Bachelor Degree Project

UNIVERSITY OF SKÖVDE

IMPLAMENTATION OF MACHINE VISION ON A COLLABORATIVE ROBOT

English

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Abstract
This project is developed with the University of Skövde and Volvo GTO. Purpose of the project is to complement and facilitate the quality insurance when gluing the engine frame. Quality defects in today's industry is a major concern due to how costly it is to fix them. With competition rising and quality demands increasing, companies are looking for new and more efficient ways to ensure quality. Collaborative robots is a rising and unexplored technology in most industries. It is an upcoming field with great flexibility that could solve many issues and can assist its processes that are difficult to automate. The project aims to investigate if it is possible and beneficial to implement a vision system on a collaborative robot which ensures quality. Also, investigate if the collaborative robot could work with other tasks as well. This project also includes training and learning an artificial network with CAD generated models and real-life prototypes. The project had a lot of challenges with both training the AI and how the robot would communicate with it.

The final results stated that a collaborative robot more specific UR10e could work with machine vision. This solution was based on using a camera which was compatible with the built-in robot software. However, this does not mean that other type of cameras cannot be used for this type of functions as well. Using machine vision based on artificial intelligence is a valid solution but requires further development and training to get a software function working in industry.

Working with collaborative robots could change the industry for the better in many ways. Implementing collaborative robots could ease the work for the operators to aid in heavy lifting and repetitive work. Being able to combine a collaborative robot with a vision system could increase productivity and economic benefits.

Certificate

Herby Axel Leidenkrantz and Erik Westbrandt declare that this bachelor degree project follows the guidelines used by the University of Skövde. The material provided in this report which is not owned by the authors is referred to using the Harvard style.

Skövde 4/6-2019
Place and date

Axel Leidenkrantz
Signature

Erik westbrandt
Signature

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1 Introduction

This chapter is an introduction to the thesis and contains a brief problem description followed by Purpose and objectives, scope, sustainability aspects and software descriptions.

1.1 *Problem description*

This project is developed by the University of Skövde in collaboration with Volvo GTO which is a truck manufacturer from Sweden with a high degree of automation. Other than trucks this company also produce construction equipment, boat engines, busses and much more. As of now, they have factories all over the world. The plant located in Skövde is their main producer of truck engines and this is where the project will take place.

In today's industry, quality inspection is considered time and money consuming. Quality inspections in assembly are performed differently from processing lines. In assembly lines, the common way to ensure quality is to have a manual inspection by the operator. Manual quality inspections are unreliable since human factors impact the outcome of the inspections. These factors can be lack of training, fatigue, laziness, unclear specification, rushed job and more (Soini, 2001).

When assuring quality during the processing stages machine vision is a regularly used method. Machine vision is a camera-based quality inspection method which origins from the 1960s. This inspection method is a popular application in a diversity of work fields such as medical diagnostics, automotive industry, food industry and robot guidance. (Brosnan, T. and Sun, D.W., 2004)

Today's machine visions have fix mounted cameras which makes them inflexible and linear in their way of working. These cameras have a problem to reach inaccessible areas of the product such as underneath, inside and in some cases around. The project focuses on implementing a camera-based vision system on a collaborative robot in an automotive manufacturing assembly line. This is to determine if a collaborative robot is an efficient solution to the flexibility issue with machine vision.

The quality inspection at hand is the application of glue strings on top of the engine before mounting the engine cover, application of the glue strings is to prevent leakage. There should be two distinct glue strings on each side of the area with a gap of 2-5 mm between each other, see figure 1.

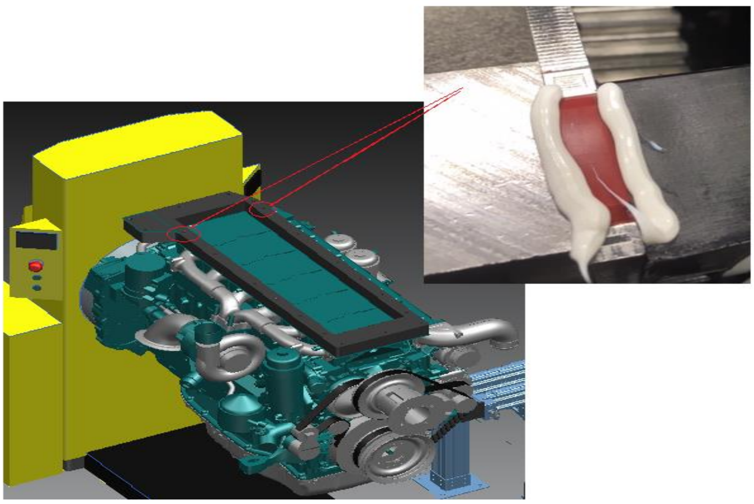

Figure 1 Glue string application

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1.2 *Purpose and objectives*

The purpose of this thesis is to determine if a collaborative robot can use machine vision efficiently, while still being capable of performing other tasks. To test this, a physical demonstration will be created on a collaborative robot. To further specify what the project will concern it will be divided into five objectives.

- A report containing a literature study concerning collaborative robots and machine vision, specified on object detection.
- Collaboration with other teams working on the same station.
- Investigate if a collaborative robot can work with a machine vision in an effective way.
- Physical demonstration of a collaborative robot working with machine vision.
- Identify if the robot can perform additional tasks beyond machine vision.
- Training the vision software.

1.3 *Scope*

To keep the project within reasonable boundaries and focused on the objectives some limitations were necessary. The project is focused at an assembly station where a string of glue is applied on a frame to mount the engine cover. Three out of four engines that are produced uses the glue string, which means that not all will need quality inspection. Other limitations concern:

- The collaborative robot is already mounted and in place which provides a fixed working station.
- Literature study only concern new technology regarding machine vision and object detection.
- Safety aspects for human-robot collaboration will not be analyzed since another team works with this.

A gant schedule was created to approximate the time that needs to be spent on each of the different tasks at hand, see figure 2.

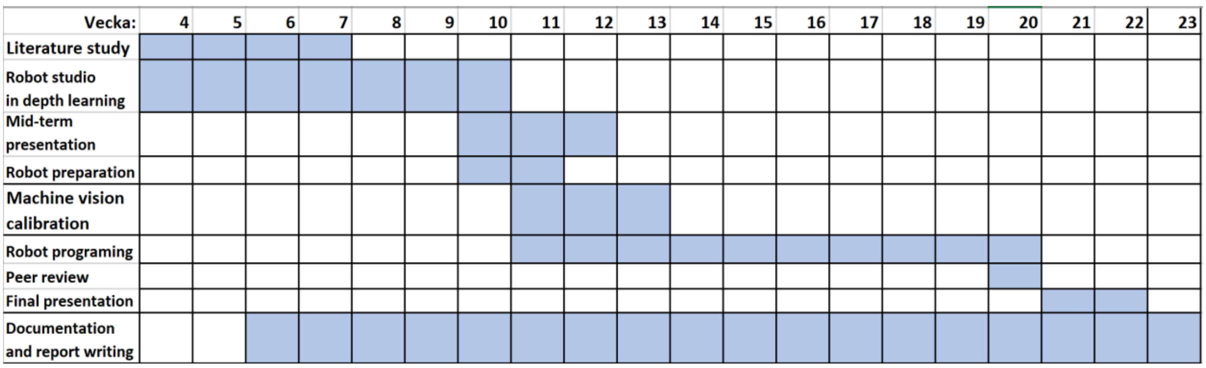

Figure 2 Gant schedule

1.4 *Sustainability*

A rapidly growing field within manufacturing is sustainability. This does not only include the ecological aspect as people may think but also economic and social sustainability.

Ecological sustainability concerns taking care of the biosphere so that the present generation does not compromise future generations standard of living. For example, maintaining biodiversity, not over consume earth's natural resources, stop water, air and land pollution. (Gulliksson & Holmgren, 2015)

A **socially sustainable** society is according to Gulliksson & Holmgren (2015), promoting equality, including all races and beliefs, fair and democratic. It should guarantee the life quality of all individuals in the present and future generations.

Maintaining an **economically sustainable** business means increasing long-term economic growth without jeopardizing ecological or social sustainability. Achieving economic sustainability might be a hard challenge, but a very important factor to grow and maintain satisfied customers. (Gulliksson & Holmgren, 2015)

As customers get more and more concerned with the environment and working conditions, the manufacturing industry need to adapt and learn to keep customers interested in their products (Groover, 2005). Throughout this report, these three different aspects of sustainability will be discussed. During this project, the most crucial aspect is social sustainability. The reason for this is the controversial debate of machines and robots replacing human workforce. (Gulliksson & Holmgren, 2015)

1.4.1 Sustainable aspect of quality control

Implementing automatic quality control will have an impact on all of the three fields of sustainability.

Concerning the **economic** aspect of sustainable development, the cost of quality defects can range as high as 40 % of total sales turnover within a company. Average sales loss due to quality defects in the industry is running close to 25 %. The cost of reworking a product increases the further along the manufacturing process the product is, see figure 3. However, not all companies work with quality improvements on a daily basis. In a study conducted by Grant Thornton which is an accounting and consulting firm in the United States, 83% of American companies reported that quality is the top priority. Yet, only less than a third of them had calculated the costs associated with it. This is one area which would greatly benefit from automatic quality control, for example using machine vision attached to a robot. (Antonaras & Lacovidou, 2010)

Figure 3 Defect costs

In this project **economic** and **ecological** aspect links together. With the reduction of quality defects by implementing automatic visual control, the need for reworked or scarped products can be limited. This will not only save money and time but also the need to use extra material to fix defects or in worst case dispose products. Discarding entire products with defects or flaws are not only bad from an economic perspective but also harm the environment. However, it is not only the extra material used that might impact the environment. When a defect is detected the product has to be reworked, which means that it has to go through some steps of the manufacturing process again. This results in more energy waste and pollution.

To minimize the **ecological footprint** of a manufacturing process, it becomes even more crucial to discover these defects at an early stage. The **ecological footprint** is as described by Wackernagel & Rees (1988), a measurement of humans demand on nature. It concerns the quantity of nature it takes to support a persons standard of living. Ecological footprint for a manufacturing process is similar to the ones of humans in most ways.

The goal when working with sustainability in the industrial sector is to achieve something called sustainable manufacturing. According to Rosen & Kishawy (2012) sustainable manufacturing is *"the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound".*

1.5 *Softwares*

1.5.1 Robot Studio

Robot studio is an offline programming software developed by ABB (ASEA Brown Boveri). In robot studio, a 3-dimensional environment is used to get as good representation of the real robot cell as possible. Offline programming is used to minimize production downtime during the implementation of a robot by doing as much as possible before installing it. Throughout this project, Robot Studio will be used to optimize the robot sequence performing the quality inspection. The software will also be used as a link between the machine vision and the robot.

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1.5.2 Image vision software

A machine vision software based on AI technology will be used. It is a supervised learning program using object detection to separate correct from incorrect. The vision software is developed by an employee at the University of Skövde.

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2 Frame of reference

The second chapter contains a background of all the areas covered in the thesis. The chapter includes what a quality inspection is, robotics in automated industries, how a machine vision is built and used, as well as a brief introduction to AI.

2.1 *Quality inspection*

To assure quality and prevent defects on products, inspection is required throughout the whole manufacturing process. Quality inspection is according to ISO/TS 9000:2015 (2015) “part of quality management focused on providing confidence that quality requirements will be fulfilled”. The 9000:2015 ISO standard applies to the following:

- Organizations wanting to implement a quality management system to gain success.
- Customers, to make sure the products they purchase reach quality standards.
- Organizations wanting to validate that their supply chain reach the requirements set up for the finished product.
- Organizations performing assessments of ISO 9001.
- Providers of education regarding quality management.

The standards are used to provide guidelines for both management and employees to strive towards the same goal. Criterias to reach ISO certificate are described further in ISO 9001:2015 and emphasizes all areas of a business.

2.2 *Robotics*

An industrial robot is defined according to ISO 8373:2012 as, “An automatically controlled, reprogrammable, multi-purpose manipulator that is programmable in three or more axes which can be either fixed or mobile for use in industrial automation” (ISO/TS, 2016). The definition aims at automated industrial applications, it states the important functions as automatically controlled, universal and reprogrammable. (Bolmsjö, 2006)

The idea of robotics in the industrial sector dates to 1954 when an American engineer named George Devol filed a patent on a **programmed article transfer**. Devol’s patent was for the first digital programmed robotics arm, this is considered the spark of robotics in the industrial sector. However, it took Devol several years to deliver a functional robotic solution. It was not until 1961 that the first robot was used in an industrial environment. General Motors implemented a robot to extract parts from a die-casting machine. (Hägele, et al., 2008)

A breakthrough in industrial robotics was achieved in 1973 when ABB introduced the first computer controlled all electric component robot, called IRB 6 (Hägele, et al., 2008). IRB 6 was a three-joint robust robot with a reported lifespan of up to 20 years. All electrical components allowed a continuous movement for the robot, which was essential to develop robotic solutions for welding and machining. Five years later Hiroshi Makino, a professor at Yamanashi University in Japan developed the first four-joint robot. Makino named this robot SCARA (Selective Compliance Assembly robot arm). The four-jointed SCARA robot was optimal for pick and place operations and was considered groundbreaking because of its low cost, while retained good precision. Since then robotics in the industrial sectors have taken huge steps forward in development and are now a part of everyday manufacturing. As many as one million industrial robots were installed in 2007 (Hägele, et al., 2008). The main users are the automotive industry, but robotic solutions are used in other industries as well.

2.3 *Industrial application for robots*

Within the industrial sector, there are certain areas and applications the robots excel on. The different applications can be divided into three different categories. These categories are assembly and inspection, material handling and processing operations. (Groover, 2005)

2.3.1 Material handling

One of the most common applications for robotics in the industrial sector is pick and place operations. This task is a simple procedure where the robot picks up a part and moves it to another location (Groover, 2005). It requires a low-technology robot, and three joints are often enough to perform this type of work. Examples of pick and place tasks for a robot could be loading and unloading a machine, picking parts from a pallet and placing it on a conveyor, loading AGV's and trucks for transportation.

2.3.2 Processing operations

Robots used in process manufacturing often include performing operations on a part. For example, grinding, spray painting and different types of welding (Groover, 2005). A tool of some sort is almost always equipped onto the end effector of the robot when performing processing operations. For example, a welding tool when performing different types of welding.

2.3.3 Assembly and inspection

Another common application for industrial robots is assembly. This procedure involves combining two or more parts to form a new entity (Groover, 2005). However, when mass producing a product the robot becomes disadvantageous when performing assembly operations. The reason for this is because the robot cannot work at the same speed as fixed-automated equipment. However, robots often benefit in production when there is a mix of different models produced at the same place. Car body assembly was early on a predominant application due to the difficulty to handle heavy metal sheets for operators. (Hägele, et al., 2008)

2.3.4 Other applications

There are other key characteristics that could indicate when a manufacturing process would benefit from implementing a robot. According to Groover (2005) these characteristics are:

- **Hazardous work for humans**: The work environment is in any way harmful to humans.
- **Repetitive work cycle**: Repetitive work cycles tend to make humans imprecise, and robots can perform repetitive work with greater consistency and repeatability then humans.
- **Difficult handling for humans**: If parts or tools are heavy or otherwise difficult to handle for humans, a robot should be considered for the work instead.
- **Multishift operation**: In operations with many and long shifts, a robot would provide faster financial payback.
- **Infrequent changeovers**: Robots have consequently been easier to justify for long production runs where changeovers are infrequent.

