on combined sources (both literature and experience). Table D.2 in appendix D shows the database for lighting advises when environment is present. Table D.3 shows the database for lighting advises when no environmental light is present. Both databases provide an advise based on the environmental light, environmental light direction, features of interest and surface finish. If the environmental light is unstable an extra advise is provided that recommends the user to check if there is a possibility to block the changing lighting in case needed and to consult an expert. Unfortunately, it is very hard to predict the behaviour.

A second link between environmental characteristics and the lighting specifications is the link between the object-camera speed and the characteristic of the lighting. When a strobing strong light (flash) is used, the shutter speed can be increased, causing the motion blur in an image to decrease (Mirbod et al., 2021) which is necessary for fast moving objects.

A last link between the environmental characteristics and the lighting specifications is the link between the contrast between the feature of interest and the background and a colour filter on the lens or light. Colour filters or coloured lighting can enhance contrast by suppressing wavelengths of the light (Anand & Priya, 2020). It is advised to investigate the abilities of coloured light or colour filters to enhance the contrast in case it is low.

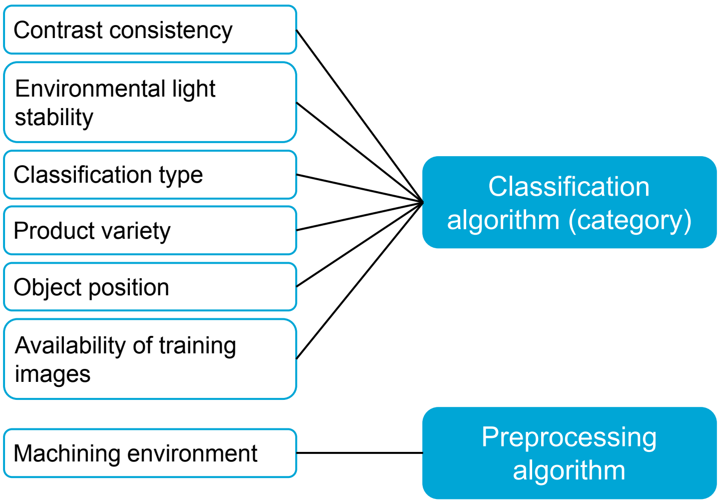


Figure 5.5: Links between environmental characteristics and algorithm specifications

Links to algorithms

Links between the environmental characteristics and the specifications of the algorithms can be found in Figure 5.5. The algorithms required for image processing of which the performance is influenced by the environmental characteristics are the algorithm for classification and the algorithm for image preprocessing. Algorithms for classification of machine vision images can be divided into two groups: algorithms without machine learning (ML) and algorithms with ML. Examples of algorithms without ML are pixel counting and edge detection. Algorithms with ML can be classified into four subcategories: Supervised, unsupervised, semi-supervised and reinforcement learning. Examples of algorithms with ML are Support vector machines (SVMs), Clustering and K-means (Szeliski, 2022).

A special group of machine learning algorithms is the group with algorithms that are based on deep learning. The major difference between classic machine learning algorithms and deep learning algorithms is the fine-tuning of model parameters. For classic machine learning algorithms, features are hand-crafted and not automatically tuned by the algorithm. For deep learning, model parameters are tuned by the algorithm. The algorithm tries to minimize the training loss (Szeliski, 2022).

The algorithms in the subcategories come in different variants, with their own pros and cons. An example is the SVM that can have different kernels and therewith have a different speed (Scikit-learn, 2024). Due to time limitations of this research, it was unfortunately not possible to get to understand the algorithms in such a way that one would be able to advise an specific algorithm for a specific case. This would require a lot of additional research, which was declared to be out of scope for this thesis. An attempt is however made to advise the decision-maker with a global idea about what algorithm to look out for. It is namely thought that one can differentiate the algorithms in cheaper/easier algorithms without machine learning and more expensive algorithms that contain machine learning and also deep learning. The first are more likely to be used for simpler, binary, classification problems whereas the second is more suited for more complex multi-class problems that require some form of recognition/human interpretation. An advice will be given to the decision-maker on which type of algorithm is probably best suited for the problem, based on four different self-defined classification algorithm categories (see

Table 5.2: Classification categories

CAT.	DESCRIPTION
D	Machine vision algorithm with no form of machine learning for binary classification (e.g. an algorithm based on pixel counting).
C	Machine vision algorithm with no form of machine learning for multi-class classification.
B	Machine vision algorithm with traditional machine learning methods for multi-class classification (e.g. SVM, Clustering, etc.)
A	Machine vision algorithm with deep machine learning methods (deep neural networks) for multi-class classification (e.g. ResNet, etc.)

Table 5.3: Algorithm category for every option

ENV. CHARACTERISTIC	OPTION	ADVISED CATEGORY
Contrast consistency	No	B
	Yes	D
Environmental light stability	Stable	D
	Varying	B
Classification type	Binary	D
	Multi-class	C
	Advanced multi-class	B
Product variety	No	D
	Yes	C
Object position	No	D
	Yes	B
Availability of training images	< 1000	A
	≥ 1000	B

Table 5.2).

Figure 5.5 shows that from the identified environmental characteristics, contrast consistency, environmental light stability, classification type, product variety, object position and availability of training images are of influence to the required classification algorithm (this is the first obseved link). For every environmental characteristic it is known what options the decision-maker is presented. For all options for all environmental characteristics, it is determined what category the classification algorithm required would belong to (see Table 5.3). The algorithm category advised to the decision-maker is than the highest required category.

A second link between the environmental characteristics and the algorithm specifications, is the link between the fact whether the solution is to be placed in a machining environment or not and the need for advanced image-enhancing algorithms. If the solution should operate in an area where there are liquids splatting or flakes flying around, there might be the need to remove those from the image to

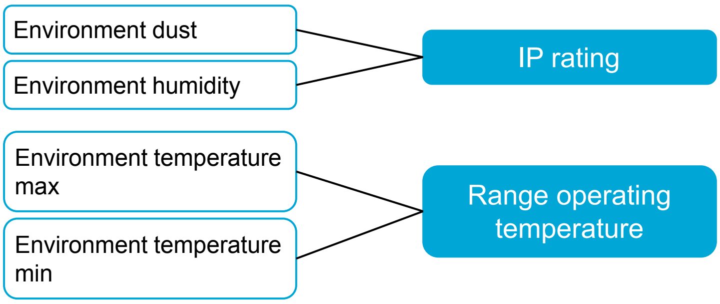


Figure 5.6: Links between environmental characteristics and general equipment specifications

enhance the results. This might be done by image-processing algorithms (Banda et al., 2022).

Links to all equipment

Finally, links between some environmental characteristics and specifications of all equipment can be established (see Figure 5.6). The first link, is the link between the environment dust, the environment humidity and the minimum ingress protection (IP) rating of the equipment that is going to be exposed to the environment that is described by the characteristics. For both the environment dust and the environment humidity, the decision-maker states what dust and water protection is required respectively, by selecting the corresponding numeral from the IP ratings guide that is based on IEC 60529 (International Electrotechnical Commission, 2024). Combining both numerals results in the minimum IP rating of the equipment.

Last, a link between the environmental characteristics and the specifications for all equipment is the relation between the maximum environment temperature, minimum environment temperature and the operating range of the equipment. The minimum environment temperature should be above the minimum operating temperature and the maximimum environment temperature should be below the maximum operating temperature.

5.1.6. Discussion creation of knowledge base

The knowledge base that has been created by executing phase I, II, III, IV and V from the method as depicted by Figure 4.1 can be considered an additional contribution to aid decision-makers in the decision-making process for the design of machine vision systems for quality control. The knowledge in the knowledge base could be used by a decision-maker in the way as it was presented in the previous sections. The decision-maker must then keep track of all links by itself and how they reflect to output on which the decision should be based. The knowledge base might be applicable to different industries then automotive as well due to the generality of machine vision systems. What might change for a different industry is the relevant environmental characteristics. If they change, the knowledge base has to be updated and new links and technologies might have to be identified. Vice versa, if a new technology arises, it should be checked how it relates to the environmental characteristics that are already identified plus it should be checked whether new environmental characteristics are important to the technology. The links in the toolbox might change as well for a different industry when databases change, or different insights regarding advises rise.

5.2. Creation of the tool

For the creation of the tool, phase VI and VII were executed at Volvo Cars as well.

5.2.1. Execution phase VI: Build

The knowledge collected in the knowledge base can be embedded into a tool in phase V, so decision-makers can interact with it. Since the tool has to process a lot of information, it is advised to build the tool in a digital way using software that can perform calculations, allow users to enter input and show output in an insightful way. The tool should guide the decision-maker, to make decisions regarding all environmental characteristics and then show them what kind of specifications for machine vision systems this results in.

The tool to help decision-makers in the decision-making process for this use case was build in Microsoft Excel. The reason for selecting Microsoft Excel as the program to build the tool in, is its capability to allow users to easily create a user interface in which information can be presented and handled as well as its capability to perform programming logic. Since the design of machine vision systems contains relatively less programming logic compared to reasoning, it was not considered beneficial to select for example a programming language like Python for creating a tool where the logic links could then automatically be created. As many links are based on a different logic that is created by reasoning, it would solely be beneficial to use a programming language if this reasoning can be automated as well. It could be argued that artificial intelligence is capable of taking care of this reasoning, however, studying these capabilities did not fit the scope of the research. Since automating reasoning was declared not feasible, the use of a programming language might even be of disadvantage since then both the programming logic and the user interface are to be captured in the programming languages syntax, which might make it more unclear in case the tool is to be altered. Microsoft Excel, provided a good combination of clear interface and capability of handling programming logic (by means of VBA) to be used for the tool.

Build-up of the tool

The tool consists of a back-end and front-end. In the back-end, all information regarding the important environmental characteristics and details for the processing of inputs is stored. The back-end is only to be accessed by engineers familiar with machine vision. Connections between the front- and back-end are made using Excel formulas, Excel Power Queries and Excel's programming language VBA.

The front end consists of six Excel-sheets which are used to collect information from the decision-maker. The first sheet named 'USER GUIDE' introduces the tool to the user and explains what the decision-maker needs to do in order to make use of the tool. The second sheet named 'INPUT 0 - Requirements', poses all requirements to the decision-maker (see section 5.1.3). Unless all requirements are fulfilled, the tool will not pose any more questions to the decision-maker since if not all requirements are met, the tool is not able to give a proper advice. As soon as all requirements are met, the decision-maker will be subjected to four new sheets: 'INPUT 1 - Physics', 'INPUT 2 - Engineering', 'INPUT 3 - Commercial' and 'OUTPUT'. The sheet 'INPUT 1 - Physics', will ask questions related to the environmental characteristics belonging to the physics domain, the sheet 'INPUT 2 - Engineering',

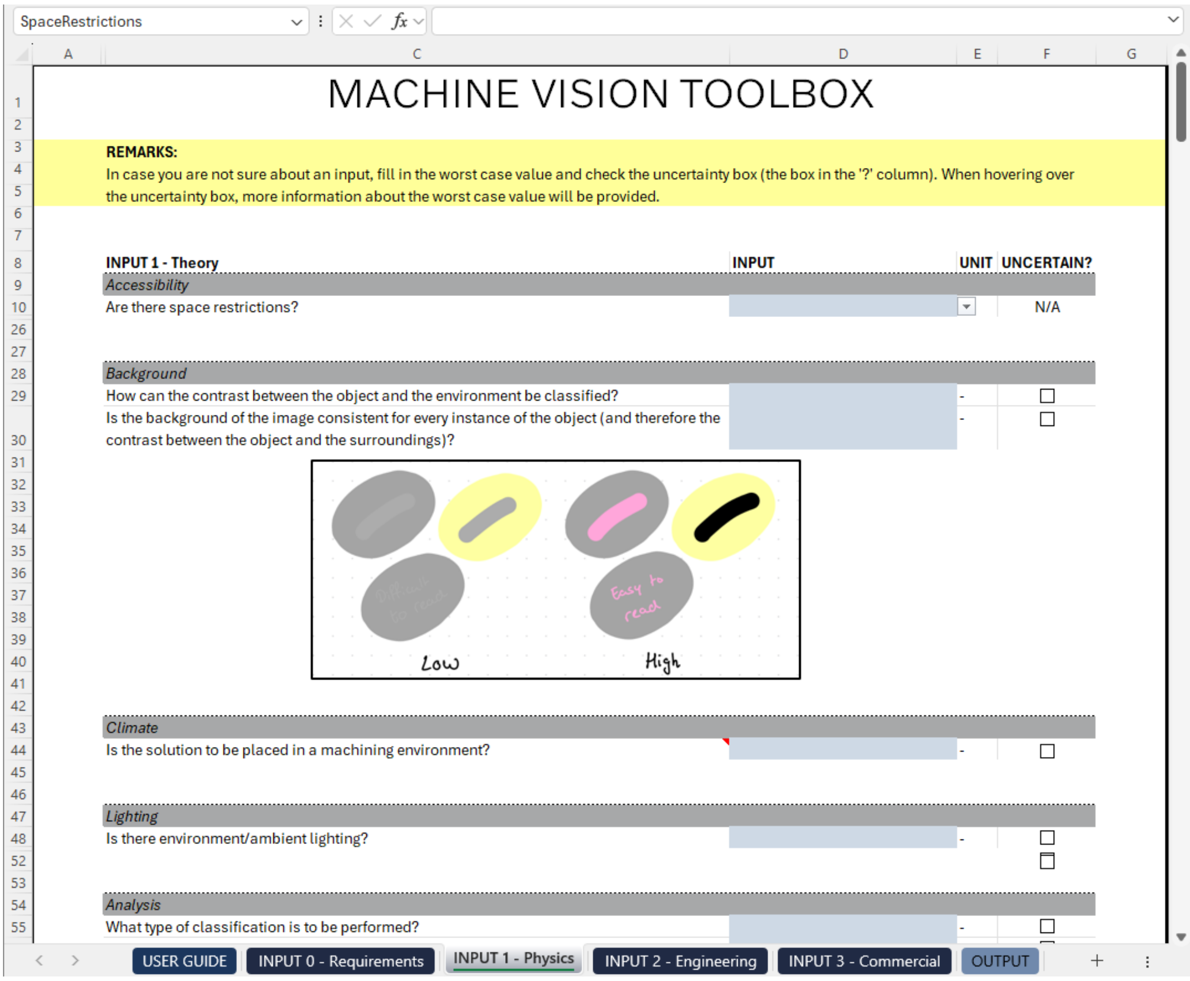


Figure 5.7: Impression of the developed tool in Microsoft Excel

will ask questions related to the environmental characteristics belonging to the Engineering domain and the sheet 'INPUT 3 - Commercial', will ask questions related to the environmental characteristics belonging to the Commercial domain. The final sheet that is part of the front end is the sheet named 'OUTPUT'. In this sheet, the decision-maker will be presented the advise as given by the tool in the form of a list of specifications for the machine vision equipment. Figure 5.7 gives an impression of the tool.

