IMAGE PROCESSING BASED OBJECT MEASUREMENT SYSTEM

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Science (Honours) Software Engineering

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May 2023

DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"IMAGE PROCESSING BASED OBJECT MEASUREMENT SYSTEM"** was prepared by **TAN CHUN GUAN** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Science (Hons) Software Engineering at Universiti Tunku Abdul Rahman.

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ABSTRACT

Object measurement systems play a critical role in various fields, including manufacturing, engineering, robotics, and scientific research where accurate and precise measurements are essential. Imaging enables non-contact object measurement which is useful for many applications. With the expansion of automation and quality control, object measurement using image processing has increased. However, it is still challenging for the imaging-based object measurement to accurately handle objects with complex structures, objects of different shapes and sizes, manage the impact of in environmental conditions, and efficiently handle high-volume measurement tasks. To investigate these problems, this research project evaluated three existing object measurement systems and compared their performance in terms of accuracy, flexibility, environmental robustness, and efficiency. These systems include systems without reference objects, systems with reference objects, and systems that utilize ArUco markers. Experiments were conducted using objects of different shapes and sizes under different environmental conditions to identify the strengths and limitations of each system. The results show that each system has its own limitations. Based on these findings, an object measurement system has been proposed and developed with the aim to enhance the strengths of the existing systems and overcomes their limitations. The proposed system utilizes image processing, feature extraction, and geometric modelling techniques to accurately estimate object dimensions and position with an average error rate of less than 2%. The outcome of this project is hoped to benefit various industrial and scientific processes that rely on precise measurement data such as manufacturing, quality control, engineering, etc.

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LIST OF SYMBOLS / ABBREVIATIONS

AI	Artificial Intelligence
AIAG	Automotive Industry Action Group
LCL	Lower Control Limit
UCL	Upper Control Limit

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

According to Yu et al. (2019), imaging-based object measurement systems have become an essential tool in industrial measurement applications. These systems use image processing and analysis techniques to extract features from digital images and estimate the dimensions and position of an object. Edge detection, image segmentation, feature extraction, and geometric modelling are among the techniques used to calculate the dimensions and position of the object accurately.

One of the significant advantages of image-based object measurement systems is their non-contact and non-destructive nature. As reported by Li et al. (2018), traditional methods, such as manual and contact-based measurements, require physical contact with the object, which can cause damage or alter the object's shape. On the contrary, imaging-based object measurement systems can measure the object without any physical contact, making them suitable for measuring delicate or fragile objects.

Furthermore, as reported by Zhang et al. (2019), imaging-based object measurement systems offer high accuracy and precision, making them suitable for measuring objects with complex shapes and structures. They also provide a cost-effective solution for object measurement, as they require minimal equipment and can be easily automated.

In conclusion, imaging-based object measurement systems offer a non-contact, highly accurate, and cost-effective solution for measuring objects of different shapes and sizes. They have improved performance across a wide range of industries, including manufacturing, transportation, and surveillance, and have the potential to revolutionize how objects are measured.

1.2 Problem Statement

However, there are still some challenges in the imaging-based object measurement system. The following problems are gathered through literature reviews and direct observation.

i. Precision for complex object dimensions

Existing imaging-based object measurement systems often need help to accurately estimate the dimensions and position of objects with complex shapes and structures. This is due to the limitations of these systems' image processing and analysis techniques. These limitations make it challenging to accurately capture and measure objects with complex shapes with varying contours and features. Therefore, there is a need to develop advanced image processing and analysis techniques that can accurately estimate the dimensions and position of objects with complex shapes and structures.

ii. Limitations in measuring the varied sizes and shapes of objects.

Existing imaging-based object measurement systems are often designed to measure objects of specific shapes and sizes. Unfortunately, this limits their ability to measure objects of different shapes and sizes, including delicate or fragile objects. For instance, some objects may need to be bigger for the existing systems to measure accurately. Therefore, there is a need to develop an image measurement-based object measurement system that can accurately measure objects of different shapes and sizes, including delicate or fragile objects.

iii. Environmental factors affect measurement accuracy.

Imaging-based object measurement systems rely on the quality of the images captured by the camera. Changes in lighting conditions, object position, and camera angles can affect the quality of the images captured, which can, in turn, affect the accuracy of the measurements made by the system. Therefore, there is a need to develop imaging-based object measurement systems that can accurately measure objects under varying environmental conditions.

iv. Efficiency requirement for high-volume tasks

Existing imaging-based object measurement systems may need to be more efficient to handle high-volume measurement tasks. For instance, some systems may take too long to process the images and make measurements, which can slow down the overall measurement process in real-time applications. Therefore, there is a need to develop imaging-based object measurement systems that are efficient enough to handle high-volume measurement tasks.