These five different characteristics indicate when a robot could replace a human operator in a manufacturing process.

2.4 *Pros and cons for industrial robotics*

When implementing robotic solutions in manufacturing processes, there is always some controversy concerning how the investment will affect the company long term. According to Niku (2010), both operator and machine have their advantages and disadvantages in a manufacturing process. This means that it is important to investigate which aspects are beneficial when implementing a robot.

2.4.1 Pros

- **Increased quality through consistency:** As described earlier, robots, when adjusted and programmed correctly will have less variance in quality outcome.
- **Higher productivity:** Robots almost always increases productivity on a manufacturing process by eliminating wastes. They can work 24 hours a day, seven days a week with next to no breaks apart from maintenance.
- **Increased safety:** Using robots for dangerous and repetitive work means fewer risks for workers, during production.
- **Higher profitability:** By increasing productivity and quality the profitability of the manufacturing process will increase.

2.4.2 Cons

- **High initial investment:** Robots require a high capital cost for installation, hardware and software, infrastructure and safety equipment.
- **Expertise:** Not only are robots costly to invest in but also require trained and knowledgeable personnel.
- **Inflexible:** A robot cannot comprehend and adapt if unforeseen things happen throughout the work process which can make them dangerous.
- **Human replacement:** One frequently discussed concern is the unemployment issue if robots replace human workforce.

2.5 *Collaborative robots*

Today's industry becomes more and more challenging concerning flexibility and efficiency. Developing a safe and efficient way of collaboration between robots and human workforce might be one way to solve this demand (Michalos, et al., 2014). According to ISO/TS 15066:2016, the objective of a collaborative robot is to combine the repetitive performance of robots with the ability and skills of human workforce.

There are several ways a collaborative robot can interact and be useful in an assembly line. For example, using a universal robot, see figure 4. The robot can deliver assembly parts to the operator, this will reduce the time spent by the operator searching and gathering parts. Another way of collaborating is having the robot and operator performing different suboperations within the same work cell. A third option is using the robot as an aid when lifting heavy objects, this prevents injuries on operators. These approaches make use of the best qualities in both robots and humans, to achieve a better working environment. (Michalos, et al., 2014)

Figure 4: UR3 robot

A big concern when implementing a collaborative robot is the safety aspect. Even though there are well-developed solutions to issue, the international safety standards for a human-robot collaborative work cell are hard to reach. These regulations are also covered by ISO/TS 15066:2016. This is the main reason why collaboration between robots and humans is far from reality in the major part of industrial manufacturing. (Michalos, et al., 2014)

Today many different companies are developing collaborative robots. The biggest names on the market are ABB, universal robots, KUKA AG to name a few. Universal robots develop three different collaborative robots, UR3, UR5 and UR10. The three robots have different reach and weight limitations. The UR3 can carry three kilos and reach 0.5 meters, UR5 has a reach of 0.85 meters and can carry up to five kilos, the largest of the three is the UR10 which can carry ten kilos and reach as far as 1.3 meters, see figure 5 and appendix 1. (UR, 2018)

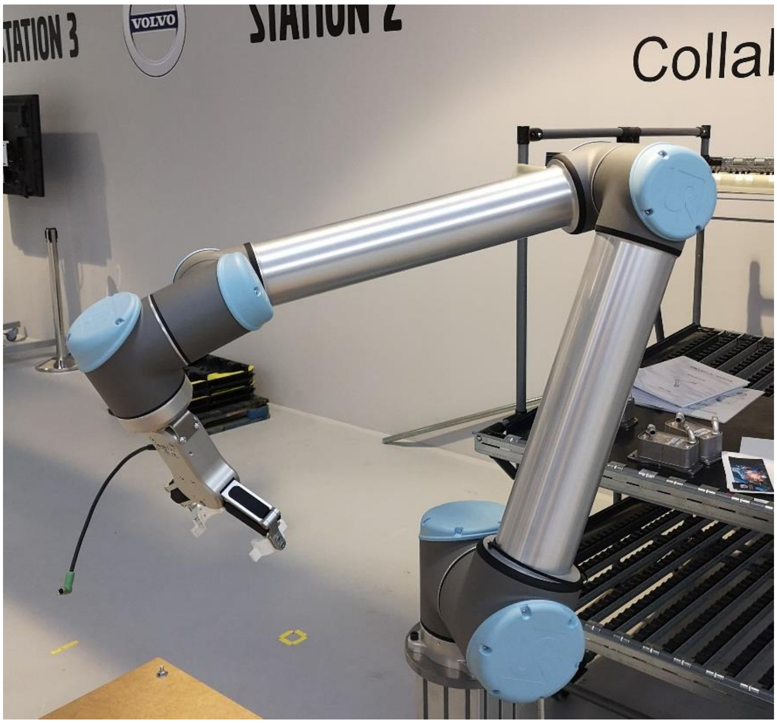

Figure 5: UR10 robot

These robots are equipped with a variety of safety applications to prevent fatal injuries to humans. For example, UR3, UR5 and UR10 all come equipped with force limitations which means that the robot will detect if abnormal force is experienced while working. Other safety applications are environment recognition with the help of force sensors, these are used to prevent the robot from crashing into other objects. (UR, 2018)

2.6 *Machine vision*

Out of the five different senses vision, hearing, smell, taste and touch, eyesight is what humans depend on the most. Vision provides most data for the brain to analyze out of all the senses. Nowadays, most manufacturing processes are highly automated. In some of the processes machine vision is needed, throughout the years this has been researched and developed. However, no general solution for creating a machine vision system has been established. Machine vision is hard to perfect since human vision is very complex and hard to replicate. (Davies, 2012)

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2.6.1 Recognition problem

One of the biggest issues when handling machine vision is the problem to recognize the object it is searching for. A way of simplifying this for the machine is to standardize the position of the image. Having a fixed spot where the images are taken might solve this issue. This will create an illusion for the system that makes it think it is working in two dimensions instead of three. By centralizing the object, it can help the vision system to recognize the object. (Davies, 2012)

A vision system needs to have different references to know what it is supposed to recognize and what it sees, character recognition is a simple way of breaking it down. The system takes advantage of how the structures of the characters are built. All characters are built by limbs which have a roughly constant width. However, since the width does not have any useful information, the patterns of different letters are thinned down to stick figures or skeletons to serve as references for the system, see figure 6. With this technique, the system can be deceived to reduce the dimension even further or at least minimizing the training necessary for effective recognition. An issue that will occur when working with character recognition is the similarities between some of the characters. Some examples are 'n' and 'h', 'C' and 'G', 'P' and 'R'. To tackle this problem a two-stage recognition scheme is implemented where the first stage recognizes the letter and the second stage creates the image in very few bits which makes it easier for the system to recognize the character. (Davies, 2012)

Figure 6: Character skeleton as references (Davies, 2012, p.5)

2.6.2 Object location

Locating an object can involve demanding mathematics which is subject to a **combinatorial explosion**, a rapid growth of complexity in the problem affected by inputs. One method is to make a suitable 'n x n' template matrix of pixels moving along the whole image, of size 'N x N'. Move the 'n x n' matrix over the whole image to find matches for the set objects. The position of the object can be determined by the template location when an exact agreement of template and object match. This method is inefficient and barely used by any machine vision in today's industry. The reason this is a combinatorial explosion is that the calculation on how many different operations needed can be calculated by equation 1. (Davies, 2012)

Equation 1

$$N^2 * n^2$$

To put this into perspective a '5 x 5' template on a '256 x 256' (low quality) image will result in over 1,5 million operations. This shows that even on low-quality images, object detection becomes complex.

There are other methods which are built upon the first but are further developed. These methods search for features of the set object on the whole image. The system features are built differently depending on what object it is searching for. When searching for features, it is often optimal to allocate a few big features rather than many small. This is in order to achieve higher accuracy in finding the object. When features of the object have been pinpointed in the image, the system searches for an exact match on those locations. These methods can drastically lower the number of operations needed compared to the first method. (Davies, 2012)

Another machine vision technique that is used in automated industry is for the system to detect a few distinct features in the image. If the system can locate all the features in the image, it will check the distance between the locations to control if the structure of the image is correct. The distance between the features needs to be known for the system to be able to determine if the object is correct. When the system searches for truly indistinguishable features an ambiguity remains since not all objects have symmetric surface if the object is rotated 180°. Because of this, generally at least three different points of features need to be allocated by the system for it to identify the range between the points. There are a lot of problems that can occur when using a set distance. For example, the object can be disoriented when a picture is taken. To prevent this, there is a tolerance for all distances for each of the features. The tolerances will be dependent on the system and how steady the object is when the picture is taken. When declaring the tolerances as many disturbance factors as possible should be considered. (Davies, 2012)

2.6.3 Applications of machine vision

According to Davies (2012), there are three different main applications that machine vision can be used for in automated visual inspection:

- Controlling the quality of a product, checking if the product has been processed correctly and rejects products that do not pass the control.
- Gathering information about how the quality of the products leaves earlier stages. An example could be in the food industry on chocolate, where the system controls the products and on how the chocolate is spreading. The system gives feedback to earlier stages to regulate the temperature accordingly to make the chocolate spread like the manufacturer prefers.
- Machine vision can also be used for the logistics of an operation. It can include parameters such as variations in the product dimensions, reject rates of the products and temperature for further planning in the future.

In today’s industry, all sorts of products with different shapes and sizes are being manufactured. When using machine vision as quality control, all these different products can be divided into two categories, metal and food. The first one can be defined as precision metal parts. These have specific shapes since they are required to fit together with other parts within a tolerance. They usually have some specific features for reference such as holes or thread sizes. The second category is typically found in the food industry and focuses more on the shape of the product. For example, there are no potatoes with the same shape. The broad difference is that the first category uses exact dimensions, while the second uses shapes to identify the product. (Davies, 2012)

2.7 *Deep Learning*

Creating machines that can think has been a thought in inventors life since ancient Greece. When programmable computers first came out, people wondered if they could become intelligent. Today, Artificial Intelligence (AI) is thriving with many researchers and committed people developing the field even further. There are a lot of industries that uses AI’s technology, which are programmed differently depending on the industry. For example, understand speech or images, make diagnoses in medicine and support scientific research to name a few. (Goodfellow, et al., 2016)

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2.7.1 AI development

In the early stages of AI research, many softwares were focused on an area where the rules were based upon a list of formal mathematical rules. One of these fields was chess, the rules of chess are quite simple but have a lot of mathematics involved. This can make it hard for humans to calculate on the spot. The true challenge did not lie within programs with set mathematical rules, but rather tasks which are easy for people to perform but hard to describe. For example, tasks that are solved intuitively like face recognition. This is because it requires an immense amount of information about the world, much of this knowledge is intuitively for humans. The computers need to capture this knowledge in order to behave in certain ways. The challenge in the development of AI's is to get this knowledge programmed into the software. To tackle this problem a solution to make computers learn from experience and understand the world in a concept of hierarchy, with concept defined in terms of its relations to simpler concepts. Using this solution avoids specifying knowledge about the world, this is called **deep learning**. (Goodfellow et al, 2016)

Some Artificial Intelligence is built upon a **knowledge base** approach, which is based on hard-coded knowledge statements. This approach has not led to any major success within the field. Even though the knowledge base artificial intelligence has not been very successful, a major discovery was made by following this path. The difficulty that hard-coded systems have is to acquire their own knowledge and need the ability to extract patterns from raw data, this is called **machine learning.** With the development of machine learning computers were able to make decisions that appear to be subjective, on problems based on knowledge of the real world. One algorithm based on machine learning is **naive Bayes**, which is an algorithm that can separate legitimate e-mail from spam e-mail. (Goodfellow et al, 2016)

The performance of machine learning algorithms is dependent on the representation of the information given to them. For example, when an AI is used to examine if a cesarean delivery is recommended when giving birth, the AI does not interact with the patient directly. Instead, the doctor feeds relevant data to the system in order to make the correct decision. The system is built to break down the information and make correlations between the information given and to the correct decision. Giving a system raw data that can be broken down and built upon is better than giving the system an MRI-scan for example. The MRI-scan does not have any correlation to the complications that can occur during delivery. When a solid system is given structured data instead of a pile of information that needs to be sorted, the structured information can be exponentially faster. The way the information should be represented or extracted is not always clear. For example, take a program that wants to detect cars. The program can take advantage of that the car has wheels and use them as a reference. Unfortunately, wheels are hard to describe in pixel values. A wheel has a simple geometry but can, for example, be disturbed by sun glare or the fender of the car. One solution to this problem is to use machine learning to teach the system the representation of the image itself. This approach is known as **representation learning**, which often results in a better performance than a hand-designed representation. By using this technique, the AI can rapidly adapt to new tasks, with minimal human intervention. (Goodfellow et al, 2016)

Representation learning can have difficulty extracting high-level abstract features from raw data. For example, a dark car in an image taken at night. At first glance, representation learning does not seem to help the development of AI's. With the help of **deep learning**, representation learning problems can be solved by expressing the representations, with simpler representations. The system builds complex concepts out of simpler concepts, see figure 7. The primal example of deep learning is **Multilayer Perceptron** (MLP). A multilayer perceptron is a mathematical function mapping set of input values to output values. Each layer provides a new representation of the input. (Goodfellow et al, 2016)

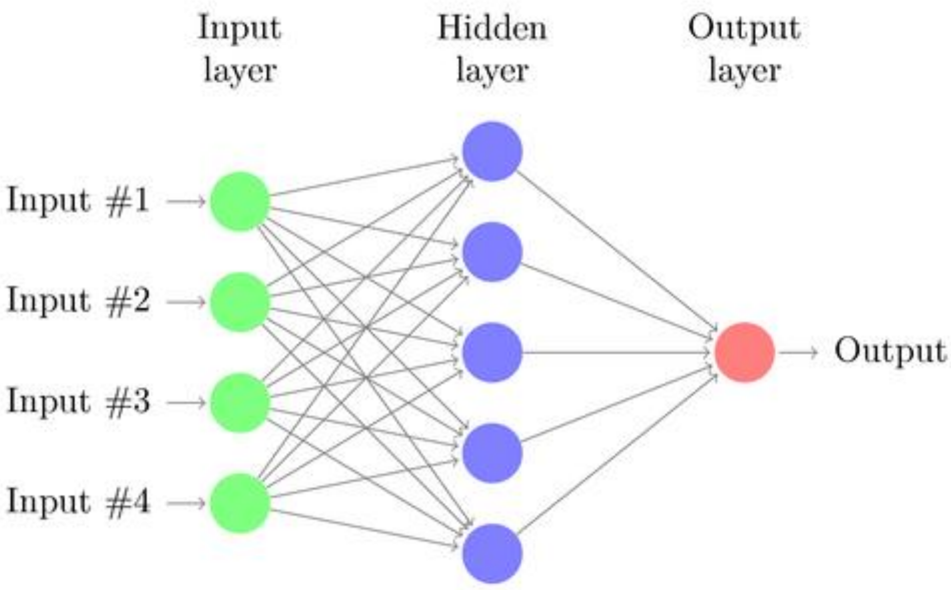

Figure 7: Multilayer perceptron (Goodfellow et al, 2016, p.6)