Decision traceability

The splitting of the environmental characteristics over the different sheets enables the decision traceability that was introduced in section 4.5. The decision-maker is able to see what characteristics influence what specification by means of the formula bar in Excel. In case there are no feasible alternatives, the decision-maker can study what environmental characteristics influence the specification that is limiting. The decision-maker can then see in what sheet, information about that environmental characteristic was asked by browsing through those sheets and clicking the different input fields. The decision-maker then knows where alterations are required in order to obtain feasible alternatives. To illustrate: if a decision-maker would be looking at the output as visible in Figure 5.8, but is not able to buy a camera lens that has a focal length between the 'f_min' and 'f_max' as indicated by the tool, then the decision-maker can select the cell that contains the output (in this case D44 is selected) and see that the output is dependent on cell C44 and `MinimumDistanceToObject`. `MinimumDistanceToObject` is an environmental characteristic from the physics domain. If cell C44 is studied in more detail by selecting it, it can be seen that it is dependent on `FOVWidth` and `FOVHeight`, which are both environmental characteristics from the physics domain as well. Since all dependent characteristics are from the physics domain, it can be concluded that no feasible solution can be found unless the actual physical situation is changed (in this case the FOV should be decreased or the working distance increased). Another example would be if no alternatives are available due to the minimum IP rating and the decision-maker finds that the environmental characteristics influencing the minimum IP rating (`EnvironmentDust` and `EnvironmentHumidity`) belong to the engineering domain. The decision-maker can then discuss with an engineering department if a box with the right IP rating can be designed so camera equipment with a lower IP rating can be used. Finally, to illustrate the decision traceability for the commercial domain, if data processing has to happen in the cloud and this leads to no feasible alternatives (since it is not allowed by company policy), the decision-maker can find out that this is due to an environmental characteristic (`DataProcessing`) in the commercial domain. The decision-maker can then reach out to the legal department of the company to better understand the issue and maybe discuss alternatives. Of course it might also be possible to talk to a (computer) engineering team, to see if a work around can be found. Environmental characteristics can overlap multiple domains. In the tool they are linked to the most relevant domain which most likely leads to the best solution.

An additional benefit of dividing the different domains over the different sheets is that it makes the tool more clear to the decision-maker.

Decision reduction

As becomes apparent in phase III (see section 4.4), some decisions are dependent on others and therefore cause decisions to be automatically made if a decision higher in the hierarchy is made. These dependencies are reflected in the toolbox by the conditional visibility of specific questions. Examples of these are the decisions that are to be made with respect to environment lighting. If there is no environment light present (related to the environmental characteristic 'Environmental light'), no decisions have to be made (and thus questions have to be asked) regarding the dependent environmental characteristics describing the direction of the environmental light ('Environmental light direction'), the characteristic of the environmental light ('Environmental light stability') and the frequency of the power grid ('Frequency power grid') as follows from the hierarchy as defined in Figure 5.2 (see Figure C.2 in appendix C for more details). The tool will therefore only show (ask) questions to obtain information regarding the dependent characteristics if, for this illustrative case, the answer to the question (branch question) 'Is there environment/ambient lighting?' is 'Yes' (see Figure 5.9a). If the answer is 'No', the questions for the dependent characteristics are not visible (see Figure 5.9b).

Uncertainty handling

In order to handle uncertainty in the inputs for the environmental characteristics, checkboxes were inserted next to every input field in the tool that can be checked by the decision-maker in case he/she is

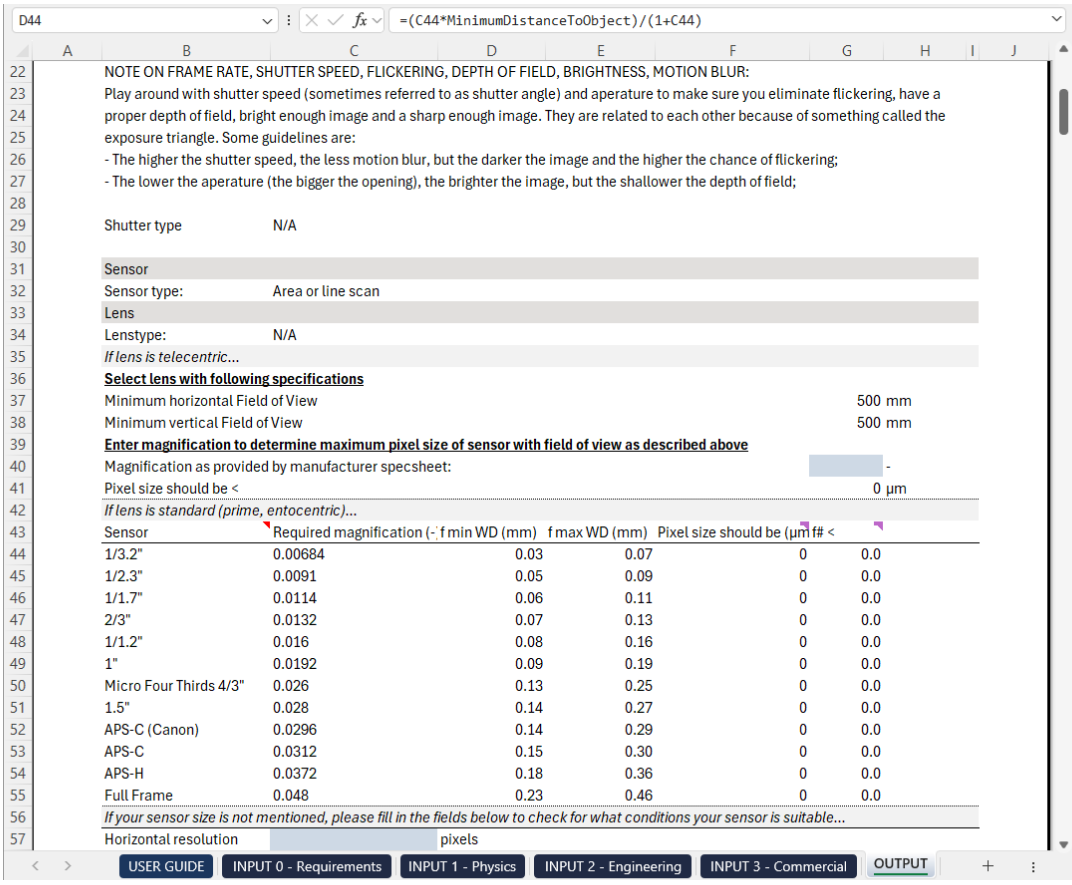
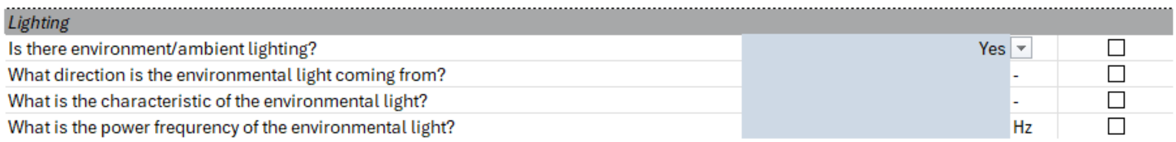


Figure 5.8: Snapshot output tool for illustration working principle of decision traceability

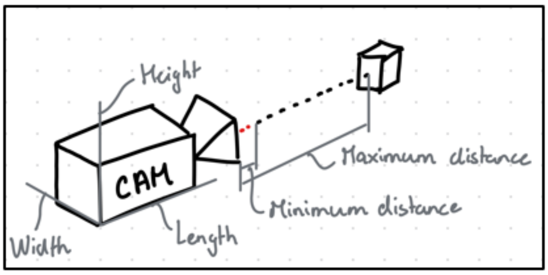


(a) When the answer to the branch question is 'Yes'

(b) When the answer to the branch question is 'No'

Figure 5.9: Snapshot input tool for illustration working principle of decision reduction

INPUT 1 - Physics	INPUT	UNIT	UNCERTAIN?
Accessibility			
Are there space restrictions?	Yes	-	N/A
What is the height of the available space where the camera equipment can be placed?	200	mm	☑
What is the length of the available space where the camera equipment can be placed?	200	mm	☑
What is the width of the available space where the camera equipment can be placed?	200	mm	☐
What is the maximum distance you can place a camera at compared to the object (maximum working distance)?	600	mm	☐
What is the minimum distance you can place a camera at compared to the object (minimum working distance)?	250	mm	☐



(a) Input with ability to check uncertainty boxes

DIMENSIONS		
Maximum height	200 mm	!
Maximum length	200 mm	!
Maximum width	200 mm	

(b) Output when uncertainty boxes are checked

Figure 5.10: Snapshots showcasing uncertainty handling features

uncertain about the entered value for that specific characteristic (see Figure 5.10a). When the checkbox of a specific environmental characteristic is checked, the output that is related to that characteristic will be written in red on the sheet 'OUTPUT' and if possible a red exclamation mark will be added to alert the reader of the output (see Figure 5.10b). In addition, if possible, the decision-maker will be advised on a value that would give the most robust result in the output.

5.2.2. Execution phase VII: Evaluate

Finally, in phase VII, the obtained knowledge and created tool were evaluated by practitioners and the obtained feedback was processed. The tool was evaluated by some of the employees that had been interviewed during phase I, but also with an employee that was responsible for the development of new vision systems and that was in direct contact with suppliers.

5.2.3. Discussion creation of the tool

The tool that has been created by executing phase VI and VII from the method as depicted by Figure 4.1 can be considered the last contribution of this research to aid decision-makers in the decision-making process for the design of machine vision systems for quality control. The tool was designed based on the use case at Volvo Cars, but is applicable to any manufacturing site from an automotive company as they are ought to be very similar. It is also expected that the tool could be beneficial to other industries for the same reasons as why the knowledge base could be beneficial to other industries: the generality of machine vision systems. What might again change for a different industry is the relevant environmental characteristics. It will change the knowledge base and when the knowledge base is changed, the tool should be updated as well.

6

Validation of the method

In order to validate the designed method as presented in chapter 4, the tool that is the result of the method and presented in section 5.2 was tested on two machine vision systems at Volvo Cars. The machine vision systems are systems that are already in place and have proven to work. They can thus be seen as alternatives in the decision making process as represented by Figure 2.1. As the machine vision systems in place are considered as alternatives, the tool should advise them as an alternative as well if it wants to aid decision-makers during the decision-making process. To test whether the tool would provide the existing machine vision systems as alternatives in the decision-making process as well, the tool was fed with information about the environment the existing machine vision system was operating in (as if there was a new system to be designed). The output of the tool was then contrasted to the existing system to see if the existing system was also sugessted by the tool. This would prove the validity of the tool. Since the tool is based on the knowledge base, the knowledge base is validated at the same time.

In the remainder of this chapter, two cases for validation will be presented. Section 6.1 will validate the tool with help of the *Collared hole system* as present in one of the stamping facilities of Volvo Cars and section 6.2 will validate the tool with help of the *Tread plate detection system* as present in one of the final assembly lines of Volvo Cars.

6.1. Validation on the Collared hole system

The *Collared hole system* is a vision system that checks whether a certain body part contains a defect free collared hole or not. A defect in this case is a missing collar or a partially complete collar. The system is already in place and well-functioning.

The tool that was derived from the method as introduced in chapter 4 was filled in by a Technical expert that was involved in the installation of the system. Completing the questions asked by the tool took just under one hour. Based on the input, the tool recommended the specifications for a

Table 6.1: Comparison collared hole system

SPECIFICATION	TOOL	MVS
Camera and lens		
Frame rate	25, 50 or 100 fps	25 fps
Sensor type	Area scan	Area scan
Lens type	Standard, zoom, wide-angle, super-zoom or macro	Zoom lens
Focal length	1.37 - 13.68 mm	2.7 - 13.5 mm
Pixel size	< 24 µm	≈ 1.02 µm
Lighting		
Spatial setup	No additional lighting is required, unless unfavourable shadows appear. In that case install dome lighting to avoid shadows.	No additional lights installed
Colour filter	Not required	No filter installed
Software		
Algorithm for classification	Category A	Category A
Algorithm for pre-processing	Not required	Not used

machine vision system that is to be designed as shown in the second column ('Tool') in Table 6.1. The specifications of the actual machine vision system in place are also presented in Table 6.1 (see column 'MVS'). When comparing the advised specifications and the true specifications, we see that the specifications from the true system are within the windows as advised by the tool. When one for example studies focal length, it can be seen that the tool recommends a focal length between 1.37 mm (if the minimum working distance is required) and 13.68 mm (if the maximum working distance is required). The camera from the true system has a focal length that can be set between 2.7 mm and 13.5 mm. These ranges overlap and therefore the true camera matches the advice. Furthermore, the advised algorithm is an algorithm of category A which matches the category in which the used algorithm falls. The overlapping of the specifications as advised by the tool and the specifications of the actual system in place together with the fact that completing the tool took under one hour, proves that the tool is providing valid alternatives in a shorter time than when no tool was used (determination of specifications might take hours up till days) and therefore it can be said that the tool following from the method is aiding decision-makers in the decision-making process..

6.2. Validation on Tread plate detection system

The *Tread plate detection system* is a vision system that checks whether the correct tread plate is mounted on a car body or not. An instance is classified as a defect in case a wrong tread plate is assembled or when a tread plate is assembled where it should not or vice versa. As for the *Collared hole system*, this system is also already in place and well-functioning so the strength of the designed method can again be demonstrated by applying the method as if the system was not there yet.

For this use case, the tool was filled in by multiple experts that were involved in the installation of the system. When comparing the advised specifications and the true specifications, we see that the the advised frame rate differs from the true frame rate. As explained in the tool, the determination of the required frame rate is very difficult and might differ from this advise if other settings (like shutter speed and aperture) are tweaked, other frame rates than the advised are not immediately classified as infeasible. For this use case the camera is use to take photos when a new instance is presented. In this case shutter speed is more important than frame rate. When looking at the advise on the sensor type and the lens type, it can be concluded that they match the true system. For the focal length, it can be seen that the tool does provide a different advise compared to the true system. The reason for this, is that the tool assumes that the FOV of interest should fully cover the sensor, which is not the case for the true system. There the FOV of the camera is much bigger than the FOV of interest. Following, the advise on the pixel size matches the true system. The maximum advised pixel size could be considered very large. The reason for this is the large feature size and the big sensor. Next, when studying the advises for the lighting, it can be concluded that they match the true system. For the algorithm advises, it can be concluded that the toolbox advises a lower category algorithm. The input causing this discrepancy is the amount of available training images. When there are less then a thousand training images, an algorithm of category A is advised, if there are a thousand training images or more, a category B algorithm is advised. This threshold of thousand images was rather arbitrarily chosen. The advise of the preprocessing matches the true system. It can be concluded that the toolbox gives a different advise that does not match the true system. However, the differences can be explained by the way in which the camera in this use case is used, more to take pictures than to create a moving feed.