1.3 Aims and Objectives

i. To develop an image-based object measurement system that can accurately and efficiently measure objects' dimensions of different shapes and sizes.

ii. To evaluate the accuracy, reliability, and performance of the proposed system, experiments will be conducted using objects of different shapes and sizes under various environmental conditions, including changes in lighting and object position.

iii. To improve the efficiency of the proposed system to handle high-volume measurement tasks.

1.4 Scope and Limitation of the Study

The limitations of the study include potential challenges in accurately measuring objects with complex shapes and structures and limitations in the system's ability to handle changes in lighting conditions, object position, and camera angles. Additionally, the proposed system may not be suitable for measuring objects with those that are too small or too large to fit within the camera's field of view. Finally, the study is limited to evaluating the proposed system's performance under specific experimental conditions and may only generalize to some real-world scenarios.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

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Object measurement techniques have been evolving with new technologies and methods. However, traditional approaches have limitations in accuracy and precision, making them less effective in practical applications. In recent years, image processing techniques, such as computer vision and machine learning, have been used to overcome these limitations. Furthermore, deep learning techniques have further improved the accuracy and reliability of measurements. In addition to these techniques, analogue and digital image processing techniques have also been used in object measurement.

This literature review aims to study the different image processing techniques, including analogue and digital image processing, computer vision, and machine learning techniques, focusing on deep learning-based methods. Additionally, this review will explore traditional object measurement techniques and machine vision in application fields. The study will also analyse each technique's applications, limitations, challenges, and future directions. Finally, based on the findings, this review proposes an enhanced object measurement system that can overcome some of the limitations and challenges of the existing systems.

2.2 Artificial Intelligence, Machine Learning, and Deep Learning for Computer Vision

Artificial Intelligence, Machine Learning, and Deep Learning techniques have been applied in various computer vision applications, including object measurement systems, to enhance their accuracy and efficiency in measuring and analysing objects.

2.2.1 Artificial Intelligence

Artificial intelligence (AI) is a field of computer science that aims to create intelligent machines or systems capable of performing tasks that usually require human-level intelligence. AI research aims to develop machines that can reason, learn, and adapt to new situations like humans (Turing, 2018; Russel & Norvig, 2021). AI is currently used as a synonym for “Deep Learning” in media. However, AI refers to many sub-fields, such as Automatic Game Solving, Natural Language Processing, Computer Vision, Logic Programming, Expert Systems, Data Mining, Intelligent Agent systems, robotics, Machine Learning, and Deep Learning. These sub-fields are not mutually exclusive. For example, Machine Learning is used for Data Mining, Natural Language Processing, Computer Vision, and Intelligent Agent systems. Relationships between AI, ML, DL and Computer Vision are represented in Figure 2.1.

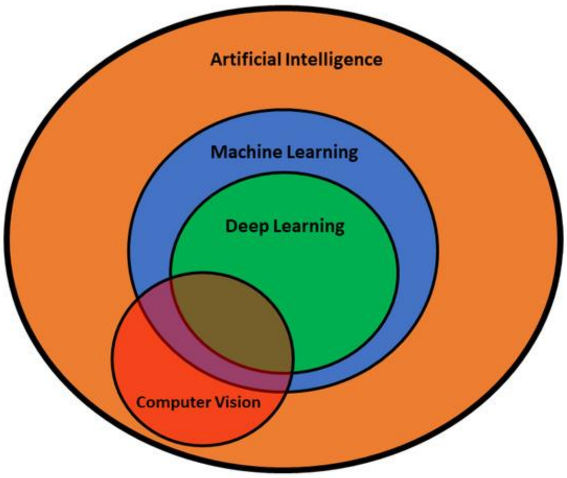


Figure 2. 1: Venn diagram of Artificial Intelligence, Machine Learning, Deep Learning, and Computer Vision

2.2.2 Machine Learning

Machine learning (ML) is a subfield of AI that enables machines to learn from data without being explicitly programmed (Goodfellow et al., 2018). It involves developing algorithms that can analyze data, identify patterns, and make predictions or decisions based on that data (Alpaydin, 2020). There are three main types of ML algorithms: supervised learning, unsupervised learning, and reinforcement learning.