2.7.2 Convolutional Neural Network (CNN)

Most AI's for object detection developed nowadays are based on CNN in some way. Detection algorithm tries to draw bounding boxes around the object of interest in the image, see figure 8. The algorithm may draw any number of bounding box in a detection case, there might be many bounding boxes representing different objects of interest or none if nothing is detected. The algorithm helps since the output layer is a variable and not a constant in these problems. This is because the number of occurrences of objects of interest is not fixed in the images. An approach to solve the problem could be to take the image and divide it into different regions interests, then use a CNN to classify the objects within the regions. The problem with the approach is that the objects within the image can have different aspect ratios, which will create a problem where the number of regions will increase massively. Therefore, algorithms like R-CNN (region CNN) have been developed to solve this problem and find these occurrences fast. (Girshick, et al., 2014)

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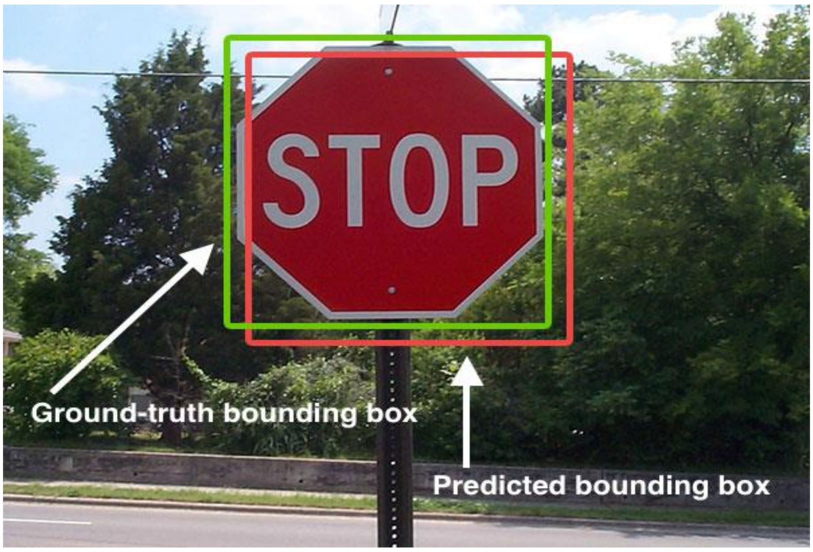

Figure 8: Bound box

The R-CNN is an algorithm built to bypass the problem of selecting a massive number of regions, Ross Girshick, et al. (2014) proposed to use it to extract 2000 regions from the image and called them region proposals. Instead of working with a huge number of regions, the amount of region are set to 2000 and are easier to handle.

According to Girshick, et al. (2014), the downsides of using R-CNN is.

- To find the 2000 region proposals takes a long time for the system to train.
- It is not feasible to implement in real time since each imaging test takes 47 seconds.
- The selective search algorithm is fixed, and no learning can happen at that stage, which can lead to bad region proposals.

The R-CNN has been further developed in FAST R-CNN and FASTER R-CNN to solve these issues and is more advanced and efficient.

3 Literature review

The literature review chapter contains information and statistics from older papers and articles about the same area as the thesis. Everything from a comparison of manual and automated quality inspection, lightning's impact on the inspection, implementation of collaborative robots and safety aspects of working together with a robot.

3.1 *Machine vision quality evaluation*

A study was made in 2016, which evaluated the quality evaluation of a machine vision system on food grains. The study was performed in order to determine if automated quality inspection is efficient enough to be a worthy investment to replace manual inspections.

The machine vision system can be implemented as an on-line inspection, which creates changes in the process but improves the efficiency and overall process control. They tested a lot of machine vision systems, with different tasks. For example, separating according to, variations of grains, size differences, wheat types and more. These tests were performed to see limitations on the vision systems. While performing the tests, some complications occurred when the systems needed to check for internal insect infestation and organoleptic properties. The system did not understand the grain components. Another issue was lightning of the images which was inconsistent and created bad results. If the images had improved quality, the processing time for the system increases. This could result in the system not being able to work in real-time. (Vithu & Moses, 2016)

Overall, most of the machines working with image processing methods need skilled laborers and often suffer from tedious problems. For example, the need for consistent quality and lightning to minimize the variance in the images. Computer orientated software are quickly developed, tested and debugged. They are highly hardware dependent which constantly needs to be upgraded when it is further developed, while still being able to work in real-time. The costs are another relevant aspect while evaluating different image acquisition systems. These systems can have enormous costs if the system has a high demand on the hardware. Which in most cases it does, if it should be able to run in real-time. High performance obtained with the usage of the system often out-weigh the downsides. (Vithu & Moses, 2016)

A machine vision system can provide rapid and accurate external quality inspection. The implementation of a vision system can increase the efficiency of the process. With the right image acquisition system for an important inspection, the integration of machine vision is often recommended. (Vithu & Moses, 2016)

3.2 *Implementing a collaborative robot in an assembly operation*

When implementing a collaborative robot in an assembly line, numerous aspects need to be taken into consideration. One crucial aspect is how the work tasks should be distributed between robot and human. Müller, et al. (2016) presented a method that analyses the elements during assembly. The method contains four different types of work between man and machine. First work type is the robot and human working on separate worktables but within the same cell. The second one is cooperation between the human and the robot where they work hand in hand performing tasks together. Another work type is synchronized work, this means that the robot and human perform their tasks one after the other in the same workspace. Lastly, and the most common one today is where the robot and human work separate from each other (Müller, et al., 2016).

Human workforce and robotics have different advantages when it comes to assembly, (Müller, et al., 2016).

Advantages of humans:

- High availability
- Handle complex components
- Precise execution of complex joining processes
- Loading magazine of components
- More flexible then robots

Advantages of robots:

- Integrated process control
- Handling of heavy and possibly hazardous objects
- Exact playback of defined paths
- Reliable in repetitive task

Fast-Berglund, et al. (2016) describes the possibilities of a collaborative robot within an assembly line as promising. Despite the numerous safety aspects that must be taken into consideration, the positives still outweigh the negatives. It could in the future even be worth to replace one human worker with a small flexible collaborative robot.

3.3 *Safe human-robot collaboration*

Robla-Gómez, et al. (2017) performed a study concerning safety of collaborative robots. The study investigates different scenarios with operators working alongside a collaborative robot and evaluates the safety risks. It examines what safety procedures can be established when removing the boundaries between working robots and humans.

The typical industrial robot is large and heavy. When robots are working, they often move at high speed. When this is the case, it is necessary to take percussions to prevent accidents between robot and humans who enter the workspace. To avoid a collision, there is often a cell surrounding the workspace and when someone enters it shuts down or lowers the speed of the robot. This percussion is taken to satisfy ISO 10218:1992, which states that prevention of collision that may cause injuries is needed. (Robla-Gómez, et al., 2017)

When implementing a human-robot collaborative work cell, it is necessary to remove the boundaries separating the human and robot. Therefore, new risks emerge which needs to be addressed. The study has approached the issue of collision in two different ways, the first one is pain tolerance and the second is to quantify the level of injury followed by a collision. (Robla-Gómez, et al., 2017)

Pain tolerance study was based on an actuator consisting of a pneumatic cylinder. The actuator tests impact on 12 different parts of the human body on volunteers to conclude a tolerable contact force, see figure 9 (Robla-Gómez, et al., 2017). The mean value of the force for pain tolerance range from 65N to 146N and min from 13N to 46N, depending on the measurement point, see figure 9 (Suita, et al., 1995).

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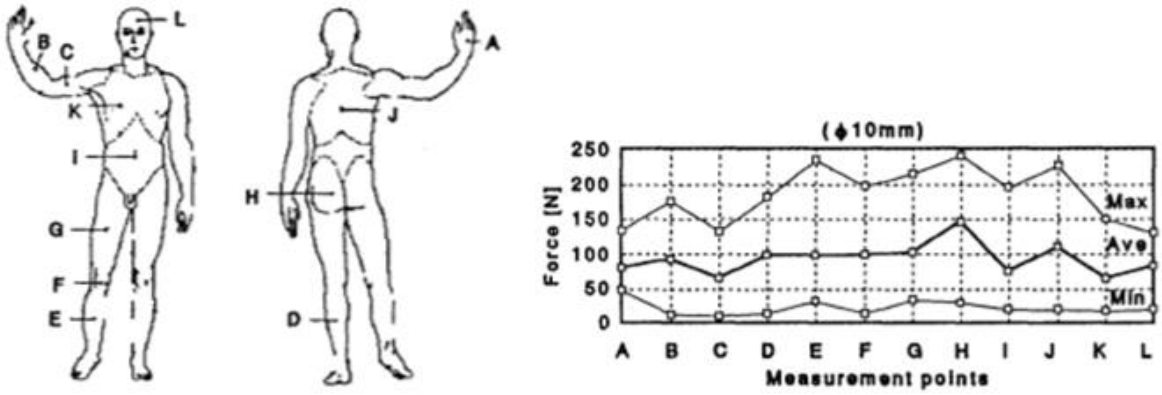

Figure 9: points of collision with the robot & result chart (Suita, et al., 1995, p.3090-3091)

The second approach was an evaluation of injury level. When studying the collision between a human and a robot, the study made use of the injury criteria that are developed for the crash-tests in the automotive industry. The conclusion in the study claims that the values of the experiment do not exceed the safety thresholds. This indicates that severe injuries are unlikely to occur when keeping within the ISO-TS 105066:2016 standard. (Robla-Gómez, et al., 2017)

When working together with a collaborative robot a human-robot collision is unavoidable. Rather than only focusing on minimizing the injuries that can occur, prevention of collision is also experimented with. One of the tests consisted of viscoelastic coatings, together with springs and dampers, it coats the robot arm to work as an *elastic absorption system*. Further development of the technique has implemented force sensors in the coating. With the sensors implemented, the robot can receive inputs to lower the speed or if human-robot collision is needed act accordingly. (Robla-Gómez, et al., 2017)

4 Method

This chapter contains information and background about the different methods used. It contains instructions on how Software prototyping, lead-through, offline programming and flow-charts methods are used and applied.

4.1 *Literature study*

A literature study involves previous research on a topic. It often consists of scholar articles, books, conference proceedings and other relevant information regarding the topic. The study should be a non-objective way to evaluate information and clarify research. It should be used as a way for the reader to get a background on the topic. The articles used must have concrete facts which support the results. This method has been used to validate the topics concerning the thesis. It contains information about machine vision, quality evaluation, implementing a collaborative robot during assembly and safety aspect with collaborative robots.

4.2 *Software prototyping*

Software prototyping is a method for testing incomplete software applications while they are being developed. It is as similar to prototyping in other fields such as design engineering, a way for personnel and users to try out and test the software before it is complete. The software model may not hold all the functionalities that the finished product will but should showcase basic requirements. This method should be a way to communicate with the end users, to obtain data for the developers and managers (Urban, 1992). Software prototyping is most beneficial in systems that have a high degree of user interaction.

There are different types of software prototyping used today. One way is **Throwaway prototyping,** also known as rapid or ended prototyping. This method focuses on building a prototype quick with minimum requirements and analysis. The model will be thrown away as soon as further requirements are obtained, and a new model will be developed. Another method is **Evolutionary prototyping**, also known as breadboard prototyping. This approach is based on building an actual functional prototype but with low functionality in early stages of development. The first model-built acts as the base and heart of all future prototypes. An advantage of using evolutionary prototyping is that requirements are added to the prototype as they appear and are understood. **Incremental prototyping** is another widely used software prototyping method, by using this method several prototypes with sub-systems are being built based on different areas of the software. These sub-system prototypes are then integrated together. (Carr & Verner, 1997)

According to Carr & Verner(1997), using software prototyping is most commonly done in four steps.

- **Initial requirements:** In the first step, it must be decided what the software is supposed to do. Developers then have to identify potential customers and what these costumers will want regarding functionality.
- **Prototype development:** Step two is the developing phase. Here the developers must consider the requirements and put together a model of how the finalized product could look.
- **Review:** When the prototype has been developed the beta tests can begin. This is a vital step for development in order to receive feedback from the users.
- **Revise:** In this step changes and improvements can be made to the software using the information obtained in the review step.

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Advantages of using software prototyping are similar to the ones of prototyping in the industrial sector. For example, using software prototyping increases the involvement of users before finalizing the product. This will result in quicker feedback, which will help the developers to provide better solutions. Defects and flaws can be detected in an earlier stage, this will save time and money. Example of flaws could be if basic functions are missing, which the test users deem important for the functionality of the software. Confusing functions and overlays can also be identified and be improved upon when using software prototyping. These are a few of the many advantages of using this method. (Carr & Verner, 1997)

As with all methods, there are disadvantages of using this as well. For example, in early stages there may be too few requirements acquired, which will make the model insufficient. Using the prototype may be complicated and confuse the user. The method can complicate the model if the scope expands beyond what was originally planned. Prototype development may become time-consuming if not monitored and limited properly. (Carr & Verner, 1997)

4.3 *Online programming*

The lead-through method of robots is carried out by programmers. The programmers guide the robot through the desired path using a teach pendant or by hand, also called **online programming**. The method includes guiding the robot through the desired path and recording the specific points. With the stored points, the robot can utilize them and create a path using movement commands. The operator programming the robot is the one with the responsibility to guide the robot in the right way and maintaining the right orientation of the robot. If the created points have a bad orientation of the Tool Center Point (TCP), there is a great chance that the robot will collide with something when running the program. (Pan, et al., 2010)

Although online programming is widely used in the industry it has several drawbacks. One of the drawbacks when using lead through method, the operator always must be sure which coordinate-system they are creating the program in. If the operator uses the wrong coordinate system when creating the program, the robot can either move in an unanticipated manner or not at all, if changed. Secondly, when guiding the robot through the path, the operator must be careful and thorough not to create any unintentional collision. This can be difficult and time-consuming, especially when the workpiece has a complex geometry. There is also the safety aspect when creating a program, it cannot run or be implemented until it has been tested thoroughly and is reliable. This is to minimize the chances of injuries when the program is running. When creating a program with the lead-through method, the program will lack flexibility and reusability. If the process has the slightest change the whole programming process must be repeated to change the program. Other drawbacks include, the robot cannot be used in production during the programming period, the operator is exposed to a hostile environment and the quality of the movements is based on the experience of the operator. (Pan, et al., 2010)

Online programming is a manual process with the freedom of moving the robot however the operator sees fit. The operator can create a program that they see as the optimal route for the robot. It is an efficient and cost-effective solution for simple robotic systems. When the systems become more complex the lead-through method becomes redundant. (Pan, et al., 2010)

4.4 *Offline programming*

Offline programming, also known as **OLP** is a method which utilizes 3D CAD models to create a virtual environment, to simulate the robot program. This method is widely used for automation systems with

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large product volumes. The programmer can test the reachability of the robot, fine-tune properties of the robot's movements and handle process-related information. (Pan, et al., 2010)