6.3. Comparison of decision-making processes

From the use cases it can be concluded that when using the tool in the decision-making process, the process is changed. The use of the tool allows the decision-maker to perform step two and three in approximately one hour if the decision-maker is well aware of the situation the machine vision system is to be placed in. Weeks of time might be saved by indicating to the decision-maker where information is to be acquired about. Step four is partially supported by providing information on the domain the environmental characteristic that is reducing the amount of alternatives to zero is part of. This change in the process has the potential to drastically reduce the time required to complete the entire decision-making process for machine vision system design. Combined with the fact that the tool does not require additional decision-makers to be involved compared to the amount of decision-makers needed in the

Table 6.2: Comparison tread plate assembly system

SPECIFICATION	TOOL	MVS
Camera and lens		
Frame rate	25, 50 or 100 fps	No continuous feed
Sensor type	Area scan	Area scan
Lens type	Standard, zoom, wide-angle, super-zoom or macro	Standard lens
Focal length	23.62 - 47.24 mm	4.74 mm
Pixel size	< 1600 µm	0.8 µm
Lighting		
Spatial setup	No additional lighting is required, unless unfavourable shadows appear. In that case install dome lighting to avoid shadows.	No additional lights installed
Colour filter	Not required	No filter installed
Software		
Algorithm for classification	Category B	ResNet50 - Category A
Algorithm for pre-processing	Not required	Not used

decision-making process where the tool is not used, the tool is a valuable asset for increasing the efficiency of the decision-making process.

7

Discussion

The goal of this thesis was to answer how decision-makers could be guided in the process of designing a machine vision system for quality control. In this chapter first a summary of the performed work to answer this question is given in section 7.1. Thereafter, the implications of the research will be addressed in section 7.2. Following, in section 7.3, the implications of the research will be highlighted. Next, section 7.4 will discuss all limitations of the research and how they should be put in perspective. Finally, section 7.5 will conclude this chapter with recommendations for future work.

7.1. Summary

As introduced, there is a demand for increasing the efficiency of the decision-making process for the design of machine vision systems for quality control in the manufacturing industry. This efficiency can be increased by aiding the decision-makers during step two, three and four of the decision-making process for machine vision system design. To support decision-makers during these steps, a method was developed with help of Design Science Research. From this research methodology, a method resulted that assists decision-makers during step two, three and four of the decision making process. The method consists of 7 phases: Understand, Identify, Map, Classify, Link, Build and Evaluate. The first five phases generate a so called knowledge base, which is a collection of information that already supports decision-makers during the decision-making process. The last two phases lead to a tool that allow decision-makers to more easily interact with this knowledge base. During the first phase (Understand), an understanding of machine vision systems should be developed by conducting a literature review following a pre-specified search strategy. During the second phase (Identify), industry specific influential environmental characteristics should be identified by interviewing practitioners, to understand what aspects of the manufacturing system are relevant to the design of machine vision systems considering a particular industry. For the third phase (Map), the identified environmental characteristics should be structured in a hierarchy to identify the space of possible decision-making choices and the internal relations it contains. For the fourth phase (Classify), the identified influential environmental characteristics should be classified based on the domain they belong to (to allow for root cause analyses) and based on their relevance to machine vision (to scope the method). In the fifth phase (Link), the links between the environmental characteristics and the specifications of machine vision equipment they influence should be described, so the effect of a change in the environmental characteristic on the equipment is understood. During the sixth phase (Build), all knowledge obtained in the previous steps should be processed into a tool that is accessible by decision-makers, so they only have to use this tool when willing to make decisions. Finally, in the last and seventh phase (Evaluate), the obtained knowledge and created tool should be evaluated by practitioners to obtain feedback on whether all relevant linkages are made and whether the tool is complete. Based on the feedback that is gained, improvements should be made in the knowledge base after which the tool should be updated again. The seven phases are to be repeated until no new feedback is mentioned during discussions with practitioners. As prescribed by Design Science Research, the developed method was demonstrated by applying it to a use case at Volvo Cars. The application led to a knowledge base and tool that were able to support decision-makers during the decision-making process for the design of a machine vision system. From the evaluation, it followed that decision-makers were supported and that the efficiency of the decision-making process was increased as the required time needed to fulfil a decision-making process was decreased while not changing other parameters than adding the support to step two, three and four. The method was documented in this report and the tool that was created with help of the method was presented to industry stakeholders.

7.2. Interpretations

With the development of the method, decision-makers are now aided during the decision-making process for the design of machine vision systems and the efficiency of these processes is increased. Less time is required to determine what information is relevant to the decision-making process and decision-makers are assisted in how to use the information. It also allows decision-makers that are no experts in machine vision to make decisions regarding the design of machine vision systems.

7.3. Implications

The research was performed for the automotive industry, but it can be said that the methodology extends to other industries as well due to its generality. This generality is mainly covered by the expert interviews, as they make sure industry specific environmental characteristics are highlighted. Besides its usefulness in different industries, it can also be argued that the method can be applied to other environments than manufacturing or functions like quality control. The method mainly describes how the decision-making process for a machine vision system can be aided and it can be said that this is independent of the purpose of a machine vision system. Also, one could say that the method aids the decision-making in the design process for other technologies like RFID or wireless communication. As long as the method is followed, relevant decision criteria should always come forward.

Regarding the knowledge base, it can be said that this can be relevant to other industries than automotive as well as to industries other than manufacturing and quality control. Especially the environmental characteristics in the physics domain will be relevant to every use case, because it describes the interaction of machine vision systems with its environment. As the tool is fully dependent on the knowledge base, the tool will also be valuable to other industries than automotive and for designing systems with an other purpose than quality control

7.4. Limitations

Both the method, the knowledge base and tool show limitations.

7.4.1. Limitations to the method

The first limitation is the assumption that the decision-making process as presented in Figure 2.1 properly reflects the true decision-making process a decision-maker has to go through when designing a machine vision system. The presented decision-making was based on observations from industry. This can be regarded as a limitation in case the decision-making process goes different. The methodology was designed for this decision-making process, so if the process differs, a different methodology might be required. It is however expected that many decision-making processes are according to the process as depicted by Figure 2.1.

The second limitation is that it is assumed that the knowledge base and the tool that are the result of the method are to be used by a human decision-maker. This implies that knowledge in the knowledge-base and the tool should be interpretable by a human, but also that parts of the knowledge base and the tool might be interpreted in a different way by different humans. Also, different humans might have different initial understanding of machine vision which might lead to them using the knowledge base and the tool in different ways. The method was designed in such a way that the knowledge base and the tool it results in, provide support to a decision-maker with no initial understanding of machine vision.

A third limitation of the method is that it makes use of human judgement in all phases to create the knowledge base and the tool, respectively. For phase I (Understand) a human needs to conduct literature search, which is prone to failure. During phase II (Identify), a human interviewer interviews a human interviewee. Both might influence the interview in such a way that important environmental characteristics are made. To solve this, multiple feedback loops are advised. For phase III (Map) and phase IV (Classify), certain relations might be overlooked because of human judgement or environmental characteristics may be classified to the wrong group. It is however not considered to be causing major issues as the environmental characteristic will still be used to advise on a proper system, the tool might only be less efficient compared to how it could be if the mapping and classification was perfectly performed. For phase V (Link), the method relies on its human developer that it understands how the links work. It is important that the developer knows how to construct the links. During phase VI (Build), the human judgement might cause different versions of the tool with different efficiencies, but the end result should be the same for all as the content of the tool is determined in the knowledge base. During the final phase (Evaluate), feedback might be missed or wrongly interpreted and therefore not reflected in the knowledge base and/or tool. Making as much feedback loops as possible aims to minimize this influence of human judgement.

7.4.2. Limitations to the knowledge base

A first limitation is the use of bins for obtaining input on some of the environmental characteristics. An example of such bins are shiny, matte and transparent which are the options a decision-maker has to choose from when it is to provide input on the surface finish of the object under study (one of the environmental characteristics). It is highly likely that different decision-makers will classify the exact same object in different bins as the bins require a form of personal judgement. For future work it is recommended to see if measurable numbers can be linked to the categories to remove human judgement. This was not done yet due to time limitations as this is just one example. Bins are used for obtaining input on other environmental characteristics as well and it was infeasible to study all of them in detail. Also because the knowledge they require is quite broad (surface finish of products versus handling of digital data).

A second limitation is the value of the advice on what classification algorithms to use. The advice can be considered as quite blunt and the categories that are suggested are quite broad. The reason for this is that the field of classification algorithms is very complex especially when both regular machine vision algorithms and machine vision algorithms containing machine learning are considered. It is very hard to advise a specific algorithm as this requires a lot of specialist knowledge. Also, the selection of an algorithm often requires testing as well, because it is hard to predict how an algorithm will perform. An advise on the type of algorithm is however given, to make the decision-maker think about the relevance of the algorithm and it is believed that for most situations at least a distinction can be made whether one needs machine learning or not.

A third limitation of the methodology is that it will only assist in the decision-making process for machine vision systems that contain one camera only. Advising on multiple cameras would increase the complexity of the method as there are endless possibilities to deal with multiple cameras. Lets say you want to image a cube with one camera. In that case you need multiple camera angles to study all faces. You can have one camera for every face of the cube (six in total), or two for aiming at the opposite corners, or just one when you mount the camera on a robot arm that circles around the object. As illustrated, there are many options for just a cube already. It depends on an engineering team how the issue is tackled. It was thought that advising on the amount of cameras would be of no added value unless much information about the surroundings was obtained to provide a tailored advise.

A fourth limitation of the designed method is the requirement of having a direct line of sight towards the object that should be checked using machine vision. Posing this requirement excludes technologies like X-ray imaging and thermal-imaging.

A final limitation is that the assumption is made that the thin lens approximation results in a proper estimation of the true lens-light interaction. The using the thin lens approximation allows for the use of the Gaussian lens formula (Hecht, 2017). If the lens of the camera is thick, these formula would lead to a wrong advise.

7.4.3. Limitations to the tool

A limitation of the tool is that human bias seeps through the designed tool. It was found that some questions from the tool (which are based upon the knowledge base) were interpreted differently by different users. For example whether there is environmental light present or not. Clearer definitions should be explained in order to further remove this bias.

7.5. Recommendations

For future research, it is recommended to see if the method can be expanded so it can assist even more with assessing and eventually even selecting different alternatives. Currently, the method allows a decision-maker to see if no feasible solutions are found because of environmental characteristics in the physics, engineering or commercial domain, but it would be of benefit if the method also assists in for example weighing different alternatives. As a suggestion for this, input from stakeholders should be obtained to understand what environmental characteristics are considered as most important compared to others.

Also, it would be beneficial to link the tool to a database containing available machine vision technologies. In that case the tool can, next to advising on specifications, directely specify on equipment. In that case it is also able to inform the user right away as soon as a decision is made that leads to all equipment becoming infeasible.

Furthermore, extra environmental characteristics could be added to the knowledge base. Examples are *Load on the network*, describing how much data is generated when images are made, *Physical connection*, describing what physical connection the camera should have to other equipment (GigE, USB3, etc.) and *Surface shape*, describing the shape of the surface under study which could be flat, uneven or curved (Martin, 2024).

In addition, it would be interesting to see if the scope of the methodology can be enlarged. Currently, it solely focusses on machine vision systems where there is a direct line of sight available and that makes use of 2D images, but there are also other imaging techniques available (like X-ray and thermal imaging or 3D imaging) and it would be beneficial if the method can also advise on those technologies.

Finally, it would be interesting to study the possibilities of using artificial intelligence to create parts of the knowledge base and/or the tool. In this way, the human judgement might be removed from the generation of both. It however requires a very advanced artificial intelligence model that is able to reason.

8 Conclusion

Summarizing, it can be said that in order to guide decision-makers (on the design of machine vision systems) in the process of designing a machine vision system for quality control a method containing seven phases can be used to guide the decision-maker during step two, three and four of the decision-making process for designing machine vision systems. The seven phases of the method are: Understand, Identify, Map, Classify, Link, Build and Evaluate. They support the decision-maker during the collection of information about decision criteria, the identification of alternatives and during the assessing and weighing of the different alternatives. The supporting method was designed using Design Science Research and therefore based on the needs from industry and the knowledge available in literature. As soon as the method was created, it was demonstrated by applying it on a use case at Volvo Cars. Volvo Cars is a major global car manufacturer that, like other companies in the automotive industry, aims to automate its quality control with help of machine vision in order to reduce waste. Application of the method at the decision-making process for the design of machine vision systems in Volvo Cars showed that the efficiency of this process can be increased. The tool following from the method allowed decision-makers that are not experienced with machine vision to quickly move through step two, three and four of the decision-making process as it is suggesting specifications for machine vision systems based on the characteristics of an environment that a decision-maker is able to describe.

The newly designed method covers the gap in literature which is the description of a decision support system that supports decision-makers in the design of machine vision systems. There are papers describing the general components of machine vision systems and papers describing how decision support systems should be built up, but no research has combined both topics yet. The method in this paper tries to cover this gap by being a general method that is applicable in every industry trying to implement machine vision for quality control.

For future work it is advised to see if the method can be expanded so it can assist even more with assessing and eventually even selecting different alternatives. Also, enlarging the scope of the method could be beneficial (e.g. also taking into account technologies like X-ray imaging) as it will enhance the decision making like expanding the method did.

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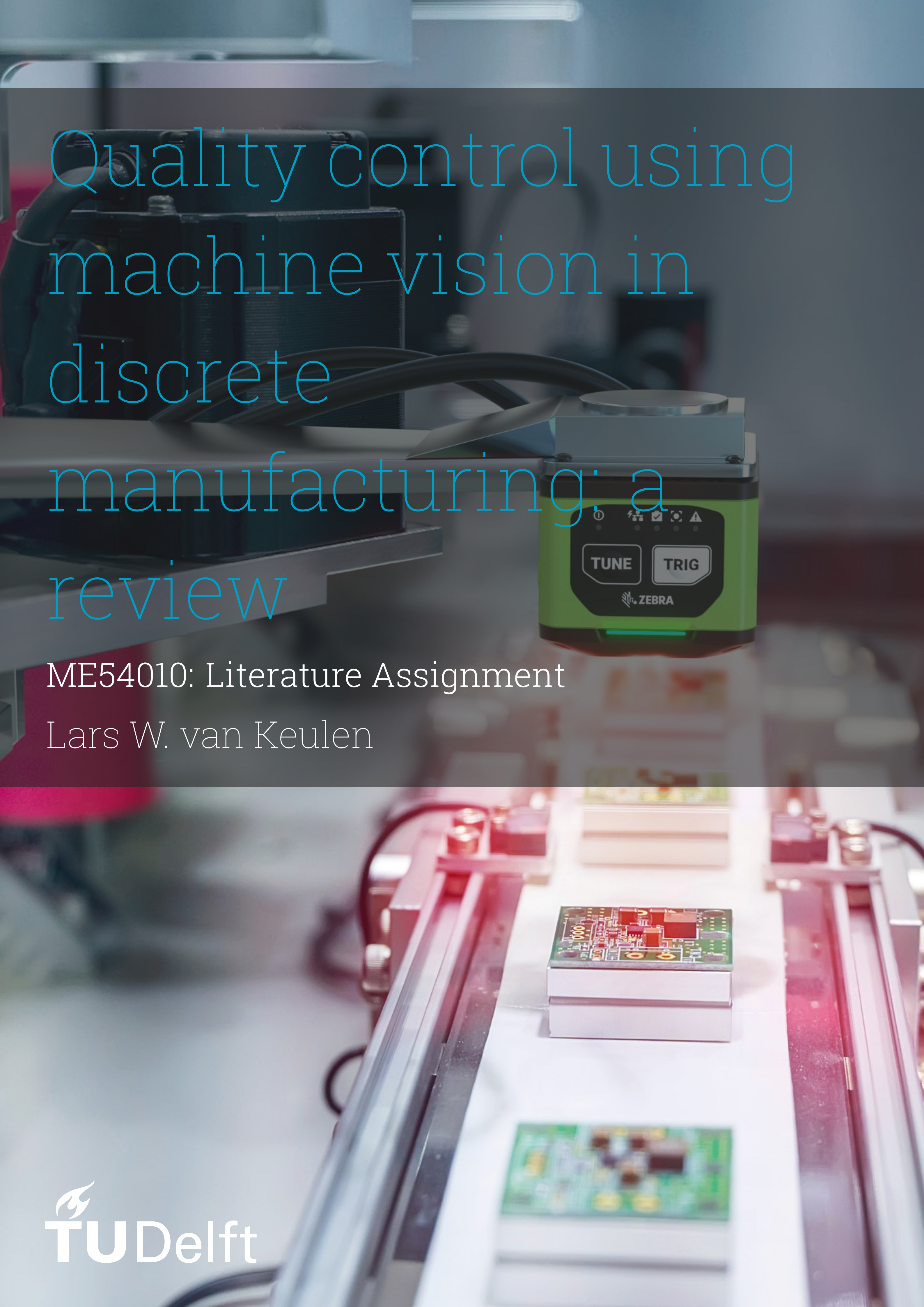
A

Report on literature research machine vision

Quality control using machine vision in discrete manufacturing: a review

ME54010: Literature Assignment

Lars W. van Keulen



TU Delft

Quality control using machine vision in discrete manufacturing: a review

by

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Project Duration:	February, 2024 - April, 2024
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TU Delft

Preface

This report describes the literature research I have conducted for the Literature Assignment of the master programme Multi-Machine Engineering at the Delft University of Technology. The assignment was to complete a 7-week literature research during which knowledge about a, to the master's relevant, topic was acquainted. I used this opportunity to gain knowledge about a field of knowledge, machine vision for quality control, that I was not too familiar with yet, but which I will be working on a lot during my master's thesis.

This report is aimed at readers who are new to machine vision and its application in quality control. It is a bird's eye view on the current available machine vision technologies and its applications in quality control. The main goal of this report is to provide an overview of these applications and technologies and therefore details regarding both are discussed to a limited extent. The framework presented in the end of this report can be used as an initial guideline for designing a machine vision system for quality control.

Also, I would like to thank my supervisors Dr. Alessia Napoleone and Rafael Leite Patrão for their guidance during the project and the sparring sessions we had. I am looking forward to continuing our collaboration during the thesis work.

Lars W. van Keulen
Delft, November 2024

Summary

Within the discrete manufacturing industry there is the will to automate quality control. It is mentioned that the automation of quality control will enhance the efficiency of the process the quality control is part of. The automation of quality control requires the digitisation of human vision which can be achieved by the introduction of machine vision. Machine vision can be defined as the ability of a machine to obtain information about its environment by sensing and thereafter processing this information. As of today, machine vision systems for quality control are already applied to a great extent. In order to create new solutions, it is believed by the author that it would be wise to study current applications and learn from choices made regarding the design of these systems.

This report answers the question "*How and to what extent are machine vision systems used across different industries to asses the quality of products and what technologies do these systems use?*" To answer this research question, a literature search was conducted to first map the different areas of application of machine vision systems for quality control and thereafter map the different technologies used in these applications.

Regarding the applications of machine vision systems for quality control, different applications were found in automotive, food and agriculture, healthcare, infrastructure, monitoring of machinery and tools and in the production of technical parts. It was also found that some tasks for machine vision are present in different areas. It was for example found that machine vision for the detection of cracks is both used in automotive, infrastructure and the production of technical parts.

Regarding the technologies, it was found that for the different tasks of a machine vision system (image acquisition, image preprocessing, image segmentation, feature extraction and classification), different technologies are available. Different criteria were also found that cause certain techniques to be more favourable over others in certain situations. An example is the better suitability of back lighting for the determination of object geometries compared to the better suitability of front lighting when information about the surface of an object is required.

The final result of the literature research is an initial framework for the design of a machine vision system. From this framework it follows that for task 1: image acquisition it is important to take into account the features of interest, object speed and object size to determine the proper lighting, frame rate, camera sensor and camera lens. For task 2: image preprocessing it is important to take into account the required image quality and again the features of interest to determine what preprocessing algorithms to use. For task 3: image segmentation it is important to consider the allowable processing time to select a proper segmentation algorithm. For task 4: feature extraction it is important to again watch for the features of interest to select the proper feature extraction algorithm(s). Last, for task 5: classification it is important to know the allowable processing time and the required accuracy, so a proper classification algorithm can be selected.

Contents

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List of abbreviations

Abbreviation	Definition
CCD	Charge-coupled device
CCN	Convolutional neural network
CMOS	Complementary metal oxide semiconductor
DNN	Deep neural network
FCN	Fully convolutional networks
GAN	Generative adversarial network
LED	Light emitting diode
MVS	Machine vision system
NN	Neural network
PCA	Principal component analysis
QC	Quality control
SDS	Simultaneous detection and segmentation
SVM	Support vector machine
TCM	Tool condition monitoring
TWM	Tool wear measurement

1 Introduction

Like for many processes within different industries, the will to automate quality control within discrete manufacturing exists as well (Brosnan and Sun, 2004; Konstantinidis et al., 2023). It is mentioned that the automation of quality control can enhance the efficiency of the process the quality control is part of (Brosnan & Sun, 2004).

A part of quality control is based on human inputs (Brosnan & Sun, 2004). In order to automate these steps, a possibility is to digitise this human vision by machine vision. Machine vision can be defined as the ability of a machine to obtain information about its environment by sensing and thereafter processing the sensed information. This information can then be used for further analyses. A machine vision system is said to be a combination of hardware and software (López et al., 2008). Another definition is that machine vision studies both the hardware, software and image acquisition techniques to be applied in real applications (Davies, 2012). Computer vision is said to be the technology that extracts information form the acquired images (Zebra Technologies Corp., n.d.), or the software for the design of vision (Davies, 2012). Computer vision, does not need technology to capture an image, it can use data that is acquired by another system (Zebra Technologies Corp., n.d.). Due to the advancements of the technologies used for both machine and computer vision (no big machines are needed for performing machine/computer vision), the terms machine vision and computer vision get used interchangeably more and more (Davies, 2012). In this report, machine vision will however still be used for describing the science of acquiring an image and analyzing this image. Computer vision will (solely) be considered as the science of extracting useful information of the acquired image.

The application of machine vision systems is booming (Akundi et al., 2022; Bagga et al., 2021; Patel et al., 2023; Zhang et al., 2022) and many different fields of application have already been found (Auger, 2010; Banda et al., 2022; Brosnan and Sun, 2004; Fernandez et al., 2020; Heger and Abdine, 2019; Levin et al., 2019; Paneru and Jeelani, 2021). Since there are many applications already available, it would be wise to learn from the choices made for these applications. It is believed by the author that it can be very interesting to study the way in which machine vision is used across different industries. To the best of the author's knowledge, no such review yet exists.

The goal of this literature review is to answer the following research question: *How and to what extent are machine vision systems used across different industries to asses the quality of products and what technologies do these systems use?* Answers to this question will be derived by answering the following sub-questions:

- *How and to what extent are machine vision systems used across different industries to asses quality of products?*
- *What are different techniques used in different machine vision systems for quality control used in different industries?*
- *Can a framework be developed for the design of a machine vision system for quality control?*

In order to answer the first sub-question: *How and to what extent are machine vision systems used across different industries to asses quality of products?*, an overview of the different areas of application for machine vision systems for quality control will be given. This overview will be created by conducting a literature search for available literature on machine vision applications for quality control. During the search, attention will only be paid to review papers since the main interest is in the overall concepts of machine vision for quality control. The different industries found in this search will be presented.

Next, to answer the second sub-question: *What are different techniques used in different machine vision systems for quality control used in different industries?*, the applications where the review papers are referring to will be studied. These technologies will then be grouped, based on the five tasks of a machine vision system. These five tasks are image acquisition, image preprocessing, image segmentation, feature extraction and classification (Bhargava and Bansal, 2021; Goutam and Sailaja, 2015; Patel et al., 2023). The five tasks of machine vision will be discussed in more detail in chapter 4.

Finally, a first iteration of a framework for the design of a machine vision system for quality control will be designed an presented in order to answer the third sub-question: *Can a framework be developed for the design of a machine vision system for quality control?* Figure 1.1 graphically represents the methodology followed to answer the main research question.

From the next chapter, the conducted research will be explained and the results will be presented. First, chapter 2 will present the methodology followed for the literature research. Thereafter, chapter 3 will present the different fields of application in which machine vision was found to be used for quality control purposes. Next, chapter 4 will present an overview of the different technologies used within machine vision systems for quality control. Next, chapter 5 will present a framework that can be followed when a machine vision system for quality control is to be designed. Finally, chapter 6 will conclude the research by summarizing work done, clearly presenting the conclusions and providing recommendations for future research.

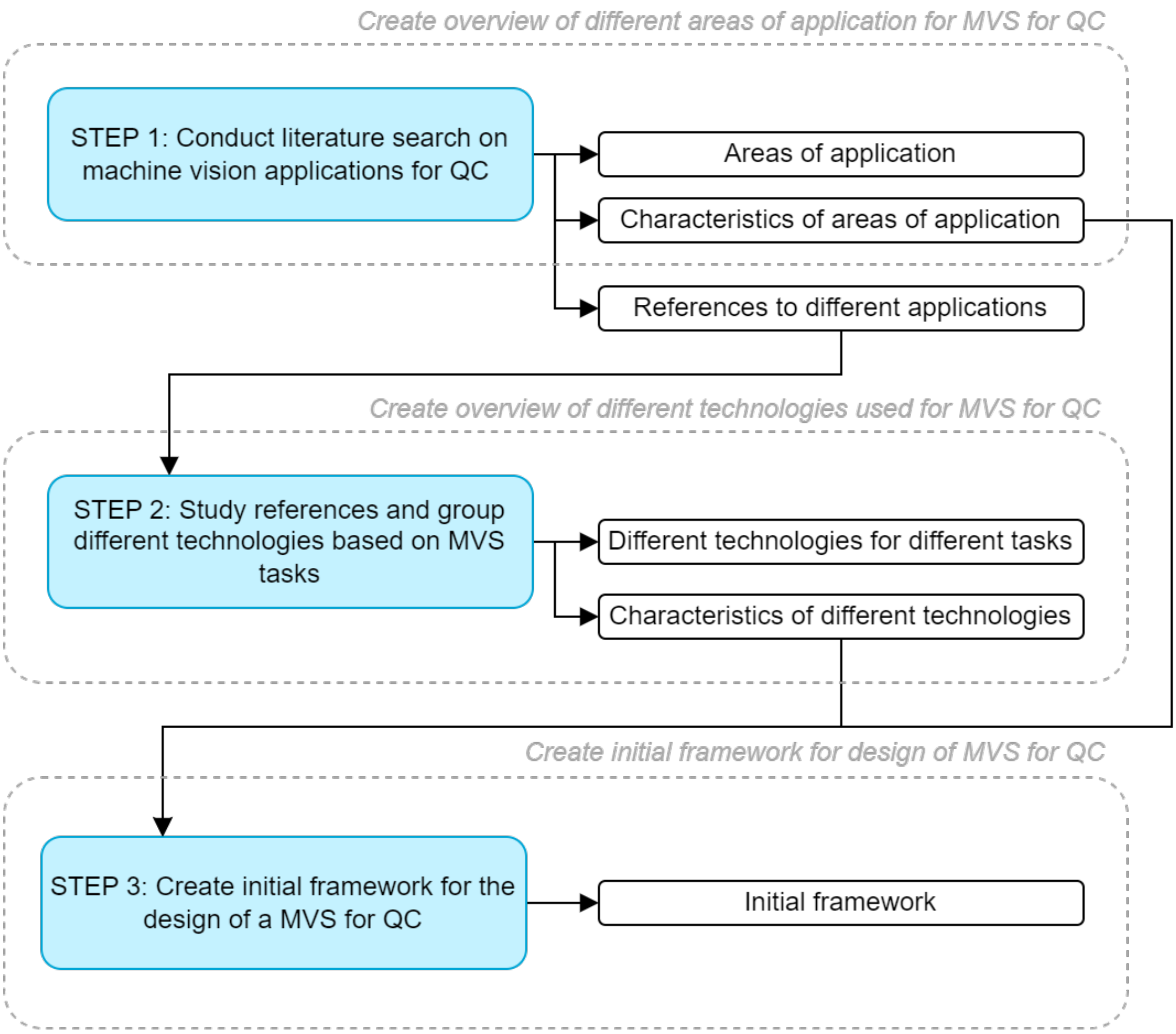

Figure 1.1: Research methodology

2

Literature search

This chapter describes the literature search conducted to map the the different application areas of machine vision systems for quality control. The first search conducted was the search for the fields of application. This search was conducted in the Scopus-database, since this database is known for its high-quality content and completeness.

2.1. Search for areas of application

In order to find the areas of industry in which machine vision systems are applied as a tool for quality control, the proper search queries had to be setup. To setup these queries, at first the keywords as presented in Table 2.1 were determined. These keywords were all found to be relevant for finding machine vision applications in quality control. With these keywords determined, the queries as presented in Table 2.2 were created and entered into the Scopus-database. In addition to the queries, the results were limited to English reviews only, since they were assumed to be the most relevant.

Table 2.1: Keywords for literature search

Keywords
Quality control - Quality inspection - Quality assurance - Quality monitoring
Machine vision - Computer vision - Robot vision
Industry 5.0
Industry 4.0
Production - Processing - Manufacturing - Assembly
Maintenance - Wear - Degradation
Tools - Tooling - Machines - Machinery

Table 2.2: Queries for literature search

Number	Query
1	`("machine vision" OR "computer vision" OR "robot vision") AND ("quality control" OR "quality inspection" OR "quality assurance" OR "quality monitoring")`
2	`("machine vision" OR "computer vision" OR "robot vision") AND ("maintenance" OR "wear" OR "degradation")`
3	`("machine vision" OR "computer vision" OR "robot vision") AND ("tools" OR "tooling" OR "machines" OR "machinery")`
4	`("machine vision" OR "computer vision") AND ("production" OR "processing" OR "manufacturing" OR "assembly")`
5	`("machine vision" OR "computer vision") AND ("industry 5.0" OR "industry 4.0") AND ("quality")`

Table 2.3: Results search queries after filters were applied

Number	Amount of results	Status checked
1	165	Fully checked on Scopus
2	76	Fully checked on Scopus
3	1,563	Partially checked on Scopus
4	1,336	Not checked
5	8	Fully checked on Scopus

An overview of the results of this search is presented in Table 2.3. As is visible in the table, even with the filters for language and document type set, a lot of literature was found. Since it was not feasible to study all literature found due to time constraints, criteria were determined that result in a study of probably the most relevant literature only. It was decided to select the highest cited review from every field of application, since they were expected to present the best overview of the status of machine vision for quality control in a specific area since they are used by many different authors. Besides, before a paper was studied, its abstract was scanned to check its relevance and attention was paid to its year of publication. If a paper was published before 2020, efforts were made to find a review that was published at a later date to make sure the most recent applications were also found. Citations of that paper might have been lower. In addition, the queries resulting in a lot of results (query 3 and 4) were not (completely) studied since the highest cited results from these queries were found to be less relevant. In the end, the amount of remaining papers was equal to 33 which was manageable to study in more depth.