OLP has many advantages over the lead-through method. One of the biggest is that the development of the system does not require a physical robot, which means that the development minimizes downtime in production. The development of a program can be programmed earlier in the production cycle and can be carried out parallel with the production rather than in series. Offline programmed systems are more flexible and adjustable than an online programmed system. Lastly, OLP method is often supported by simulation. With the help of simulation, the programs can be verified if the functions work as intended and to reassure safety issues. (Pan, et al., 2010)

Offline programming is more complex than online programming, not only does it need to acquire the 3D targets, but also need to plan the operation and motion of the robot beforehand. There is more time-consuming optimizing the program in OPL than with lead-through method. To help with this OPL has a set sequence to follow, which makes the process easier and smoother, see figure 10. (Pan, et al., 2010)

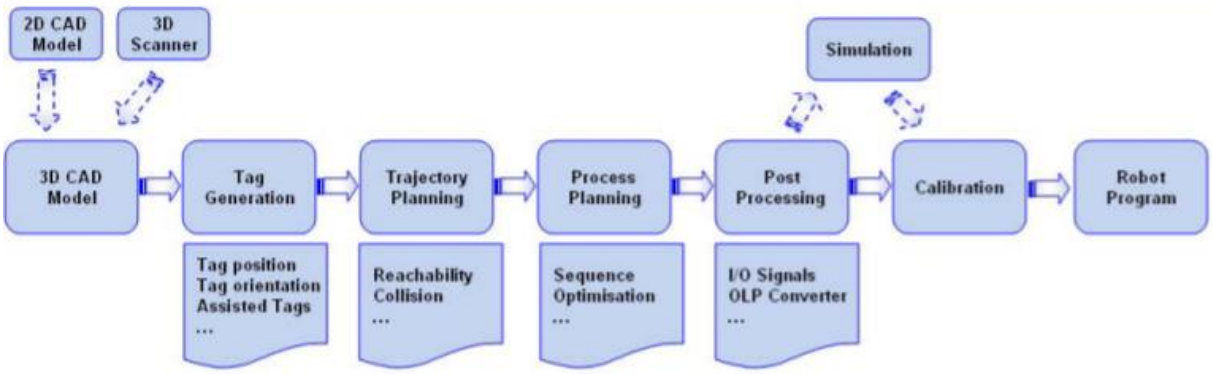

Figure 10: OLP sequence (Pan, et al., 2010, p.622)

Although OPL has all these advantages, smaller companies often avoid using it as a programming method since the economic aspect of the process can be a constraint for them. The high cost of the OLP package often outweighs the reason to use it for smaller productions. The level of competence needed for developing a specific application can be an issue for small companies. This is due to the complexity when programming robots. (Pan, et al., 2010)

5 Experimental study

This chapter contains experiments made during the project. These experiments were performed to evaluate and achieve the best possible result. The experiments contain camera selection, AI training, communication testing, robot configurations and robot programming.

5.1 *Camera selection*

To make the system work the robot need a camera mounted on the arm to provide images to evaluate. A camera needs to be chosen and an experimental study was performed to make sure the right camera was selected. Three different cameras were looked upon, one external normal web camera with wire, one wireless and one from UR which is compatible with the UR system. When choosing the three different cameras, the performance of the camera was not the focus. The system is supervised learned and the resolution of the camera is not as important since the system learns from the pictures given.

5.1.1 Logitech - C922 PRO HD STREAM WEBCAM

The C922 PRO is a webcam which can film 1080p with 30 frames per second (fps) or 720p with 60 fps. Since the system is going to be working in real time and does not have an issue with a bit lower quality, the camera would be working with 720p, 60 fps. C922 PRO is equipped with lightning and focus self-adjustments, to make the camera more reliable during streaming. Camera dimensions are 29mm x 95mm x 24mm in height x width x depth, weight 162g, 1,5-meter cable and has self-installation through USB cable. The camera can capture an image with a 78° view angle. (Logitech, 2019)

5.1.2 Logitech – C930e 1080p webcam

The C930e camera has the same resolutions as the C922, 1080p with 30 fps and 720p with 60 fps. It has almost the same dimensions 29mm x 94mm x 24mm, which means it only lost 1 mm in width from the C922. It is equipped with lightning and focus self-adjustments. When comparing the weights between the C922 and C930e, C930e is a bit lighter with a weight of 159g. The main difference is that the C930e is wireless. (Logitech, 2019)

5.1.3 Robotiq – Wrist Camera

Robotiq's wrist camera does not have any specific resolution specified. The resolution is dependent on the software version the robot is running. New versions often improve the resolution but will not exceed 720p. When implementing the camera, it is attached to the robot between the tool and the robot arm. Because of this, the camera does not take much space, but the TCP needs to recalculate. The weight of the camera is 160g and still must be considered when implementing. (Robotiq, 2019)

5.1.4 Camera Evaluation

While evaluating the cameras, a **Pugh's evaluation matrix** is used to get the best possible outcome. The method is done with each camera set against different criterions in a matrix, the cameras are then given a positive, a negative or a neutral grade on each of the criterions. A positive grade equals +1, negative equals -1 and neutral equals 0. The grades are then added to create a ranking system and a camera can be selected.

The graded criterions are safety, implementation, easy function, weight, resolution and communication, see figure 11. This is when the camera is implemented on one of the UR robots, which is used in this experiment, see Appendix B.

	C922 PRO	C930e	UR Camera
Safety	-	0	0
Implementation	0	0	+
Easy function	-	-	0
Weight	0	0	0
Resolution	+	+	0
Communication	-	-	+

Figure 11: Pugh's evaluation matrix

5.1.5 Evaluation of scores

Safety: C922 PRO got a negative score since it is an external camera which will need to be mounted on top of the robot and will make the robot less flexible when used and connected with a wire. While C930e and UR cameras got a neutral score since the C930e is wireless and UR camera does not have to be mounted on top of the robot.

Implementation: The web cameras score a neutral score since they are easy plug-in installations but need an external computer to function. The wrist camera can be implemented directly onto the robot, which gave it a positive score.

Easy function: UR-wrist cameras had a neutral score since the images or videos from an URL is not the optimal choice, but not a negative one. The web cameras will need an external computer with software to take pictures or videos, which gave them a negative score.

Weight: All the cameras weigh the same, which gave them all a neutral score. However, the aspect of weight is still important to look at since the robots have a max limit they can lift.

Resolution: The resolution of the web cameras is better than the wrist camera and gave them a positive score because of this.

Communication: There needs to be communication between the vision system and the robot during the quality inspection. With the wrist camera, the signals can go directly through the robot and makes the communication easy. While the external web cameras will need a software to take the picture, which means that the communication needs to go through three programs instead of two.

The evaluation shows that the UR-wrist camera is the optimal one to continue working with these aspects taken into account. This means that the rest of the experiments and results will continue with an UR-wrist camera.

5.2 *AI training*

In order to train the AI most efficiently, different approaches were proposed. However, many of them were discarded in an early phase due to time limitation. The final solution was to create CAD-models representing the frame where the glue string is attached. With these models then apply correct and incorrect strings.

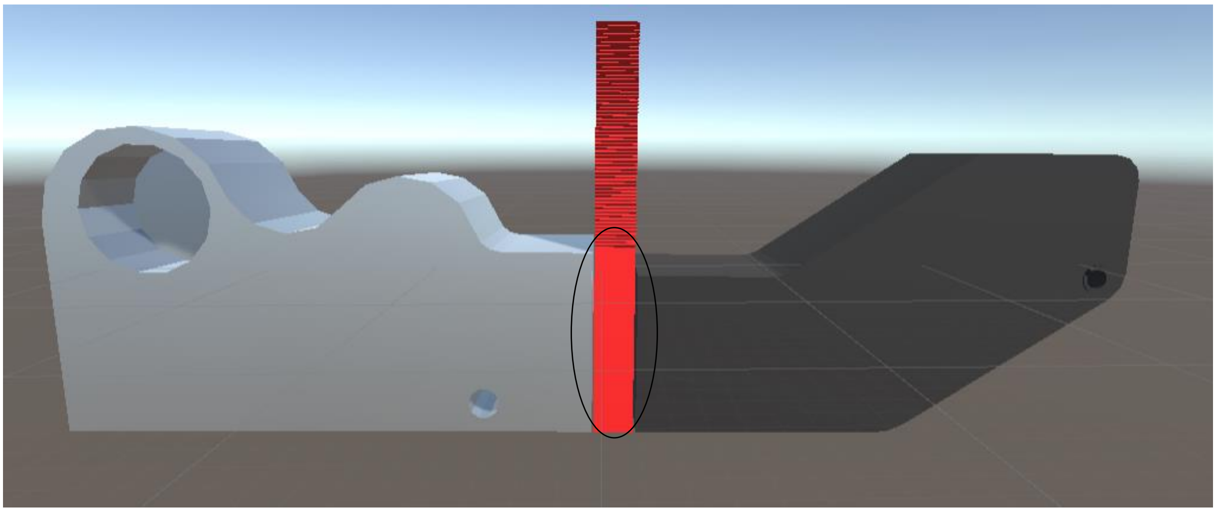

Figure 12: CAD-model

When the CAD-model was created, glue strings had to be attached to each side of the red area, see figure 12. This was done in pairs of two, ten different glue strings were generated and paired together to create 20 different pairs, see figure 13. The pairs could be built from the same or different glue strings. The pair were then separated into NOK (not ok), see appendix C-F. The rest were placed in the OK categorie, see appendix G-J. This was done in a program made in unity. Unity was then used to generate numerous photos with different settings such as light intensity, photo angles transformations and more. These photos were then used to train the AI to make it possible for it to separate correct from incorrect pairs.

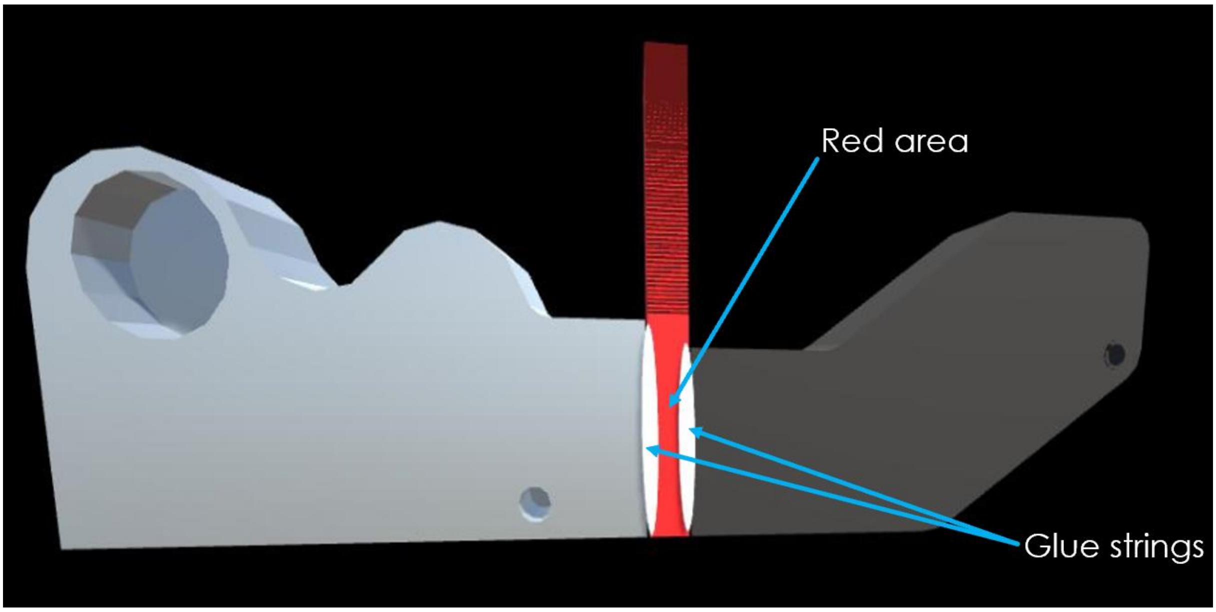

Figure 13: CAD-model with glue strings

When training the AI the pictures will be divided, 80% of the pictures will be taken to train the AI, while the other 20% will be kept for the evaluation. By dividing them the evaluation ensures that the pictures

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that the AI is evaluating has never been seen by the AI. To further train the AI and be able to validate the result a real-life prototype of the frame had to be made, see figure 14. This was done using 3D-printing with the same CAD-files used in the earlier stage. Due to size limitations of the printer, the part had to be reduced to a smaller size. However, this should not affect the final results since the AI is trained on a specific part of the on the prototype

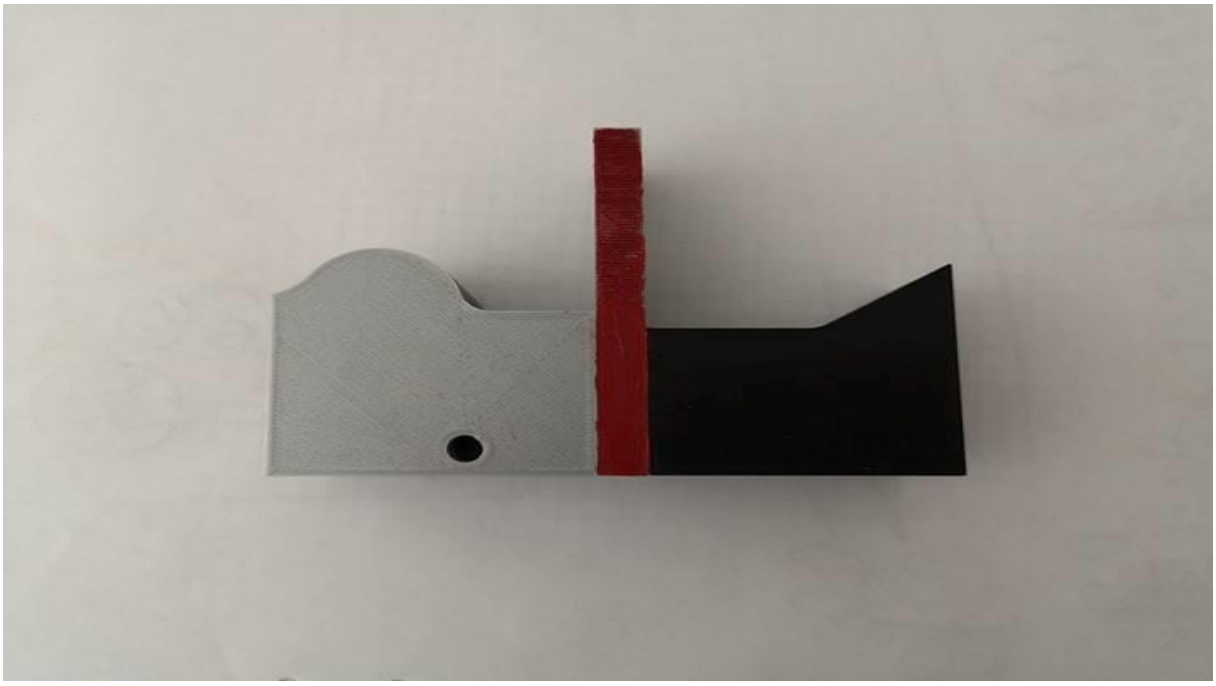

Figure 14: 3D-printed prototype

To test the real-life prototype, toothpaste was used to resemble the glue strings. 50 new photos were taken, and the AI was trained on these photos as well to get an even more accurate result, see figure 15. These images were separated like the virtual pictures into NOK, some can be seen in appendix K and L. Some OK images can be seen in appendix M and N. Out of the 50 images that the AI trains on 40 pictures and the remaining ten is for the evaluation phase.