3 Applications

This chapter provides an overview of the different areas of application where machine vision systems were found to be used for quality control. The areas were found by following the methodology as described in chapter 2. Figure 3.1 shows a graphical representation of these application areas. Some applications of machine vision were found in different fields. For example, crack detection using machine vision was found to be used in infrastructure (Hu et al., 2021; Kheradmandi and Mehranfar, 2022; Sarkar et al., 2024), the production of technical parts (Chaiyasarn & Buatik, 2021) and in the automotive (Konstantinidis et al., 2023). In Figure 3.1, applications that are found across different field of application are marked in the same colour. In the remainder of this chapter, the areas of application will be discussed in more detail. They will be discussed in alphabetical order since no area of application is ought to be more important than the other.

3.1. Automotive

A first industry where machine vision systems are found to be used for quality control is the automotive industry. The applications are found to be used in several stages within car manufacturing (Konstantinidis et al., 2023). A first example is the use of machine vision for the quality control of pressed metal parts (Block et al., 2021; Heger and Abdine, 2019). Another example is the quality control of painted surfaces (Molina et al., 2017; Chang et al., 2020). Besides these examples, many other applications were also found in the body shop, assembly shop and part production (Konstantinidis et al., 2023).

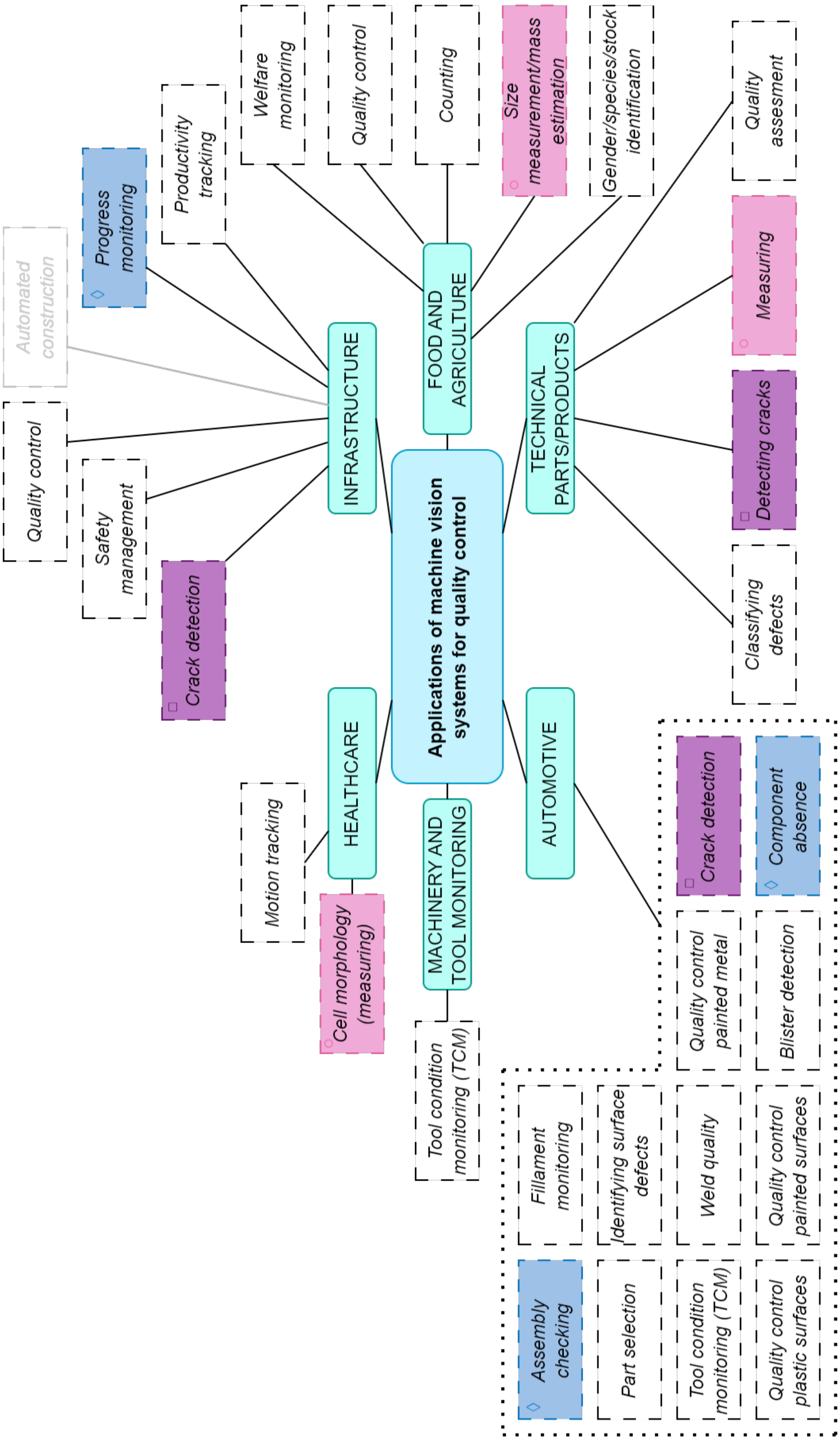

Figure 3.1: Overview of application areas of machine vision systems for quality control

3.2. Food and agriculture

Also, in the sector of food and agriculture, machine vision can be found to be used for quality control (Bhargava & Bansal, 2021). An advantage of the use of machine vision for quality control is that computer vision can make the process of quality control more objective (Brosnan & Sun, 2004). This can have significant impact since the price and ”best-if-used-before date” of products may be based on quality assessed via quality control (Bhargava & Bansal, 2021). Other advantages of using machine vision for the quality control in the food and agriculture sector is that it eliminates tedious human inspection tasks. It is also more hygienic and less destructive (Brosnan & Sun, 2004).

Another domain within the food and agriculture sector where machine vision is used for quality control is aquaculture. Within this industry, machine vision is used for counting, size measurement and mass estimation, gender identification and quality assessment, species and stock identification and welfare monitoring (Zion, 2012).

3.3. Healthcare

Computer vision for quality control is also found to be used in healthcare. Among others, it is used to examine the human sperm morphology by measuring different morphological features of sperm cells. These results can then be used to classify sperm cells as normal or abnormal. An advantage of using computer vision is that it allows for precise and reproducible measurements of cell structures which is different compared to the measuring capabilities of humans from which the results might vary (Auger, 2010).

Another example of the application of computer vision for quality control in healthcare, is the tracking of tool, hand and eye motion of a surgeon performing a surgery. This data which is then collected can on its turn be used again to provide feedback on the surgeons on the execution of the surgery (Levin et al., 2019).

3.4. Infrastructure

Another sector where machine vision is found to be used for quality control is the infrastructure sector. Among others, machine vision is used for crack detection in roads (Hu et al., 2021), pavements (Kheradmandi & Mehranfar, 2022) and concrete (Sarkar et al., 2024). Another interesting application of machine vision for quality control within the infrastructure domain is the use of machine vision on the construction site. Applications were found where machine vision was used for productivity tracking, safety management, progress monitoring, quality control and automated construction (Paneru & Jeelani, 2021). A more concrete example is the use of machine vision to determine the progress of construction work based on the presence of structural components like columns (Maalek et al., 2019).

3.5. Machinery and tool monitoring

Another field of application in which computer vision is used for quality control is the area of machinery and tool monitoring. For this type of application, cameras are used to perform the tool condition monitoring (TCM). Different types of camera sensors were found to be used (both charge-coupled device (CCD) sensors and complementary metal oxide semiconductor (CMOS) sensors). The images made with these cameras are forwarded to computer vision software which performs the eventual machine vision for TCM. The advantages of using machine vision for TCM is that the user of the machine can be alerted for bad conditions of the tool before catastrophic failure occurs. Also, manual handling of tools may eradicate traces that provide information on the wear of a certain tool. Machine vision does not require a physical connection with the tool under study and will therefore do no damage to the tool (Banda et al., 2022). Another advantage of using machine vision for TCM is that it does not obstruct the machining process (Patil-Mangore et al., 2023). Different failure modes that can be detected using machine vision are flank wear, crater wear and tool breakage (Kurada & Bradley, 1997). A big challenge for implementing machine vision for TCM is that the camera has to be mounted in a difficult industrial environment (Banda et al., 2022).

3.6. Technical parts/products

It was also found that machine vision is used to asses the quality of certain technical parts/products. One example is the assessment of PV modules on anomalies (substring failures, diodes or cell fracture). The anomalies are detected by image processing techniques (Buerhop et al., 2022). Also, machine vision was found to be used for the detection of cracks in tiles that are placed on a building (Chaiyasarn & Buatik, 2021). Other applications were found to be surface defect detection (Huo et al., 2023), train wheel diameter measuring (Chen et al., 2022), defect detection in wind turbine blades (Du et al., 2020), weld quality assessment (Fan et al., 2021) and assessment of aircraft parts (Yasuda et al., 2022). Also, applications in the semiconductor industry (Huang & Pan, 2015), additive manufacturing industry (Kim et al., 2018) and textiles/fabrics/materials industry (Meister et al., 2021; Ngan et al., 2011; Q. Wang et al., 2022) were found.

4 Technologies

When studying machine vision systems, it can be said that they have to perform five consecutive tasks: image acquisition, image preprocessing, image segmentation, feature extraction and classification (Bhargava and Bansal, 2021, Patel et al., 2023 and Goutam and Sailaja, 2015). In this chapter, different technologies found in different industries for the different tasks will be discussed. The technologies were found by studying the references used in the review papers (snowballing) found during the literature search as described in chapter 2. The order of discussion will be the order in which the tasks are performed. At first, section 4.1 will discuss the different techniques used for image acquisition. Thereafter, section 4.2 will discuss the different techniques used for the preprocessing of the acquired images. Next, section 4.3 will discuss the techniques used for segmentation of the preprocessed image. Following, section 4.4 will discuss the technologies used for feature extraction. Finally, section 4.5 will discuss the different technologies used for the classification of the extracted features.

4.1. Task 1: Image acquisition

The first task for a machine vision system is to acquire an image from the object under study (Bhargava & Bansal, 2021). This image can then be fed to the next tasks of the process. For the acquisition of images, different systems can be used. Depending on the property of the object on which information is wanted, a different image acquisition technique might be needed (Abdullah, 2016). For example, an ultrasound system might be needed for determining the moisture content of certain food products (Steele, 1974), whereas an infrared system is required when unwanted matter is to be detected between food products (Ginesu et al., 2004). Also, the use of x-ray technology was found to be used in the food industry (Brosnan & Sun, 2004). Other systems that can be used to acquire images including certain properties are tomographic imaging systems and computer based camera systems (Abdullah, 2016). The latter will be discussed in more detail.

Computer based camera systems in general consist of an illumination source, a camera to acquire the image, an image capture board, computer hardware and computer software (Abdullah, 2016 and Brosnan and Sun, 2004). In this research attention will only be paid to the different illumination sources and the different possible cameras (sensors and lenses).

4.1.1. Camera sensors

The sensors that are found to be used for machine vision applications are charge-coupled device (CCD) sensors and complementary metal oxide semiconductor (CMOS) sensors. Both are solid-state imaging techniques (Waltham, 2013). In general, CCD image sensors provide a more compact and high image quality camera compared to a camera with a CMOS sensor. The advantages of CMOS sensors their lower power consumption and their lower production costs (Mehta et al., 2015).

During the search for applications, it was found that for most applications CCD sensors are used, which can possibly be explained by the higher image quality CCD sensors provide. It is not unthinkable that high resolution images are required to perform quality control using machine vision. Especially, if there is also the urge to detect very small quality defects. Among others, various applications of CCD sensors were found in tool wear measurement (TWM) systems (Banda et al., 2022). Also, many CCD sensors were found in machine vision systems for surface monitoring (e.g. on roughness) (Bradley and Wong, 2001; Patel et al., 2020; Dhanasekar and Ramamoorthy, 2010). Next to the application of CCD sensors in machining related environments, CCD sensors were also found to be applied in machine vision systems for dimension measurement (Li, 2018), food applications (Bhargava & Bansal, 2021) and moulding applications (Zhang et al., 2022).

Next to CCD sensors, CMOS sensors were also found to be applied in machine vision systems for TWM and surface roughness monitoring (Banda et al., 2022). Also, applications of CMOS sensors were found in machine vision systems for food applications (Bhargava & Bansal, 2021) and for part surface inspection (Akundi et al., 2022). When contrasting the use of CMOS sensors to the use of CCD sensors based on the results of the performed search in this report, it can be said that the use of CCD sensors is more common.

Besides the difference in sensor type, there can be a difference in the way in which the photosensitive elements are positioned. They can either be arranged in a line (the camera is then of the line scan type) or they can be arranged in a small area (then the camera is of the area type) (Brosnan & Sun, 2004). Line scan cameras are of good use for fast moving applications. Area scan cameras are best suited for objects that are stationary (Anand & Priya, 2020).

4.1.2. Camera lenses

In addition to the camera sensor, the used lens can also be of great influence to the quality of the image (Williamson, 2018). During the search for applications of machine vision systems in quality control, different types of lenses were found to be used in different applications. The lenses found are telecentric lenses, fixed focal length lenses and macro zoom lenses.

Telecentric lenses (see Figure 4.2a) make sure that all objects that are present in an image are magnified to the same extent. Irrespective from their distance to the lens. This property allows these types of lenses to be well suited for measuring using machine vision (Williamson, 2018). Figure 4.1

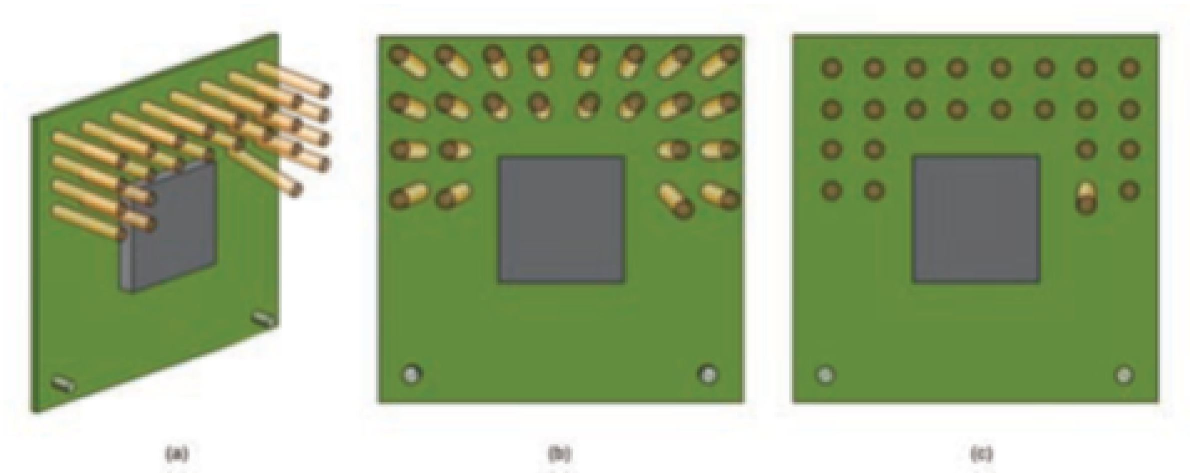

Figure 4.1: Illustration use telecentric lens (from Williamson (2018))

shows the difference in acquired image of a printed circuit board (PCB) with a bent pin (Figure 4.1a). Figure 4.1b shows an illustration of the image that would be acquired with a standard entocentric lens and Figure 4.1c shows the image that would be acquired with a telecentric lens (Williamson, 2018). Examples of applications of machine vision for quality control where telecentric lenses were used are TWM (Banda et al., 2022) and the monitoring of grinding operations (Xu et al., 2020). A potential drawback of telecentric lenses is that the area of the lens needs to be as least as big as the area of the object under study (Williamson, 2018).

When objects under study are of a fixed size and are placed on a fixed distance from the lens, fixed focal length lenses (see Figure 4.2b) are mostly used. A drawback of these lenses is that they produce perspective effects (Williamson, 2018). Applications of machine vision for quality control where these lenses are found are again TWM (Banda et al., 2022).

A last category of lenses used are macro zoom lenses. These lenses can be used when the object under study is approximately of the same size as the camera sensor used (Williamson, 2018). Examples of applications machine vision systems where macro zoom lenses are used are again TWM (Banda et al., 2022).

4.1.3. Illumination systems

According to Davies (2012), within a machine vision system, everything depends on the illumination of the object under study. A distinction can be made between front lighting and back lighting (Novini, 1989). Front lighting is used when surface quality attributes are to be inspected (e.g. colour, texture or defects) (Brosnan & Sun, 2004). Applications of front lighting in machine vision systems for quality control are therefore found in food applications (Brosnan and Sun, 2004; Bhargava and Bansal, 2021).

Back lighting is well suited for measuring (Novini, 1989) since they make edges of an object clearly visible. Applications of back lighting can be found in TWM (Kumar & Ratnam, 2019), the monitoring of grinding operations (Xu et al., 2020) and in food applications (Brosnan & Sun, 2004).

It was found that a variety of sources regarding lighting in combination with machine vision are available, it can be considered as a science on its own. Therefore, details about lighting in combination

(a) Telecentric lenses (TECHSPEC® TitanTL® Telecentric Lenses from Edmund Optics, Ltd)

(b) Fixed focal length lenses (TECHSPEC® UC Series Fixed Focal Length Lenses from Edmund Optics, Ltd)

Figure 4.2: Different types of lenses (retrieved from www.edmundoptics.co.uk)

with machine vision will not be discussed in this report. An interesting lighting technique that the author does want to highlight is the use of deflectometry. This technique is used in the automotive industry to detect surface defects based on a lighting pattern that is projected on the body part under study (Molina et al., 2017). Also, it is important to take into account the frequency of the power supply the lighting is connected to. The frequency of the current that is provided to the lamp(s) can cause a ripple on the acquired images (Novini, 1989). Ripple is no issue when light emitting diodes (LEDs) are used for illumination (Davies, 2012).

4.2. Task 2: Image preprocessing

The next step in a machine vision application after an image has been acquired is to preprocess the image (Goutam & Sailaja, 2015). Different operations are assigned to the preprocessing stage, namely scale conversion, image super-resolution, denoising and image reconstruction.

4.2.1. Scale conversion

Scale conversion of image preprocessing is the conversion of the colour scale of an image to a grayscale or even a binary scale. In order to perform scale conversion, different technologies were found to be used in machine vision applications for quality control.

A first technique that was found to be used is thresholding. With thresholding, a certain pixel gets classified as either black or white (binary) based on its value compared to a predefined threshold (Bagga et al., 2021). Applications of this technique were found in TWM (Bagga et al., 2021), food processing (Arlimatti, 2012) and crack detection (Y. Zhou et al., 2016).

Another technique for scale conversion is grayscale processing. Grayscale processing is converting an acquired colour image into a grayscale image using a correlation algorithm. The conversion to a grayscale image reduces the amount of required operations for later image processing (Li, 2018). Applications of grayscale processing in machine vision applications for quality control were found in dimension measurement (Li, 2018).

4.2.2. Image super-resolution

Image super-resolution is the principle of restoring the image to enhance its resolution (Banda et al., 2022). A found technique to perform this image super-resolution is a generative adversarial network (GAN) (Banda et al., 2022). GANs are known for their ability to learn deep representations without having a large amount of annotated training data (Creswell et al., 2018). A found use case of GANs for image super-resolution was the removal of smearing from an image for tool wear monitoring (Banda et al., 2022).

4.2.3. Denoising

Denoising is the process of removing noise from the acquired image. A first technology that can be used for image denoising is the Richardson-Lucy technique. This technique can be used to remove the blur from an image that is caused by motion. An application of this technique in a machine vision application for quality control was found in the machining industry (Dhanasekar & Ramamoorthy, 2010).

Another technique used to remove noise from an image is wavelet. An application of this technique in a machine vision system for quality control was found in a system for dimension measurement (Li, 2018).

Other techniques that can be used to remove noise from an image are mean filtering, median filtering and homomorphic filtering (Q. Wang et al., 2022). The latter was applied in a quality control machine vision system in the wood industry (Yusof et al., 2013).

4.2.4. Image reconstruction

Image reconstruction is the process of filling the corrupted parts of an image (Banda et al., 2022). Deep neural network (DNN) technologies that can be used for image reconstruction are PatchMatch, PixelRNN, PixelCNN, partial convolutional layer and bandpass filtering CNNs (Banda et al., 2022). According to Banda et al. (2022), image reconstruction can be applied in machine vision systems for quality control in TWM applications.

4.3. Task 3: Image segmentation

When the preprocessing is completed, the image is to be segmented. Image segmentation is ”... a process of dividing an image into different regions such that each region is, but the union of any two adjacent regions is not, homogeneous” (Cheng et al., 2001). According to Golnabi and Asadpour (2007), ”[Image] Segmentation seeks to partition an image into meaningful regions that corresponds to part or whole objects within the scene.” From the search for machine vision applications for quality control, two different types of technologies were found for performing image segmentation, namely thresholding-based image segmentation and edge detection-based image segmentation. Besides, a technology called simultaneous detection and segmentation (SDS) was encountered. Indicators have been found that there are also other types of technology for image detection available (region-based, watershed-based and clustering based) (Bandyopadhyay, 2021), but these technologies have not been found during the search for applications of machine vision for quality control and they are therefore not included in this report.

4.3.1. Thresholding-based image segmentation

Generally speaking, it can be said that thresholding-based image segmentation separates the foreground from the background of an image since it is based on separating the darker and lighter parts of an image from each other. A major difficulty with thresholding-based image segmentation is automatically determining the optimum threshold. A proper choice of lighting can improve the way in which thresholding-based image segmentation is performed (Davies, 2012).

A first thresholding-based image segmentation technique that was encountered within a machine vision system for quality control is Otsu's algorithm (Thakre et al., 2019). Otsu's algorithm is a simple algorithm providing high accuracy. Its drawbacks are its high susceptibility to noise, its difficulties to distinguish between background and objects and its lack in robustness (Q. Wang et al., 2022). Applications of Otsu's algorithm in a machine vision system for quality control were found in the TWM industry (Thakre et al., 2019), the wood processing industry (Q. Wang et al., 2022) and in the food industry (Meng & Wang, 2015). Another thresholding-based image segmentation technique that was encountered within a machine vision for quality control is the iterative thresholding method. This method has the advantages that it is very efficient, accurate and simple. Its drawback is that it has difficulties with difficult background images. The last thresholding-based image segmentation technique for machine vision for quality control encountered was the maximum entropy threshold algorithm. The advantage for this algorithm is its high accuracy. Drawbacks are its computational time and the limited applicability (Q. Wang et al., 2022). Both techniques were used for segmenting wood images (Q. Wang et al., 2022).

4.3.2. Edge detection-based image segmentation

Two main methods of edge detection (template matching and differential gradient) have the aim to find the locations in an image where the gradient magnitude is of a particular size that it can be considered to be part of the edge of the object (Davies, 2012). During the search for applications of machine vision for quality control, different applications using edge detection-based image segmentation were found. Among others, examples were found in TWM (Bagga et al., 2021; J. Zhou and Yu, 2021) and in the field of geometric measuring (Li, 2018).

4.3.3. Simultaneous detection and segmentation

A bit of an odd technique in this chapter is simultaneous detection and segmentation (SDS), since it both segments and detects an object (Banda et al., 2022). All other technologies solely perform segmentation. Different DNN technologies that can be used for simultaneous detection and segmentation are fully convolution networks (FCN), DeepLab-LargeFOV, DeconvNet, SegNet and R-CNN. A suggestion is to use these technologies for segmenting the wear region of tools (Banda et al., 2022).

4.4. Task 4: Feature extraction

The next step in a machine vision system after the image has been segmented is feature extraction. According to Golnabi and Asadpour (2007), feature extraction "... in general seeks to identify the inherent characteristics or features, of objects found within an object." There are different types of features that can be extracted from images: colour features, texture features and shape features (Tian, 2013). Other authors also report statistical features (Mutlag et al., 2020) and motion, localization and face features (Salau & Jain, 2019). These last four features will not be taken into account in this report since their use was encountered to a smaller extent compared to the first three mentioned feature types.

4.4.1. Colour features

Different colour features that can be extracted from acquired images are the mean, standard deviation and skewness (Mutlag et al., 2020). An application has been found where the mean, standard deviation, skewness and Kurtosis of an image were retrieved in order to recognise a piece of fruit (Jana et al., 2017)

4.4.2. Texture features

Different texture features are among others entropy, contrast, roughness, etc. Different technologies can be used to obtain these features (Mutlag et al., 2020). One of the techniques used to obtain texture features is wavelet texture analysis. An example of the use of this technique for a machine vision application for quality control is its use for texture feature retrieval of glass substrates (Žuvela et al., 2020). Another commonly used technique for texture feature extraction is the gray-level co-occurrence matrix (GLCM) method. Applications of this method have been found in the quality control of glass substrates (Žuvela et al., 2020), the classification of machined surfaces (Patel et al., 2019), the identification of wood (Kobayashi et al., 2019) and the identification of fruits (Jana et al., 2017). A next technique that can be used for the texture feature retrieval is wavelet co-occurrence signature which is an extension of the GLCM method. An application was again found in the quality control of glass substrates (Žuvela et al., 2020). Other, less common, used techniques found are the GABOR filtering method, local binary picture method and also uniquely developed methods (Q. Wang et al., 2022).

4.4.3. Shape features

Shape features are the final type of features that can be retrieved from an image. Examples are area, slope, convex area, etc. (Mutlag et al., 2020). They were found to be used in TWM (Castejón et al., 2007). A technique used to obtain certain shape features is the active contour algorithm. An application of this algorithm was again found in the TWM industry (Schmitt et al., 2012).

4.5. Task 5: Classification

Classification is the final step to be performed in a machine vision application. It is the process of categorizing detected objects based on the dominant features (Banda et al., 2022). Two types of classification can be distinguished: binary classification and multi-class classification. Binary classification is the classification method for which an image is classified as (containing) an object or not. Multi-class classification is the classification method for which images are also given a label with the type of object present in the image (Banda et al., 2022). The algorithms that perform the different types of classification can be categorized into three different categories: supervised, semi-supervised and unsupervised, referring to the way in which the algorithms are trained to perform the classification.

During the search for applications of machine vision in quality control, different techniques for classification were encountered. A first technique used for classification are neural networks (NNs). Different types of neural networks were found to be used in different applications of machine vision for quality control. Patel et al. (2019) and Moldovan et al. (2017) used artificial neural networks (ANNs) to classify machined surfaces and tool-flank images for TWM, respectively. Another type of neural networks that are commonly used are convolutional neural networks (CNNs) and its derivatives (deep convolutional neural networks, BP neural networks). They were found to be applied for the location of cracks (Yuan et al., 2021), detection and classification of wood surface defects (He et al., 2020), detection of car bumper surface defects (Block et al., 2021) and for the detection of workers and equipment on construction sites (M. Wang et al., 2019).

A second technique used for classifications are support vector machines (SVMs). They were found to be used for the classification of machined surfaces (Patel et al., 2019), the identification of wood samples (Q. Wang et al., 2022) and the classification of fruits (Jana et al., 2017).

5

Framework for machine vision systems for quality control

After having gained insight in the fields of application of machine vision systems for quality control and after having obtained a mapping of the technologies used, an advice for a framework for the design of a machine vision system for quality control will be given in this chapter (see Figure 5.1 for a graphical representation of the proposed framework). In the following section, the framework will be discussed

5.1. Initial framework

When designing a machine vision application for quality control, it is advised to for every task decide what would be the most suitable technical solution. For task 1: image acquisition, it is important that features of interest, speed of the object relative to the camera and object size are taken into account. It should be known what information about the object under study is to be required (features of interest). If the dimensions of an object are to be measured, back lighting would most likely be the best solution. When surface defects are to be studied, front lighting is advised (special variants of front lighting like deflectometry should be considered as well). The speed of the object is relevant since it determines the required frame rate and the object size helps to select the proper lens.

With the first task completed, it should be considered what preprocessing operations have to be fulfilled in order to complete task 2. It can be considered to add algorithms to the solution that enhance the image resolution, remove noise from the image, convert the image into a grayscale or binary image and/or reconstruct the image in case of corrupted parts. The usefulness of converting an image into a grayscale or binary image depends on the characteristics that are to be obtained from the object under study. If dimensions are to be retrieved, converting the image to a binary image would be advised since it allows dimensions to be determined and it reduces computational time. If for example surface roughness is important, a grayscale image might be useful. The use of an algorithm for image super resolution, noise removal and/or image reconstruction can depend on the required image quality.

For task 3, image segmentation, no particular advantage or disadvantage could be found for both techniques (thresholding-based segmentation or edge-based segmentation). It is advised to consult developers of the algorithms on the performance of the algorithms. A criteria that is then advised to take into account is the speed of the algorithm.