Figure 15: 3D-printed prototype with glue strings

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5.3 *Robot configuration*

When trying out the AI with the UR10e robot, different configuration on the robot such as the angle of the camera and backlight may impact the results. The range of the UR10e is 1.3 meter, meaning there are several different angles and the distance from which the photo will be taken can vary. To get the optimal solution, different robot configurations were tested. Distance from which the robot takes a photo will be adjusted so that the picture will have a clear resolution. The picture has to be clear enough for the AI to identify the right area to evaluate and do so in a correct manner. Another factor that might impact the outcome of the pictures is light intensity. The light should not have a big impact on how the AI evaluates the glue strings. Depending on the backlight, it might impact if the AI finds the glue string at all.

5.3.1 Robot programming

Programming the robot will not be put much effort into since other project groups have this as their main objective. Andersson & Hovbjer (2019) are in charge of programming the robot sequences where the quality control only will be a small part. The robot only needs to be placed into position for the camera to locate the glue strings.

5.4 *Communication testing*

There are several different ways for the robot to communicate with external devices. Universal robot provides different communication protocols to use when connecting the robots. A common way of connection type is using an ethernet cable. The most common protocols are Modbus and XLMRPC. These protocols already exist within the UR-software, which makes it easier to use. Another way is using UR-scripts connecting the robot with a software called Test Socket. However, all these different approaches have different advantages and disadvantages. The first thing is to determine which component will be used as a server, there are three different approaches to this.

- Use the UR-robot as a server and from there control the other components.
- Have an external computer, which has the AI on it acting as a server as well.
- Using another computer which only acts as a server and therefore having three components running the system.

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6 Results

In this section, the results of the project are presented. It contains the results of training and communication setup.

6.1 *Virtual AI training*

Using a virtual method for training the AI resulted in an almost perfect outcome. The software could evaluate given training pictures with 100% accuracy. When presenting the AI with pictures CAD-generated glue strings it had not seen before the result were perfect. As seen in figure 16, the AI could find the area which it was looking for and also evaluate it with perfect precision. This glue string pair the AI evaluated NOK due to the tight gap between them.

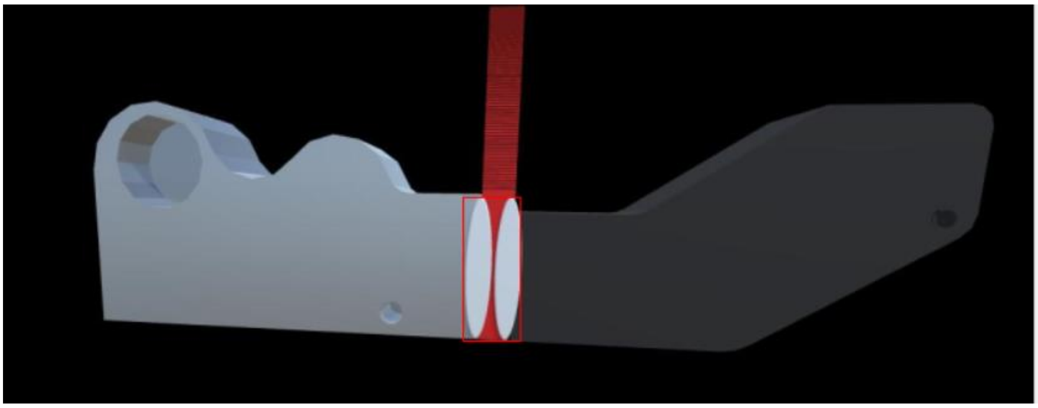

Figure 16: Not ok glue string pair

In figure 17, the AI could determine that the glue strings were placed correctly. An OK pair need to have a distinct gap between the strings. The width of the strings may differ some in size but not too much.

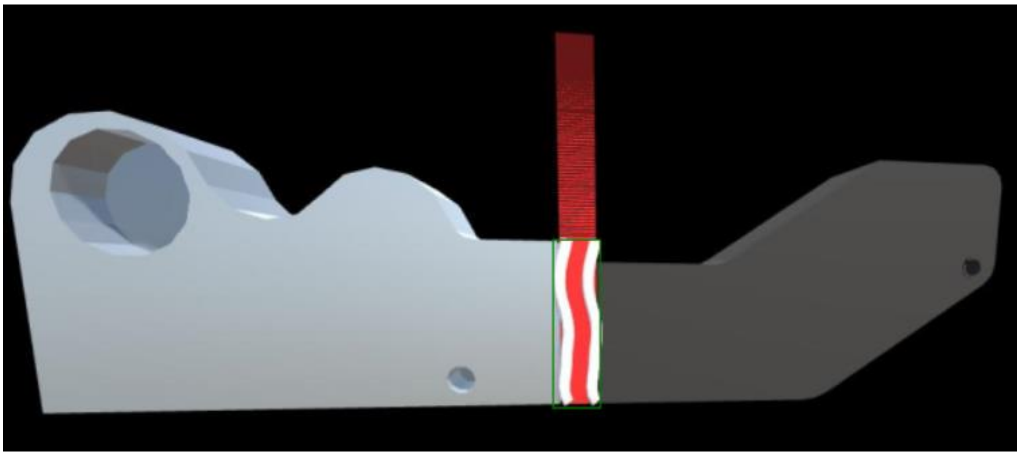

Figure 17: OK glue string pair

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6.2 *Communication*

Since the quality control is only a small part of the intended robot sequence, the program has to cooperate with other tasks the robot has. Communication between the work groups was vital to create a working robot sequence.

Communication between the robot and server were considered a problematic issue to resolve at first. When experimenting with different options, the easiest way was using a computer as a server host. The connection was established via Modbus, which was the easiest and most efficient way since the UR-software already has built-in functions to send and receive signals. The communication setup was divided into several different steps, see figure 18. The server will excess pictures via a URL-link of the robot cameras live feed to obtain data to send further for the AI to evaluate.

6.2.1 Communication steps explanation

1. When the robot sequence has reached the quality inspection step, the robot will move to a specified position to take the picture.
2. The picture is then sent via an URL-link for the server to obtain.
3. When the server receives a signal that the robot is in place, it will save the image from the URL-link.
4. The picture will be then be sent further along for the AI to evaluate.
5. When the vision software received the picture, it will evaluate it with okay or not okay.
6. AI will then send the results back to the server.
7. Depending on results from the AI, the server will send different signals back to the robot.
8. When the robot then receives the signal from the server, it will move depending on what the signal was. If the inspected part were considered OK, the robot sequence would proceed to work as intended. However, if the vision software deems the product not to be of sufficient quality, an indicator of some sort will alert an operator to investigate the problem.

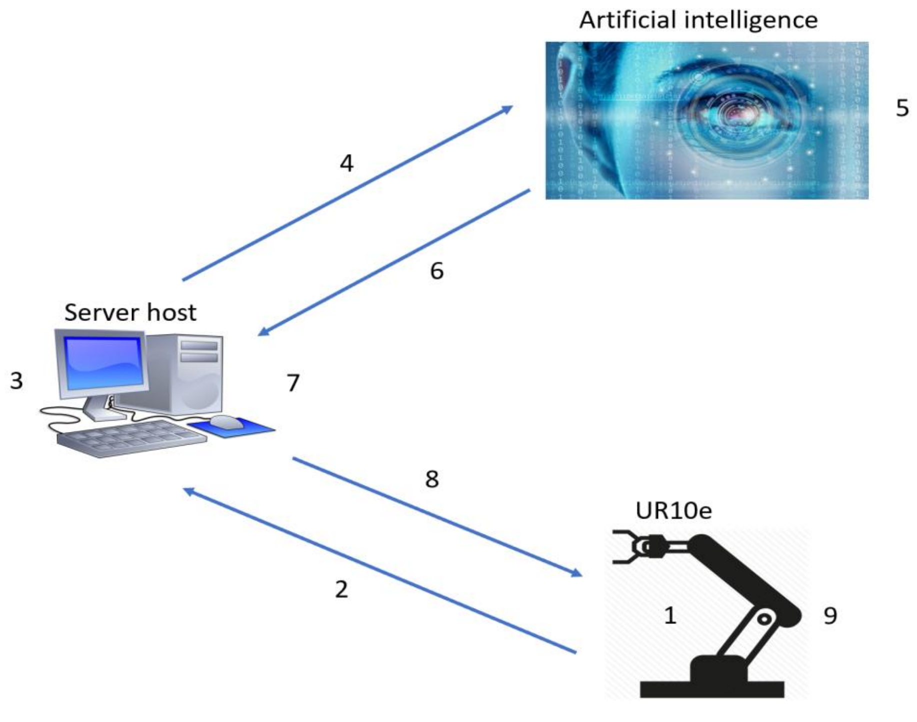

Figure 18: Communication flowchart

7 Discussion

Chapter seven includes a discussion of the results and what difficulties were encountered during the project. It also includes suggestions on how to further develop and improve different applications concerning the project.

7.1 *Results*

The results of the project were not immediately sufficient for a good result, there were a few hiccups along the way. When training the AI for the first time, the recognition of the glue strings was not accurate. During the first training, there were only ten different glue string pairs, which results in 720 different images the AI will be training on. The training only contained 2000 iterations before it was tested. The result from this made it obvious that more iterations and images were needed to make the AI more accurate. The overall accuracy of the AI was around 30%, where it only hit 1 of the OK images. In some cases the AI does not recognize or find the area to evaluate this result in a background guess, see figure 19.

Result Guess	Background	OK	NOK	Accuracy
Background	0	115	71	
OK	0	1	0	0,00862069
NOK	5	0	101	0,5872093
Total	0	116	172	0,297915

Figure 19: Test training results

The last training session in virtual supervised training was done with 20 different glue string pairs (1440 images), which means that the AI train upon 1152 images while saving the other 288 for the evaluating stage. When training the AI did 50 000 iterations to have a more accurate result. This got a perfect result when the AI was tested, see figure 20.

Result Guess	Background	OK	NOK	Accuracy
Background	0	0	0	
OK	0	122	0	1
NOK	0	0	166	1
Total	0	122	166	1

Figure 20: Final training results

Even though the results were perfect, it was on virtual images. When testing the virtual trained AI on real-life pictures, the AI could not find glue strings. The annotations zones were off and the software did not know what to evaluate, see figure 21. 50 more pictures from real life scenarios were taken to fix this issue. These pictures annotations zones were then edited and adjusted to have a good outcome and used to train the software further, see figure 22. The red annotations zones were limited only to surround the glue strings when editing the pictures.

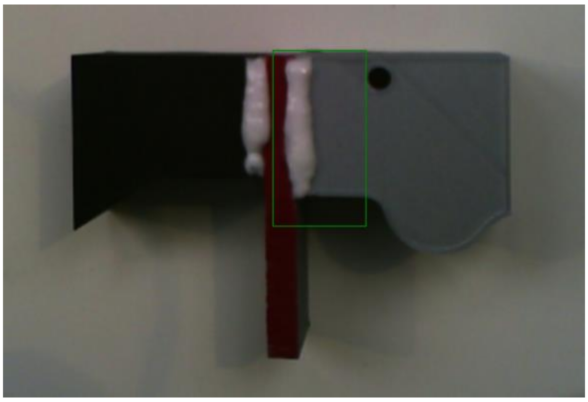

Figure 21 Incorrect annotations zone

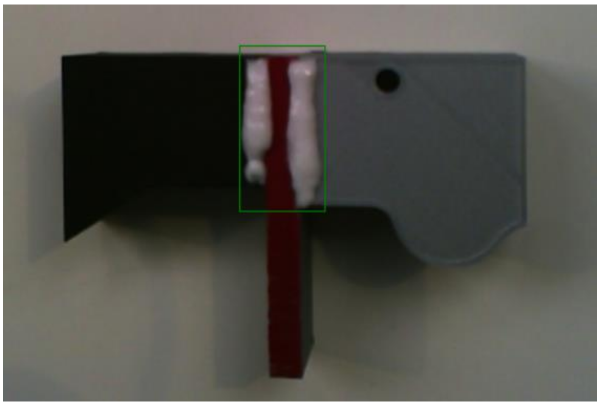

Figure 22 Correct annotations zone

After training the AI with the newly edited images, the results were much better. Now the software could detect both incorrect and correct strings. The annotation zones were improved and surrounded the strings, see figure 23 & 24. The Accuracy of the AI was quite good, the AI could identify correct from incorrect around 90% of the time. The issue at hand was that the AI could not always identify the area were the glue strings was applied, which meant that it did not evaluate the images. The robot must have certain configurations to find them, such as height, angle and light settings.

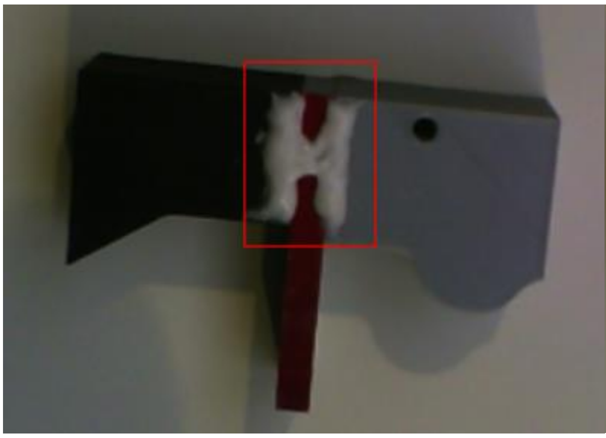

Figure 23: Not OK strings

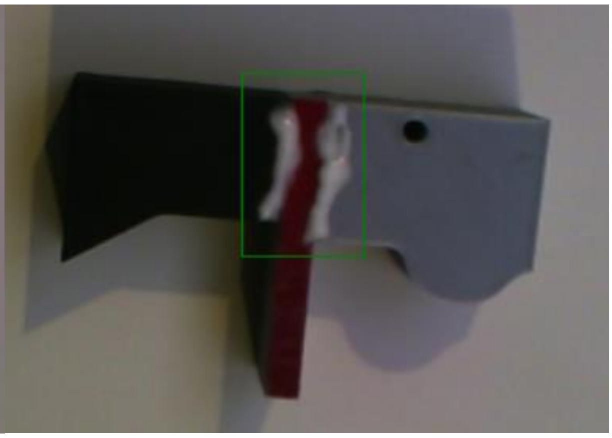

Figure 24: OK strings

When we taught the system, there was no previous experience in using virtual supervised learning, that is one of the reasons why we tested it out during the project. The positives of using virtual images is that generation of the pictures is easier. In the learning of the AI, 1440 images were generated in under one minute and took around 30 minutes to setup. While capturing real-life images of the problem could take around two to three minutes per image. If the virtual method turns out to be more efficient, the set-up time of the images will drastically decrease. The tests proved that virtual images were not sufficient to create a working application. There will need to be a combination of virtual and real-life images.

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7.2 *Difficulties*

7.2.1 Robot configurations

When first trying out different configurations with the robot, we did not know how sensible the AI would be to different solutions. It was not until later throughout the project it was discovered that different configurations had a big impact on how the AI would be able to evaluate the glue strings. For example, height differences had a big impact when evaluating the strings. Even a couple of centimeters could determine if the AI would detect the right area to evaluate or not. This might be because of the selected camera since it is not able to take photos in more than 720p or different light settings. These possibilities will need further investigation to determine which is the deciding factor. Another factor that might have impacted the result is the downscaling of the real-life prototype. Since we did not have time to investigate if this had an impact on the result, it is also a factor who need further investigation.

Due to the project being in close collaboration with other work groups, the different approaches of configuration possible were limited. Since the robot is supposed to carry out other tasks then the quality control, limitations were set to where the robot was placed. This resulted in difficulties to reach both of the areas that are to be evaluated. Solving this issue were considered problematic since there are different factors from other parts of the robot sequence that has to meet as well. However, this should be a problem that can be solved, but as of now, there is no viable solution.

7.2.2 AI software

Since the AI is still in a development phase, there were numerous issues encountered during the project. We spent time troubleshooting many problems that could not be corrected. For example, there could be different versions of the software not working as intended due to updated files in another part of the software. This was problematic since we spent a lot of time trying to work out what we were doing wrong and could not move the project forward at the speed we wanted.

Another issue that we stumbled upon during the training phase was when the software learned from the CAD-models. The annotations zones were off by a big margin, which caused a problem when trying out the software with the real-life prototype. This was due to the AI not being able to separate different shader colors from the CAD-models. The issue was resolved by changing the shader color of the area on which the glue string was placed in.

7.2.3 Communication

When first investigating the communication, many different approaches could be taken. The main issues were the limited knowledge we had using any communication protocol. Fortunately, there were guides provided by the universal robot developers on how to connect the robot with external devices. Using these guides and with the help of our supervisor, a working communication could be made.

7.3 *Future work*

When working with machine vision, there are a lot of different approaches and angles that can be taken to develop a software capable of completing the given task. Combining machine vision with collaborative robots can be a real revolution in the production industry and needs to be further studied to see if it is a reliant way of implementing quality inspections.

There are a lot of potential and improvements that can be made on the project. Since the Machine vision is AI-based, it is easy to make it learn other quality issues with supervised learning. When the software is working together with an UR10e, the implementation of the collaborative robot and the system will need to follow safety guidelines. In order for it to work at another station with other quality inspections, the software needs to be retaught. Using the software on any robot brand other than UR-series, there will be more complications. Since the camera “Robotiq wrist-camera” is only compatible with UR robots there will be a change in camera and highly likely an external web camera. When there is an external camera taking the image, there will need to be a slight adjustment to the communication between the robot, camera and quality inspections software. New external software will need to be developed to handle the web camera, which will oversee the image handling. Implementing an external web camera will have an impact on the flexibility of the robot, which will need further research and development.

The quality inspection does work as intended and has quite a bit of flaws. The software has a limited range in which it can recognize the glue strings. This is an issue that could be further investigated to increase the range and the probability of evaluating the glue strings correctly.

During the bachelor project, virtual supervised learning was used to make the AI learn correct from incorrect. There is no concrete evidence that the virtual supervised learning of the AI has a positive effect when teaching it. It was done as a test during the project and needed to be evaluated and tested on different scenarios to confirm the positive influence it may have. In this project, it was clear that virtual supervised learning is not enough to make the AI accurate, but there were fewer images needed for the system to see the difference in the glue strings. Working with more realistic virtual images is something that could be further investigated to improve the system.

Comparing normal machine vision and a vision system based on AI is quite hard. Both systems have their merits and weaknesses. AI-based vision systems are flexible and can learn new and different quality issues. But developing an AI system can take years to complete and even longer to perfect. A normal machine vision is not as complicated to develop. The downside is that it is not flexible at all, it is often set on efficiently performing a specific quality inspection. The system needs to be reprogrammed fully or add the new quality inspection code in the old when the same system gets a new task. The system used in this project was not completely developed, but was still relatively easy to handle. When AI’s is further developed the technology will probably be changed in most of the productions to get a more flexible system. Then in the future, when the AI’s are easier to handle, they will probably even be usable by the engineers out in production.

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8 Conclusion

Conclusion chapter explains if the goals set out at the beginning of the project were met, if the gant schedule were followed and a general conclusion of the project.

8.1 *Goals*

When evaluating the project, it is important to go back and compare the goals towards the results. During the project, the goals and limitations changed. This was due to unforeseen issues and complication during the project. During the project, it was discovered that the AI would need training. When this was realized we took it upon our self to include this in the project. This led to changes in the delamination of the project to include training of the AI.

- **A report containing a literature study concerning collaborative robots and machine vision, specified on object detection:**
  - This goal has been met, the report contains a general explanation regarding each of the topics listed in the goal. Some parts were more in-depth than others, this was due to their complexity.
- **Collaboration with other teams working on the same station:**
  - Collaboration between the groups has been an important factor. Especially working together with the workgroup creating the robot sequence with the quality control. Good collaboration with this group was achieved during the entire project.
- **Investigate if a collaborative robot can work with a machine vision in an effective way:**
  - A collaborative robot can work with vision software to ensure quality. However, further investigation has to be made to validate the best possible solution.
- **Physical demonstration of the collaborative robot working with machine vision:**
  - AI needs further training to work flawlessly with the robot. It is possible as of now to demonstrate short sequences and evaluate glue string if the robot is placed in a specific position.
- **Identify if the robot can perform additional tasks beyond machine vision:**
  - Additional tasks the robot can perform other than a quality inspection is handled by another workgroup. Andersson & Hovbjer (2019) are in charge of evaluating if and which additional tasks can be carried out by the robot.
- **Training the vision software:**
  - During the project, this goal had to be added when it was realized that the AI would not function without training. This goal was met to some extent, it works in specific cases.

The original extent of the project was to include additional possibilities for the collaborative robot to work with humans. Focus of the project shifted for two reasons. The first reason was that the AI needed more work than intended. Second reason was the fact that Andersson & Hovbjer (2019) took responsibility for the robot sequence. This led to less focus on the human-robot-collaboration part of the project. Time was instead spent on teaching the AI.

8.2 *Time plan*

Due to unforeseen reasons, the Gant schedule does not fully represent how the project turned out. For example, robot studio was not used as intended throughout the project. At first, the thought was to use robot studio for offline programming. It was then realized that offline programming was not going to be needed. This was because the project shifted focus when the AI needed more attention than originally planned. It also had to do with the fact that Andersson & Hovbjer (2019) changed the content of their work and took responsibility for the whole robot sequence. The time set out for programming the robot was instead used to train and develop the AI, see figure 25 & 26.

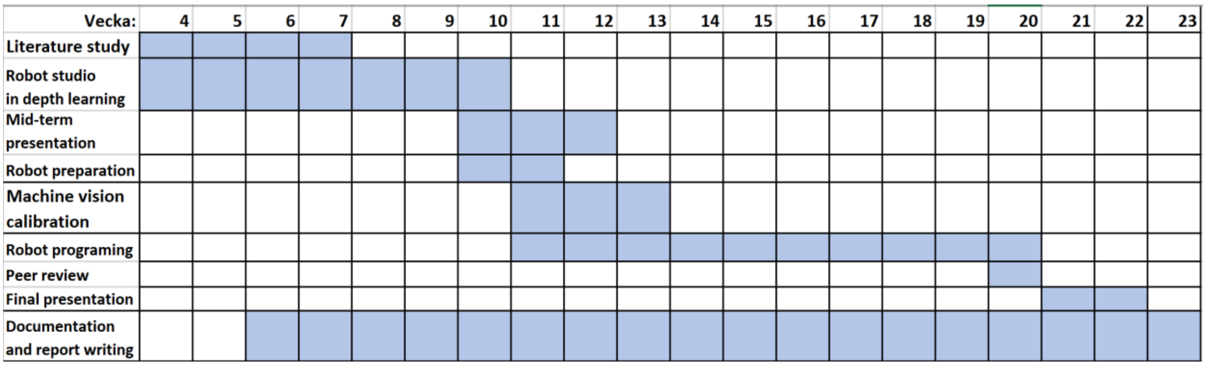

Figure 25: Gant schedule

As can be seen in figure 25 & 26, the Gant schedules varies quite a lot. Figure 25 represents the Gant schedule set out before the project began. Figure 26 represents how the time was spent throughout the project. This shows that not all project turns out as first intended. However, this is not always a negative thing. As this project proceeded, the training of the AI became more important than the robot sequence. Therefore, focus shifted and all the time was instead spent on developing a working software for quality assurance.

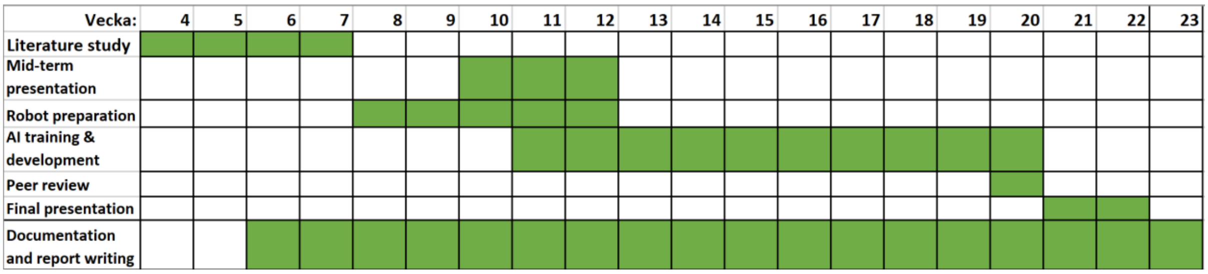

Figure 26: Updated Gant schedule

8.3 *General conclusion*

The final results stated that a collaborative robot more specific UR10e could work with machine vision. This solution was based on using a camera which was compatible with the built-in robot software. However, this does not mean that other type of cameras cannot be used for this type of function. Using machine vision based on artificial intelligence is a valid solution but requires further development and training to get the software working in a production line.

This way of working could change the industry for the better. For example, implementing a collaborative robot could ease the work for operators and aid in heavy lifting and repetitive work. Being able to combine a collaborative robot with a vision system could increase productivity and economic benefits.

Training the AI with only virtual material was not a viable solution in our case. When we tested this, the result ended up being incorrect and had a hard time finding the right annotations zones. However, with more realistic CAD-models there is still a possibility that virtual training can have a better result. When technology develops and the software become even more reliable, this field will grow even bigger.

With further development, it should be possible to implement a collaborative robot with machine vision at Volvo GTO. This will need more in-depth analysis with other parts of the company to create the best possible solution. With technology advancing at a high rate, it is important to develop and keep up with the newest software and solutions. This means that it is important to update the system continuously to stay ahead of the competition.

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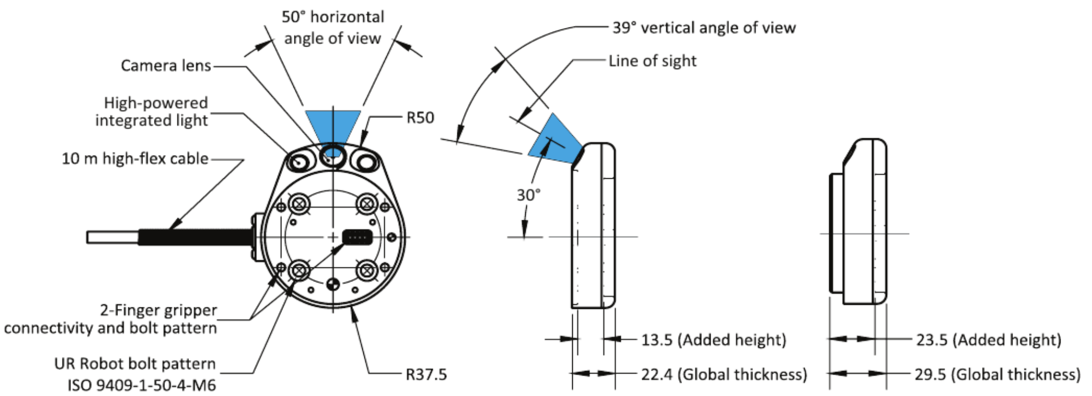
Appendix A

UR10e

Approx. 350 W using a typical program	
17 advanced adjustable safety functions incl. elbow monitoring. Remote Control according to ISO 10218	
EN ISO 13849-1, Cat.3, PL d, and EN ISO 10218-1	
100 N	
2.0 N	
5.5 N	
10 Nm	
0.02 Nm	
0.60 Nm	
0-50°C	
90%RH (non-condensing)	
10 kg / 22 lbs	
1300 mm / 51.2 in	
6 rotating joints DOF	
Polyscope graphical user interface on 12 inch touchscreen with mounting	
+/- 0.05 mm, with payload, per ISO 9283	
Working range	Maximum speed
± 360	±120°/Sec.
± 360	±120°/Sec.
± 360	±180°/Sec.
± 360	±180°/Sec.
± 360	±180°/Sec.
± 360	±180°/Sec.
	1 m/Sec. / 39.4 in/Sec.
IP54	
5	
Less than 65 dB(A)	
Any Orientation	
Digital in 2 Digital out 2 Analog in 2 Analog out 0 UART interface (9.6k-5Mbps)	
12V/24V 600mA continuous, 2A for shorter periods	
Ø 190 mm	
Aluminium, Plastic, Steel	
M8 | M8 8-pin	
6 m / 236 in	
33.5 kg / 73.9 lbs	

Appendix B

ROBOTIQ CAMERA TECHNICAL DATA



CAMERA SPECIFICATIONS

Maximal resolution	5 Mpx @ 2fps	2560 X 1920
Maximal framerate	30 fps @ 0.3 Mpx	640 X 480
Active array size	2592 X 1944	
Focus range	70 mm to infinity	
Autofocus	Yes	
Integrated lighting	6 LED diffuse white light	

MECHANICAL SPECIFICATIONS

Added height	13.5 mm (Without tool plate) 23.5 mm (With tool plate)	Distance between the robot flange and the tool base
Weight	160 g	Without the cable
Maximum load	10 kg	
Operating temperature	0°C to 50°C	
Environmental protection	Water-tight	
Operating conditions	Environment free from powerful electromagnetic interference and corrosive or explosive liquids or gases Non-condensing humidity level Lense must be free from dust, soot and water	

ELECTRICAL SPECIFICATIONS

Nominal supply voltage	24 V DC ±20%	
Quiescent power consumption	1 W	
Maximum power consumption	22 W	When light is on
Communication interface	USB 2.0	Software package available for Universal Robots

VISION SPECIFICATIONS*	UR3	UR5	UR10
Minimum field of view (cm)	10 x 7.5	10 x 7.5	10 x 7.5
Maximum field of view (cm)	36 x 27	64 x 48	100 x 75
Minimum part size (% of field of view)	10%	10%	10%
Maximum part size (% of field of view)	60%	60%	60%
Maximum part height: smallest dimension	1:1	1:1	1:1