After the image has been segmented, features are to be extracted with task 4 of a machine vision system. For feature extraction it is important to know the object characteristics of interest. If information on the quality of the colour of the object is wanted, it is advised to use technologies that extract colour features from the object. When there is interest for surface finish of the object under study, the retrieval of texture features is advised (maybe even in combination with colour features). An algorithm for extracting shape features is advised when information is required about the geometry or shape of an object.

Finally, after the features have been extracted from the detected objects, the features can be classified within certain bins during the final task of a machine vision system: classification. Different types of algorithms can be selected for the classification. These can be algorithms based on neural networks or on support vector machines. The algorithms can differ in accuracy and computational time. These are therefore criteria to be taken into account when selecting the classification algorithm.

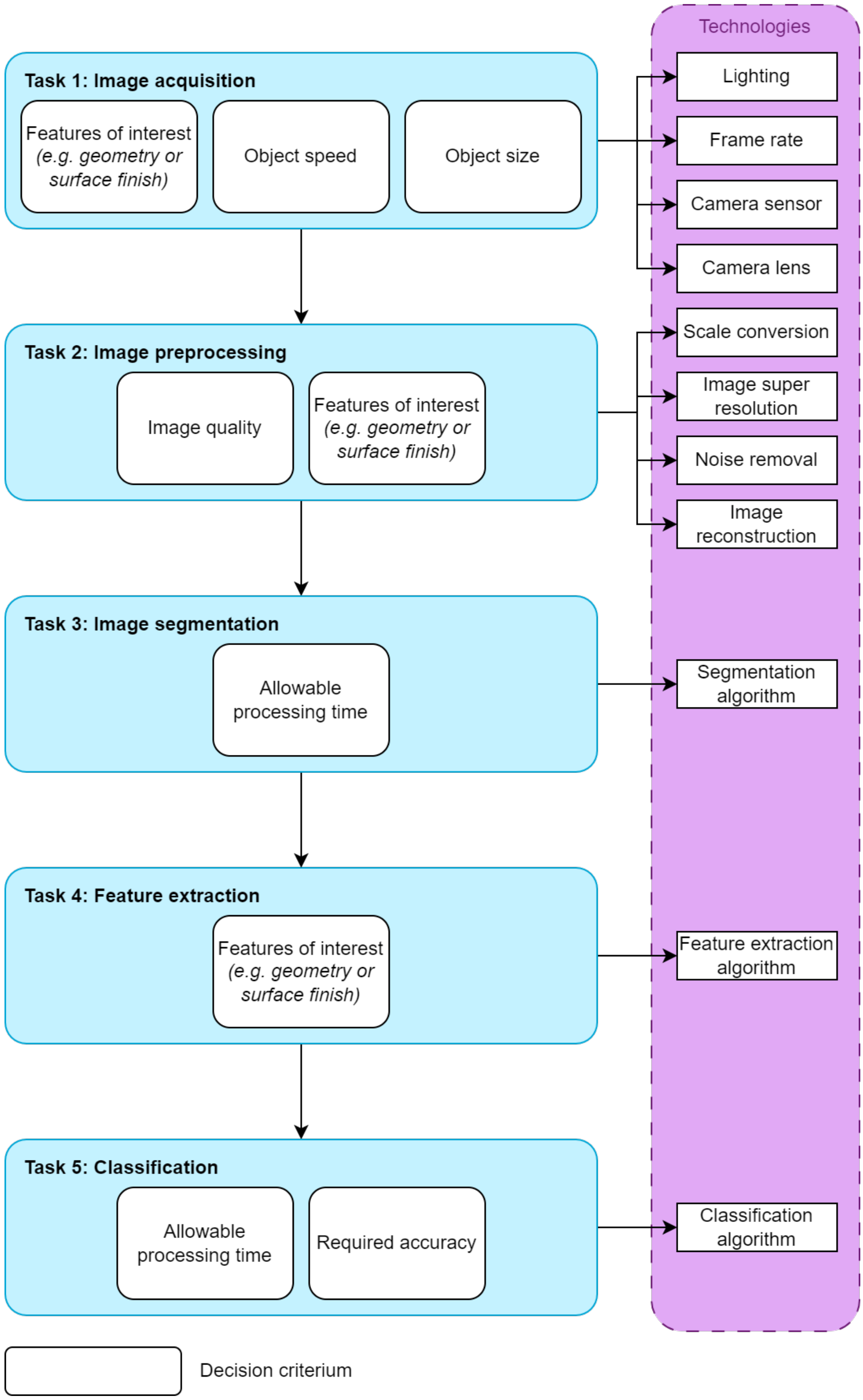

Figure 5.1: Framework for the development of a machine vision system

6

Conclusion and recommendations

To conclude, in order to answer the research question: *How and to what extent are machine vision systems used across different industries to asses the quality of products and what technologies do these systems use?*, a literature search was conducted and the results are presented in this report. At first it was determined in what industries machine vision systems are used for quality control. It was found that machine vision for quality control is used in many different fields of application among which are automotive, food and agriculture, healthcare, infrastructure, machinery and tool monitoring and in the production of technical parts. Within each field of application, different goals for the use of machine vision were found. Examples are crack detection, measuring, surface quality control and assembly monitoring. Figure 3.1 provides an overview of all fields of application and the different use cases within these fields.

Secondly, after the fields of application were determined, the different technologies used in the different applications were studied and clustered per machine vision task. For machine vision systems it was found that they have to perform five consecutive tasks: image acquisition, image preprocessing, image segmentation, feature extraction and classification. For task 1: image acquisition, it was found that different types of camera sensors, camera lenses and illumination systems are of influence on the performance of the machine vision system. For task 2: image preprocessing, it was found that different actions can be taken among which are scale conversion, image super-resolution, denoising and image reconstruction. For task 3: image segmentation, there are technologies available that perform thresholding-based image segmentation, edge detection-based segmentation and simultaneous detection and segmentation. For task 4: feature extraction, it was found that depending on the aim of the machine vision system, different features can be extracted. The main features are colour features, texture features and shape features. For task 5: classification, it was found that many technologies exists. A big difference was found between neural networks (NNs) and support vector machines (SVMs).

Finally, with the technologies mapped, the initial framework is created that can be used as a guideline to design a machine vision system that has to be capable of performing quality control. For task 1 it is important to take into account the features of interest, object speed and object size to determine the proper lighting, frame rate, camera sensor and camera lens. For task 2 it is important to take into account the required image quality and again the features of interest to determine what preprocessing algorithms to use. For task 3 it is important to consider the allowable processing time to select a proper segmentation algorithm. For task 4 it is important to again watch for the features of interest to select the proper feature extraction algorithm(s). Last, for task 5 it is important to know the allowable processing time and the required accuracy, so a proper classification algorithm can be selected. Figure 5.1 presents the initial framework.

For future research it is recommended to study the used technologies in more depth which is expected to improve the proposed flow chart. It is for example expected that better solutions will be proposed by the flowchart if it can distinguish between different types of neural networks since different neural networks can have different performance metrics.

Furthermore, it would be interesting to compare the framework presented in this report to a framework that is created based on only information from a particular industry (for example automotive). The results of this comparison might say something about the robustness of the proposed framework. If the framework presented in this report would look similar to a framework set up based on information from a particular industry only, it might indicate that the framework works for any industry. If the framework in this report would already be very different compared to a framework based on a particular industry, it might indicate that a general framework will not be optimal for the design of machine vision systems for quality control.

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B

Environmental characteristics

ENVIRONMENTAL CHARACTERISTCS		CLASSIFICATION	
Characteristic	**Question**	**Domain**	**Relevance to MV**
Ability to test	Do you want and/or have to test the system in the plant?	BRANCH	General
Ability to test (money)	What is the budget available to test the solution in the plant?	Commercial	General
Ability to test (time)	What is the time available to test the solution in the plant?	Commercial	General
Acquisition time	How much time is there to acquire data about the object under study?	Engineering	General
Availability of training images	How much training images are or can be made available?	Commercial	Specific
Availability of training parts	How much training parts are or can be made available?	Commercial	General
Available height	What is the height of the available space where the camera equipment can be placed?	Theory	Specific
Available length	What is the length of the available space where the camera equipment can be placed?	Theory	Specific
Available width	What is the width of the available space where the camera equipment can be placed?	Theory	Specific
Classification type	What type of classification is to be performed?	Theory	Specific
Connectivity	Should the system be connected to other systems in the plant?	BRANCH	General
Connectivity (hardware)	Should the system be connected to other systems in the plant with help of cables?	Engineering	General
Connectivity (wireless)	Should the system be wireless connected to other systems in the plant?	Engineering	General
Contrast	How can the contrast between the object and the environment be classified?	Theory	Specific
Contrast consistency	Is the background of the image consistent for every instance of the object (and therefore the contrast between the object and the surroundings)?	Theory	Specific
Cybersecurity	Should the solution comply with all cybersecurity regulations?	Engineering	General
Data processing	How should data be processed?	Engineering	General
Data storage	How should data be stored?	Engineering	General
Decision time	How much time is there before you need a decision on the quality of the object?	Engineering	General
Dependency on supplier during implementation	Can you be dependent on the supplier during implementation?	Commercial	General
Dependency on supplier during operation	Can you be dependent on the supplier during the operation?	Commercial	General
Environment dust	Is the equipment to be placed in a dusty environment?	Engineering	Specific
Environment explosiveness	Is the equipment to be placed in an explosive environment?	Engineering	General
Environment humidity	Is the equipment to be placed in a humid environment?	Engineering	Specific
Environment temperature max	What is the maximum temperature of the environment?	Engineering	Specific
Environment temperature min	What is the minimum temperature of the environment?	Engineering	Specific
Environmental light	Is there environment/ambient lighting?	BRANCH	Specific
Environmental light direction	What direction is the environmental light coming from?	Theory	Specific

Environmental light stability	What is the characteristic of the environmental light?	Theory	Specific
Feature size	What is the minimum feature size the camera should be able to capture?	Theory	Specific
Features of interest	What are the features of the object you want information on?	Theory	Specific
FOV height	What is the height of the area you want to capture (FOV height) using one camera?	Theory	Specific
FOV width	What is the width of the area you want to capture (FOV width) using one camera?	Theory	Specific
Frequency power grid	What is the power frequency of the environmental light?	Theory	Specific
Implementation costs of the solution	What are the maximal implementation costs for the solution?	Commercial	General
Implementation time	When should the solution be implemented?	Commercial	General
Installation hours required	How much working hours are available for the installation of the solution?	Commercial	General
Line of sight	Is there a direct line of sight towards the feature of the object you want to study?	REQUIREMENT	Specific
Machining environment	Is the solution to be placed in a machining environment?	Theory	Specific
Maintenance requirements	How many maintenance hours are available every month?	Commercial	General
Maximum distance to object	What is the maximum distance you can place a camera at compared to the object (maximum working distance)?	Theory	Specific
Method of report generation	What should be included in the quality report?	Engineering	General
Minimum distance to object	What is the minimum distance you can place a camera at compared to the object (minimum working distance)?	Theory	Specific
Object position	If the camera would be fixed to a certain location, would the orientation of the object under study be constant for every instance of the object?	Theory	Specific
Object-camera speed	What is the speed of the object compared to the camera?	Theory	Specific
Operational costs of the solution	What are the maximal operational costs (licenses, consumables, maintenance, etc.) for the solution?	Commercial	General
Personal safety	Do human operators need to work in close proximity of the machine vision solution?	Engineering	Specific
Product variety	Can the fault/part be different for every scan?	Theory	Specific
Receive info via XPS	Should the solution be able to recieve information via XPS?	Engineering	General
Required accuracy	What is the minimum required rate of reliable solutions (accuracy of the algorithm)?	Theory	General
Send info via XPS	Should the solution be able to send information via XPS?	Engineering	General
Signaling method	How should the system act in case of a defect?	Engineering	General
Space restrictions	Are there space restrictions?	BRANCH	Specific
Surface finish	How does the surface of the object under study look like?	Theory	Specific
Sustainability	Should the solution be sustainable?	Commercial	General
System flexibility	Do you want to be able to use the system in different configurations?	Commercial	General
Worldwide implementation	Is the solution (HW and SW) to be implemented worldwide?	Commercial	General

C

Hierarchy environmental characteristics

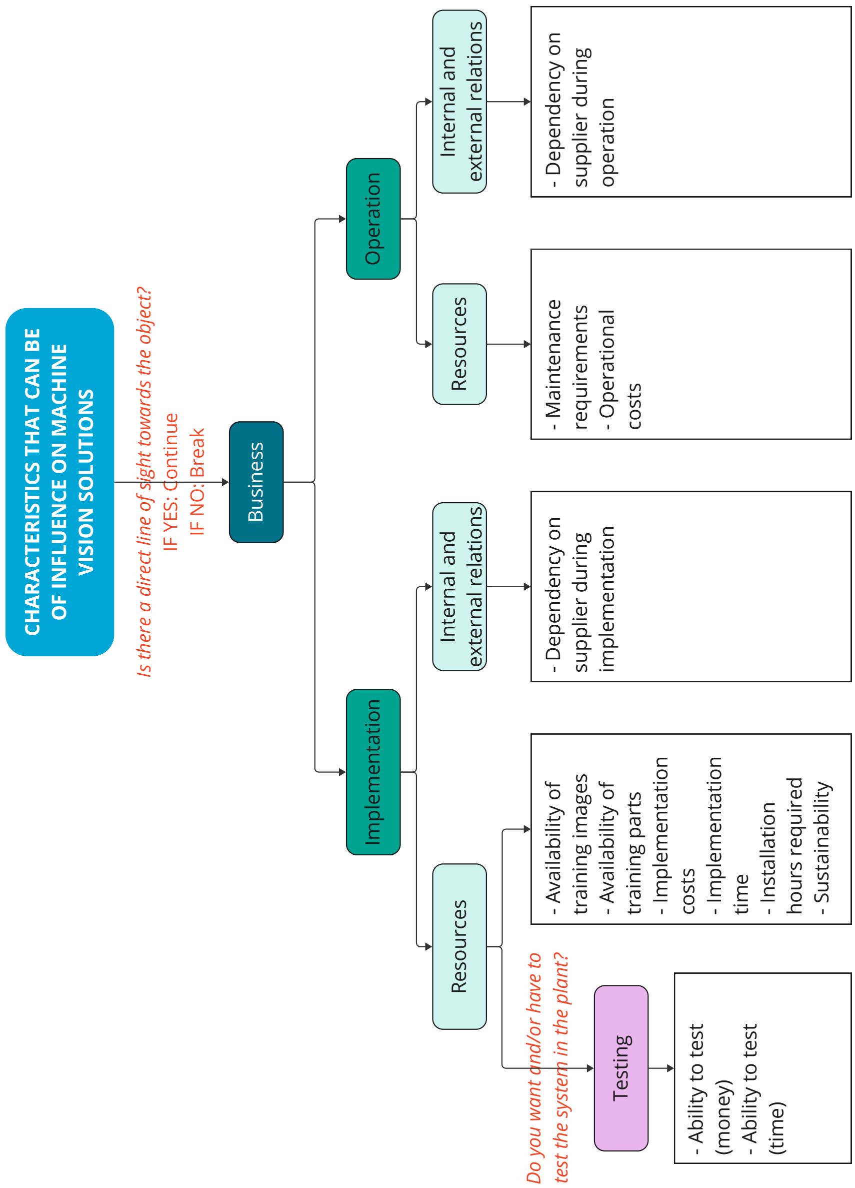

Figure C.1: Hierarchy of environmental characteristics (business)