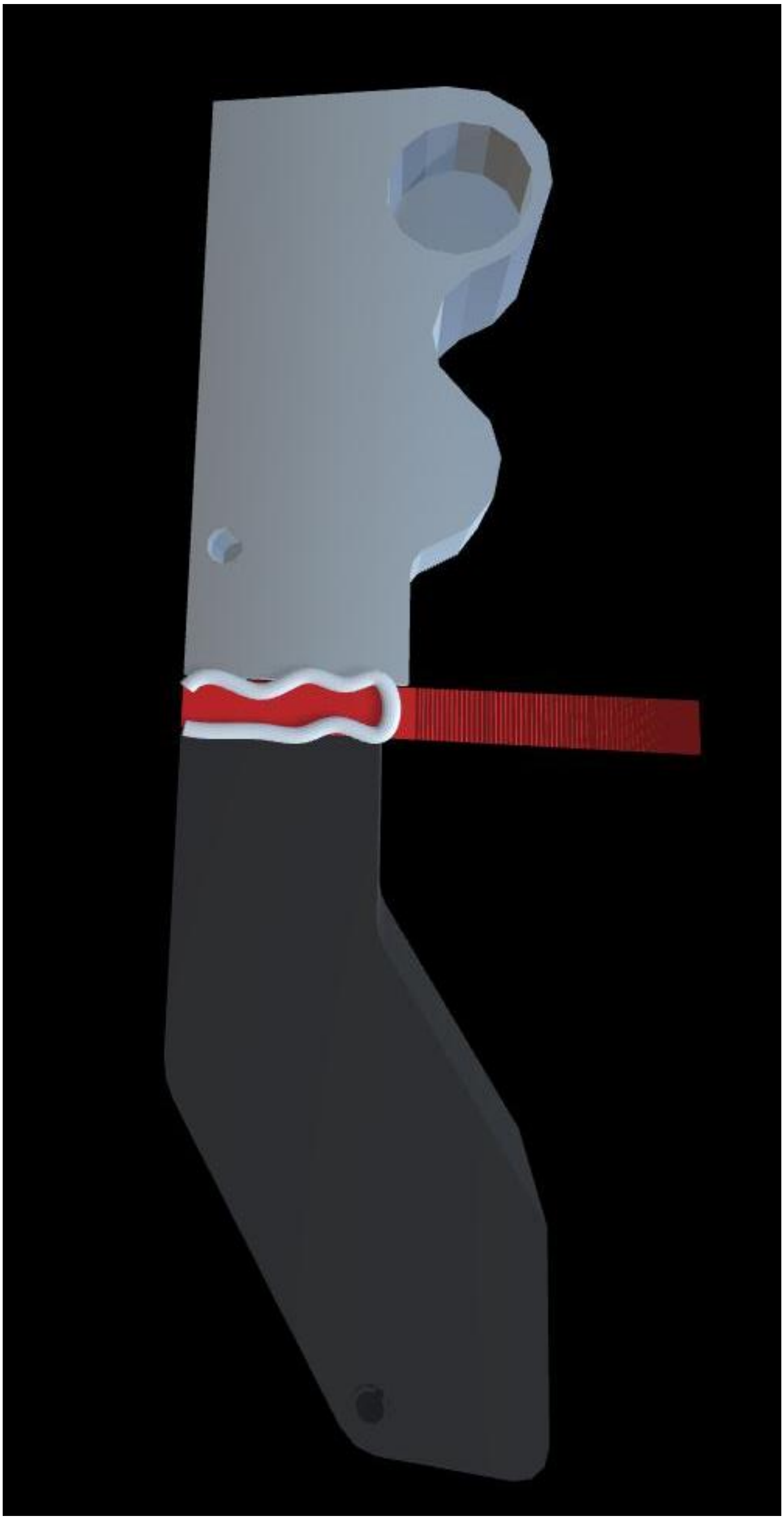
* Vision spec will change according to the teached snapshot position, see instruction manual for details

Compatibility: Universal Robots UR3, UR5 & UR10 with controller CB3.1 or higher only

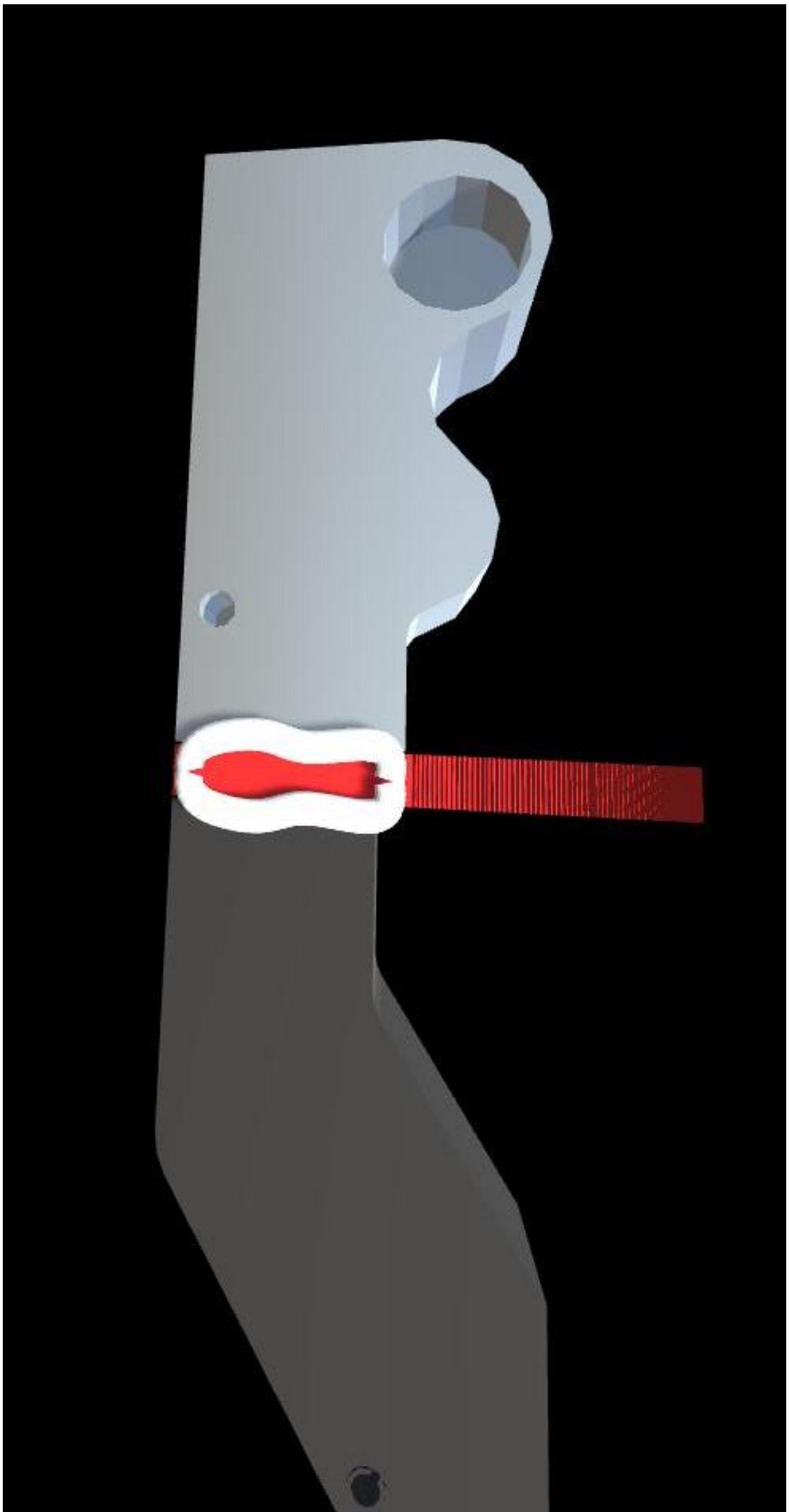
robotiq.com
info@robotiq.com
T: 1.418.380.2788

Updated on September 9, 2016
Specifications subject to change without notice

Appendix C



Appendix D



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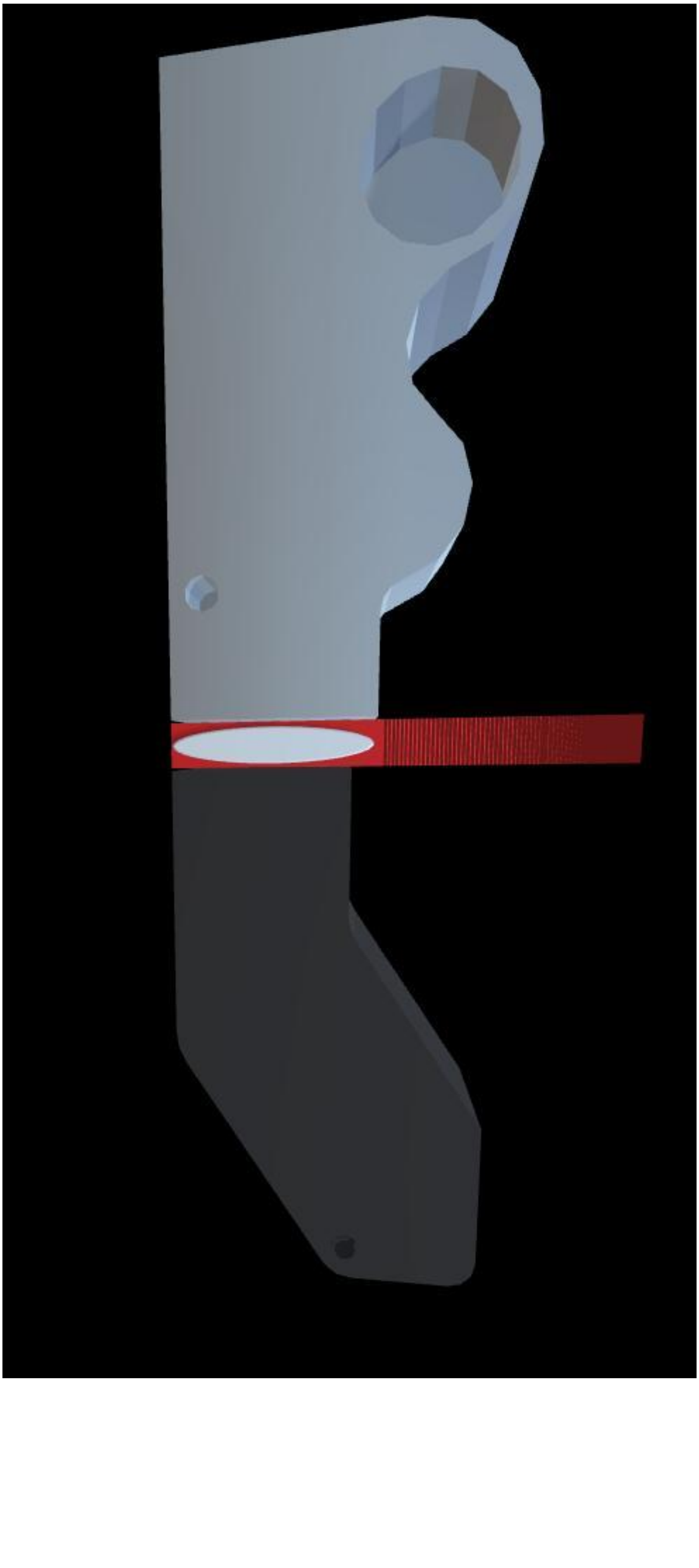
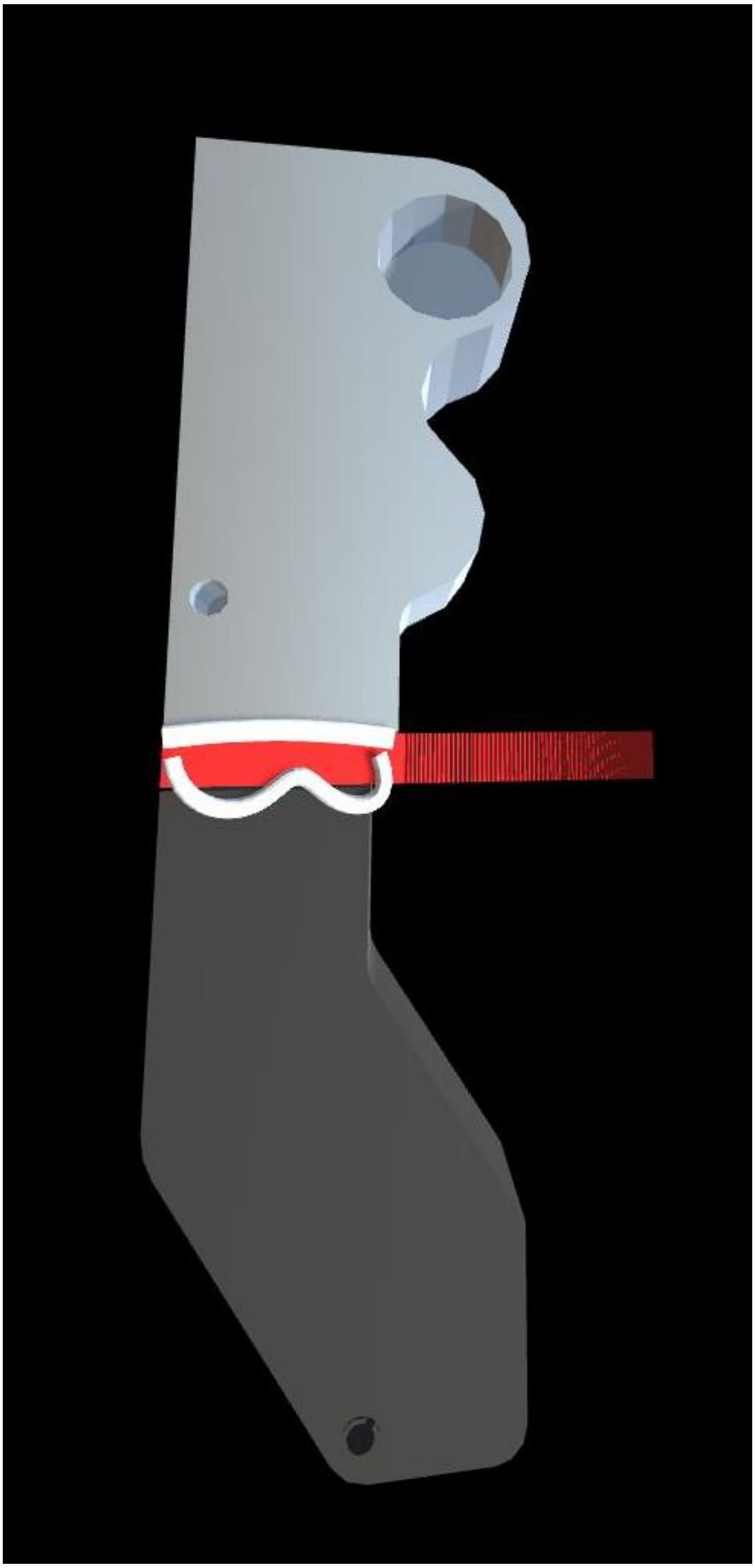
Appendix E