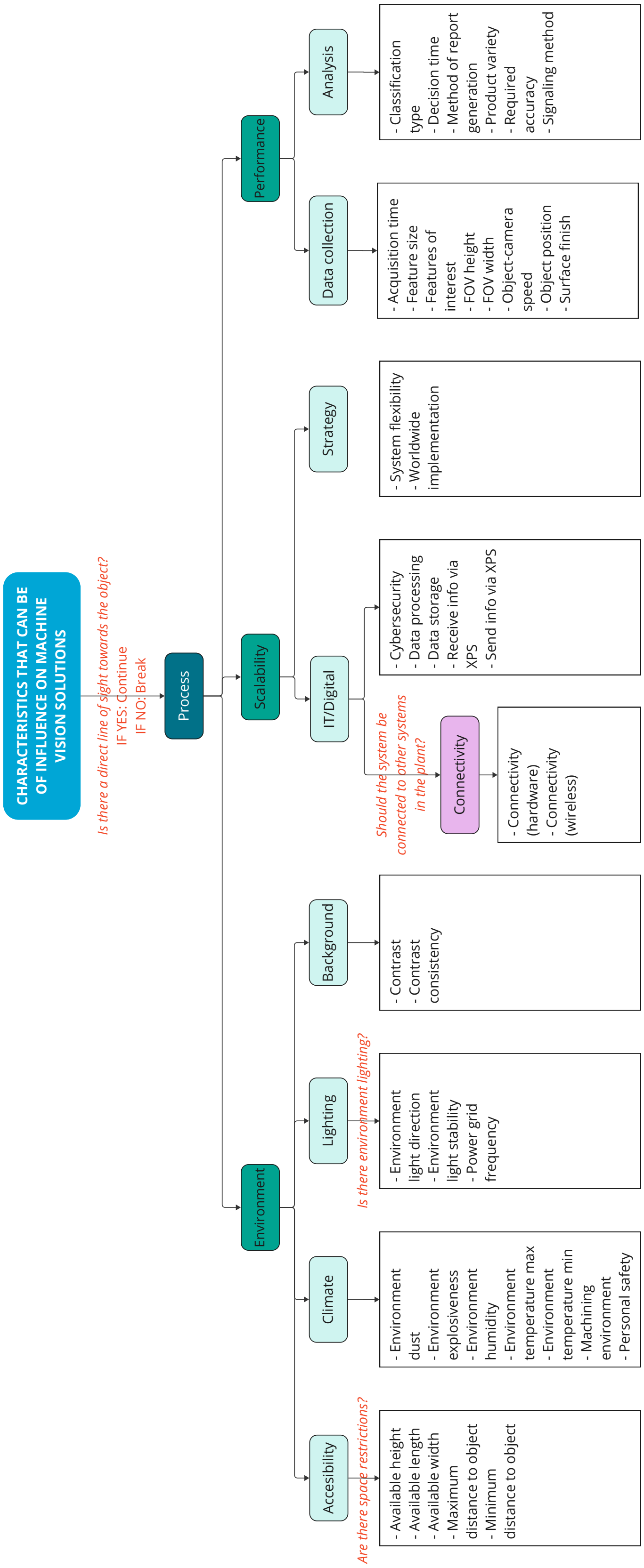

Figure C.2: Hierarchy of environmental characteristics (process)

D

Additional information on the links

D.1. Link to frame rate

Table D.1: Speed versus frame rate based on the research of Bartosinski et al. (2012)

Speed (m/s)	Frame rate (fps)
0	5
1	5
2	6
3	7
4	9
5	10
6	12
7	13
8	15
9	16
10	17
11	19
12	20
13	22
14	23
15	25
16	27
17	28
18	30
19	32
20	33
21	35
22	37
23	38
24	40
25	42
26	43
27	45
28	46
29	48
30	50
31	51
32	53
33	55
34	56
35	58
36	60

D.2. Link to focal length

Gaussian Lens Formula:

$$\frac{1}{f} = \frac{1}{s_i} + \frac{1}{s_o} \tag{D.1}$$

Where:

- f = focal length (m)
- s_i = the distance between the lens and the image plane (m)
- s_o = the distance between the lens and the object plane (m)

Rewriting results in:

$$\frac{s_i}{f} = 1 + \frac{s_i}{s_o} \tag{D.2}$$

Given $\frac{s_i}{s_o} = M$ (M = magnification):

$$\frac{s_i}{f} = 1 + M \tag{D.3}$$

$$\frac{s_i}{s_o f} = \frac{1+M}{s_o} \tag{D.4}$$

$$\frac{M}{f} = \frac{1+M}{s_o} \tag{D.5}$$

$$f(1+M) = M s_o \tag{D.6}$$

$$f = \frac{M s_o}{1+M} \tag{D.7}$$

Given $s_o = WD$ (WD = working distance):

$$\boxed{f = \frac{M \cdot WD}{1+M}} \tag{D.8}$$

D.3. Link to spatial setup

Table D.2: Database for lighting advise when environmental light is present

Environmental light direction	*Features of interest*	*Surface finish*	*Advise*
From behind the camera	3D shape	Shiny	No additional lighting required, unless unfavourable reflections or shadows appear. In that case install a dome light and block lighting from the back.
From behind the camera	3D shape	Matte	No additional lighting required, unless unfavourable reflections or shadows appear. In that case install a dome light and block lighting from the back.
From behind the camera	3D shape	Transparant	Consult lighting expert
From behind the camera	Characters/text	Shiny	Block lighting from the back and install dark field lighting
From behind the camera	Characters/text	Matte	Block lighting from the back and install dark field lighting
From behind the camera	Characters/text	Transparant	Block lighting from the back and install dark field lighting
From behind the camera	Colour	Shiny	If the light from the back has a strong intensity, block light and install diffuse lighting. Check if the colour of the light does not influence the colour of the part you want to asses.
From behind the camera	Colour	Matte	If the light from the back has a strong intensity, block light and install diffuse lighting. Check if the colour of the light does not influence the colour of the part you want to asses.
From behind the camera	Colour	Transparant	N/A
From behind the camera	Dimensions	Shiny	Block lighting from the back of the camera and install strong backlighting of the object.
From behind the camera	Dimensions	Matte	Block lighting from the back of the camera and install strong backlighting of the object.

From behind the camera	Dimensions	Transparant	Block lighting from the back of the camera and install strong backlighting of the object.
From behind the camera	Texture	Shiny	Block lighting from the back of the camera and install dark field lighting.
From behind the camera	Texture	Matte	Block lighting from the back of the camera and install dark field lighting.
From behind the camera	Texture	Transparant	Block lighting from the back of the camera and install dark field lighting.
From behind the camera	Shape	Shiny	Strong backlighting advised. Unless light from behind the camera is not very strong, block the light.
From behind the camera	Shape	Matte	Strong backlighting advised. Unless light from behind the camera is not very strong, block the light.
From behind the camera	Shape	Transparant	Strong backlighting advised. Unless light from behind the camera is not very strong, block the light.
From behind the camera	Surface defects	Shiny	Block lighting from the back of the camera and install dark field lighting.
From behind the camera	Surface defects	Matte	Block lighting from the back of the camera and install dark field lighting.
From behind the camera	Surface defects	Transparant	Block lighting from the back of the camera and install dark field lighting.
Towards the front of the camera	3D shape	Shiny	Block lighting from behind the object and install diffuse dome lighting
Towards the front of the camera	3D shape	Matte	Block lighting from behind the object and install diffuse dome lighting
Towards the front of the camera	3D shape	Transparant	Consult lighting expert

Towards the front of the camera	Characters/text	Shiny	Block lighting from the front and install dark field lighting
Towards the front of the camera	Characters/text	Matte	Block lighting from the front and install dark field lighting
Towards the front of the camera	Characters/text	Transparant	No additional lighting is required
Towards the front of the camera	Colour	Shiny	Install diffuse lighting from the back of the camera. If light from behind the object influences the image, block it. Check if the colour of the light does not influence the colour of the part you want to asses.
Towards the front of the camera	Colour	Matte	Install diffuse lighting from the back of the camera. If light from behind the object influences the image, block it. Check if the colour of the light does not influence the colour of the part you want to asses.
Towards the front of the camera	Colour	Transparant	N/A
Towards the front of the camera	Dimensions	Shiny	Additional backlighting might be necessary because of criticality of dimensions.
Towards the front of the camera	Dimensions	Matte	Additional backlighting might be necessary because of criticality of dimensions.
Towards the front of the camera	Dimensions	Transparant	Additional backlighting might be necessary because of criticality of dimensions.
Towards the front of the camera	Texture	Shiny	Block lighting towards the front of the camera and install dark field lighting

Towards the front of the camera	Texture	Matte	Block lighting towards the front of the camera and install dark field lighting
Towards the front of the camera	Texture	Transparant	Block lighting towards the front of the camera and install dark field lighting
Towards the front of the camera	Shape	Shiny	No additional lighting is required
Towards the front of the camera	Shape	Matte	No additional lighting is required
Towards the front of the camera	Shape	Transparant	No additional lighting is required
Towards the front of the camera	Surface defects	Shiny	Block lighting towards the front of the camera and install dark field lighting
Towards the front of the camera	Surface defects	Matte	Block lighting towards the front of the camera and install dark field lighting
Towards the front of the camera	Surface defects	Transparant	Block lighting towards the front of the camera and install dark field lighting
From (one of) the sides	3D shape	Shiny	Install diffuse dome lighting and if necessary block lighting from the sides.
From (one of) the sides	3D shape	Matte	Install diffuse dome lighting and if necessary block lighting from the sides.
From (one of) the sides	3D shape	Transparant	Consult lighting expert
From (one of) the sides	Characters/text	Shiny	No additional lighting is required unless light from the sides is to weak. Then intstall additional dark field lighting.

From (one of) the sides	Characters/text	Matte	No additional lighting is required unless light from the sides is to weak. Then intstall additional dark field lighting.
From (one of) the sides	Characters/text	Transparant	Install lighting from the back and block light from other directions.
From (one of) the sides	Colour	Shiny	No additional lighting is required. Check if the colour of the light does not influence the colour of the part you want to asses.
From (one of) the sides	Colour	Matte	No additional lighting is required. Check if the colour of the light does not influence the colour of the part you want to asses.
From (one of) the sides	Colour	Transparant	N/A
From (one of) the sides	Dimensions	Shiny	Strong backlighting advised, if necessary block lighting from the sides.
From (one of) the sides	Dimensions	Matte	Strong backlighting advised, if necessary block lighting from the sides.
From (one of) the sides	Dimensions	Transparant	Strong backlighting advised, if necessary block lighting from the sides.
From (one of) the sides	Texture	Shiny	No additional lighting is required unless light from the sides is to weak. Then intstall additional dark field lighting.
From (one of) the sides	Texture	Matte	No additional lighting is required unless light from the sides is to weak. Then intstall additional dark field lighting.
From (one of) the sides	Texture	Transparant	Install additional dark field lighting
From (one of) the sides	Shape	Shiny	Strong backlighting advised, if necessary block lighting from the sides.
From (one of) the sides	Shape	Matte	Strong backlighting advised, if necessary block lighting from the sides.
From (one of) the sides	Shape	Transparant	Consult lighting expert
From (one of) the sides	Surface defects	Shiny	No additional lighting is required unless light from the sides is to weak. Then intstall additional dark field lighting.

From (one of) the sides	Surface defects	Matte	No additional lighting is required unless light from the sides is to weak. Then intstall additional dark field lighting.
From (one of) the sides	Surface defects	Transparant	Install additional dark field lighting
Diffuse	3D shape	Shiny	No additional lighting is required, unless unfavourable shadows appear. In that case install dome lighting to avoid shadows.
Diffuse	3D shape	Matte	No additional lighting is required, unless unfavourable shadows appear. In that case install dome lighting to avoid shadows.
Diffuse	3D shape	Transparant	Consult lighting expert
Diffuse	Characters/text	Shiny	Very likely no additional lighting required. If additional lighting is required, install additional diffuse dome lighting.
Diffuse	Characters/text	Matte	Very likely no additional lighting required. If additional lighting is required, install additional diffuse dome lighting.
Diffuse	Characters/text	Transparant	Very likely no additional lighting required. If required, install strong backlight.
Diffuse	Colour	Shiny	Check if the colour of the light does not influence the colour of the part you want to asses.
Diffuse	Colour	Matte	Check if the colour of the light does not influence the colour of the part you want to asses.
Diffuse	Colour	Transparant	Check if the colour of the light does not influence the colour of the part you want to asses.
Diffuse	Dimensions	Shiny	Strong backlighting advised
Diffuse	Dimensions	Matte	Strong backlighting advised

Diffuse	Dimensions	Transparant	Strong backlighting advised
Diffuse	Texture	Shiny	Install dark field lighting. Possibly block ambient lighting.
Diffuse	Texture	Matte	Install dark field lighting. Possibly block ambient lighting.
Diffuse	Texture	Transparant	Install dark field lighting. Possibly block ambient lighting.
Diffuse	Shape	Shiny	Strong backlighting advised
Diffuse	Shape	Matte	Strong backlighting advised
Diffuse	Shape	Transparant	Strong backlighting advised
Diffuse	Surface defects	Shiny	Install dark field lighting. Possibly block ambient lighting.
Diffuse	Surface defects	Matte	Install dark field lighting. Possibly block ambient lighting.
Diffuse	Surface defects	Transparant	Install dark field lighting. Possibly block ambient lighting.

Table D.3: Database for lighting advise when no environmental light is present

Features of interest	*Surface finish*	*Advise*
3D shape	Shiny	Install diffuse dome lighting.
3D shape	Matte	Install diffuse dome lighting.
3D shape	Transparant	Consult lighting expert.
Characters/text	Shiny	Install dark field lighting.
Characters/text	Matte	Install dark field lighting.
Characters/text	Transparant	Install back lighting.
Colour	Shiny	Install diffuse dome lighting. Check if the colour of the light does not influence the colour of the part you want to asses.
Colour	Matte	Install diffuse dome lighting. Check if the colour of the light does not influence the colour of the part you want to asses.
Colour	Transparant	N/A
Dimensions	Shiny	Install back lighting.
Dimensions	Matte	Install back lighting.
Dimensions	Transparant	Install back lighting.
Texture	Shiny	Install dark field lighting.
Texture	Matte	Install dark field lighting.
Texture	Transparant	Install dark field lighting.
Shape	Shiny	Install back lighting.

Shape	Matte	Install back lighting.
Shape	Transparant	Install back lighting.
Surface defects	Shiny	Install dark field lighting.
Surface defects	Matte	Install dark field lighting.
Surface defects	Transparant	Install dark field lighting.