Appendix F



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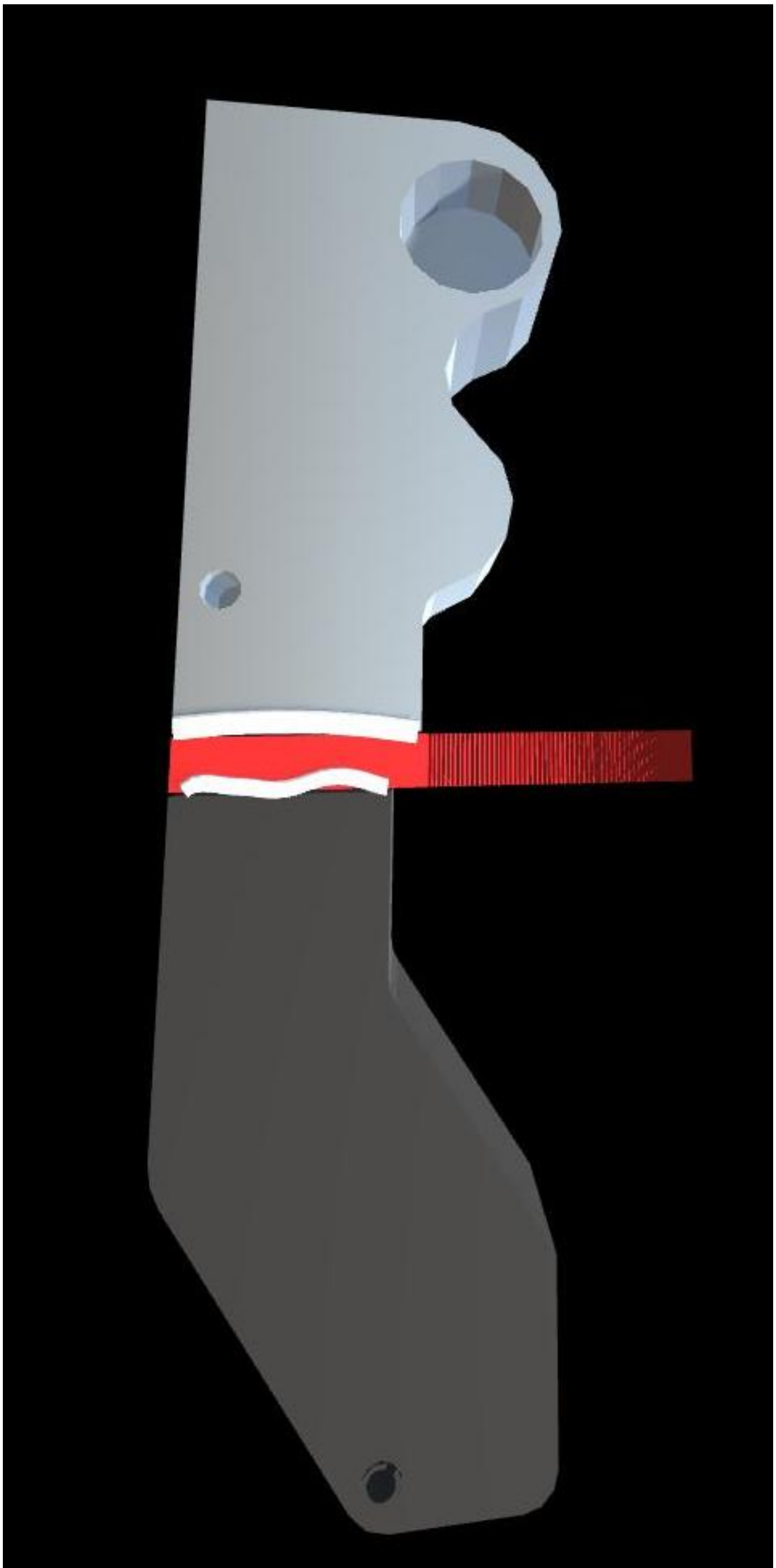
Appendix G



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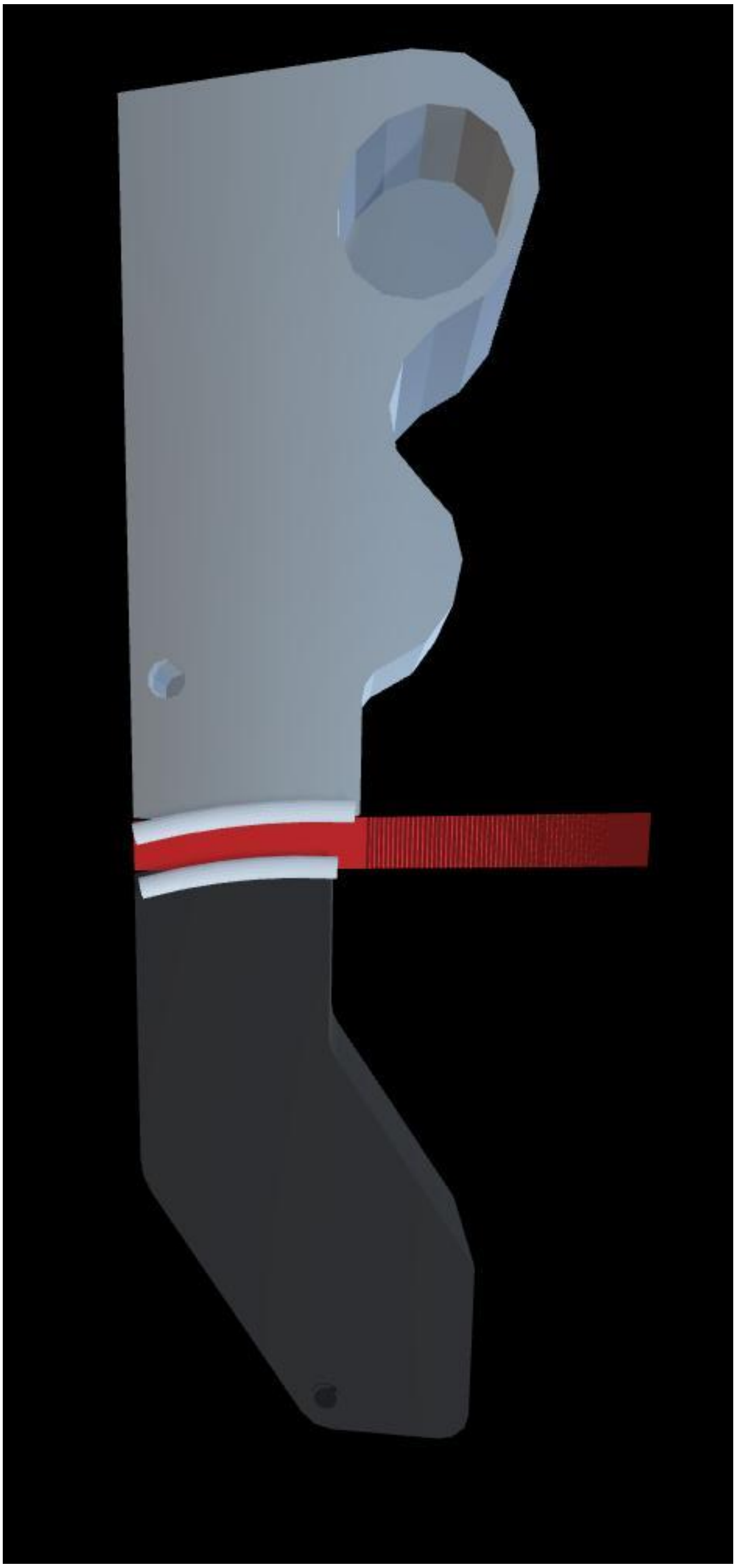
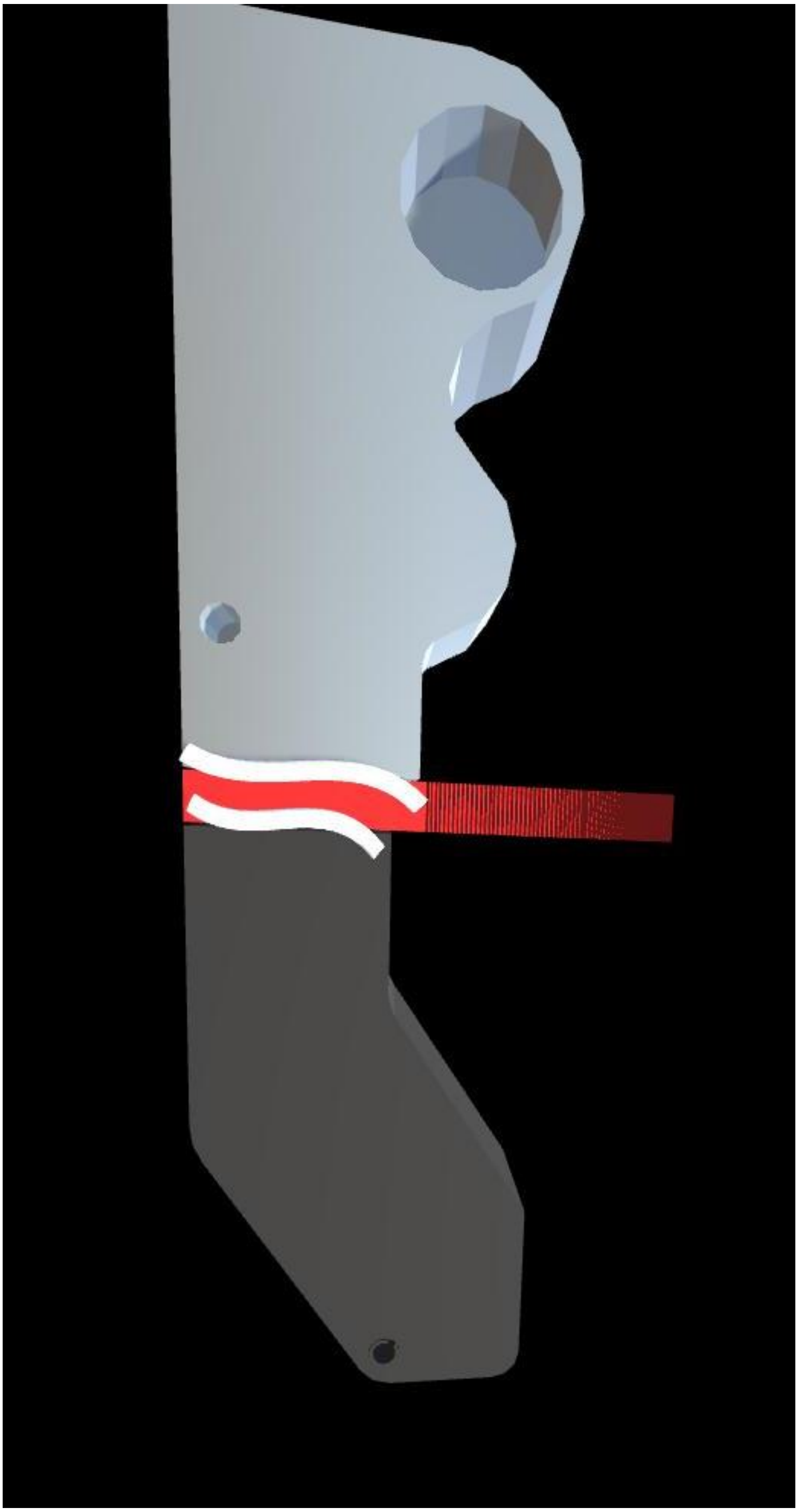
Appendix H



Appendix I



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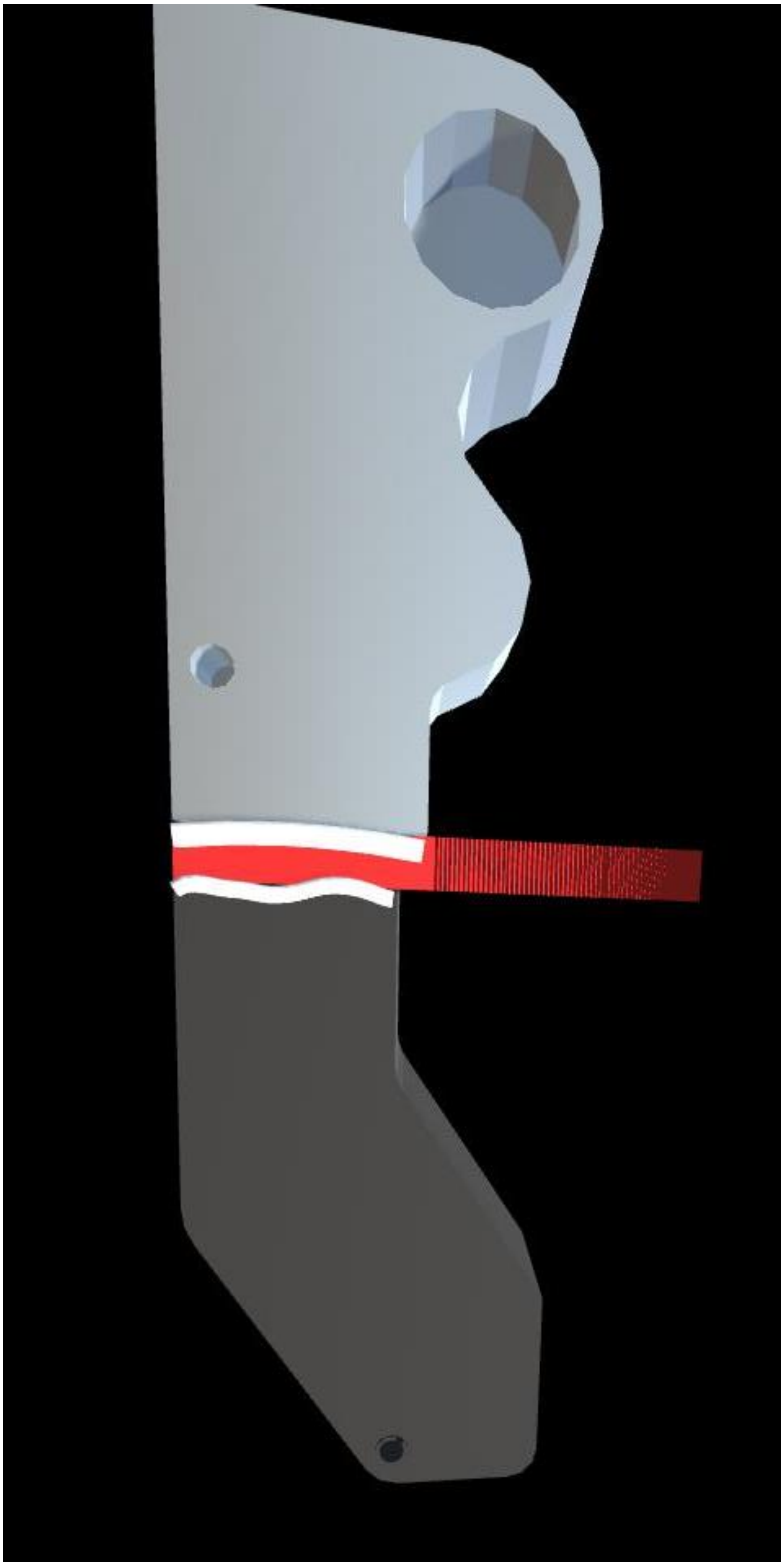
Appendix J



Appendix K

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Appendix L

Appendix M

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Appendix N