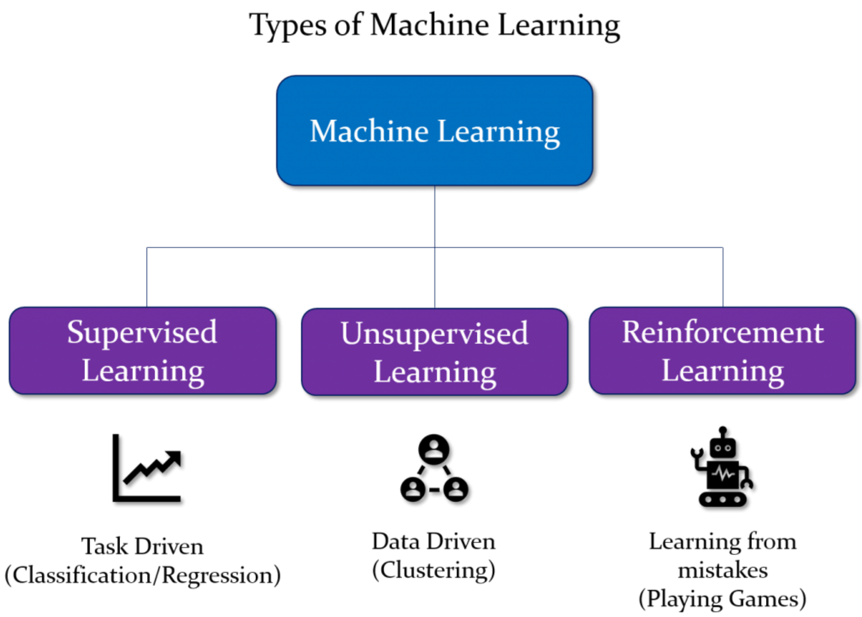


Figure 2. 2: Types of Machine Learning

2.2.2.1 Supervised Machine Learning

Supervised machine learning is a type of machine learning that involves training a machine with labelled data to make predictions about new data. In supervised learning, the data is labelled with the correct output, allowing the machine to learn from examples and make predictions about new data based on those examples. For example, if we want a machine to identify whether an image contains a cat or a dog, we can train it on a labelled dataset of cat and dog images, providing it with the correct label for each image.

According to a study by Singh and others (2020), one of the key advantages of supervised learning is that it can be used for classification and regression problems. In classification problems, the machine is trained to classify input data into different categories based on the labelled data. For example, a machine can be trained to classify email messages as either spam or not. On the other hand, in regression problems, the machine is trained to predict a constant output value based on the labelled data. For example, a machine can be trained to predict the price of a house based on its size, location, and other factors.

Supervised machine learning has numerous real-world applications, including image and speech recognition, natural language processing, and recommendation systems (Goodfellow et al., 2018). For example, supervised learning can train machines to recognize speech patterns, allowing them to transcribe spoken words into text. Similarly, supervised learning can be used to develop recommendation systems that suggest products or services to users based on their past behaviour or preferences.

2.2.2.2 Unsupervised Machine Learning

Unsupervised machine learning is a type of machine learning that does not involve labelled data. Instead, the machine is trained on an unlabeled dataset, allowing it to identify patterns and relationships in the data without specific guidance or supervision. One of the primary applications of unsupervised learning is clustering, which involves grouping similar data points based on their features or attributes.

According to a study by Géron (2019), clustering is an essential technique in unsupervised learning, where the machine identifies clusters of similar data points and assigns them to different groups or categories. One popular clustering algorithm is k-means clustering, which groups data points into k number of clusters based on their distance from a specified centroid. Another algorithm is hierarchical clustering, which creates a tree-like structure of nested clusters based on the distance between data points.

Unsupervised learning has several real-world applications, including anomaly detection, data compression, and dimensionality reduction. For example, unsupervised learning can detect anomalous behaviour in credit card transactions or network traffic (Alom et al., 2019). In data compression, unsupervised learning can be used to identify patterns and similarities in data, which can then be used to reduce the dataset size without losing essential information (Géron, 2019). Similarly, unsupervised learning can be used for dimensionality reduction, where the machine identifies the most important features or attributes in a dataset, allowing for more accessible analysis and visualization of the data.

2.2.2.3 Reinforcement Learning

Reinforcement learning is a type of machine learning where an agent learns by interacting with the environment through a trial-and-error process. The agent takes action in the environment and receives feedback in the form of rewards or punishments. The agent's goal is to maximize the cumulative reward it receives over time. Reinforcement learning does not require labelled data like supervised learning and instead learns from its experiences.

Deep reinforcement learning, which uses deep neural networks to represent the value function, has shown promising results in playing complex games such as Go and Poker (Brown & Sandholm, 2018). Another area of application for reinforcement learning is in robotics. Robots can learn to perform complex tasks by trial and error in a simulated environment before being deployed in the real world (Hwangbo et al., 2019).

Reinforcement learning problems are commonly formalized as Markov decision processes (MDP). An MDP consists of a set of states, actions, and rewards. The agent interacts with the environment by selecting actions and receiving rewards. The environment transitions to a new state based on the current and chosen actions.

2.2.3 Deep Learning

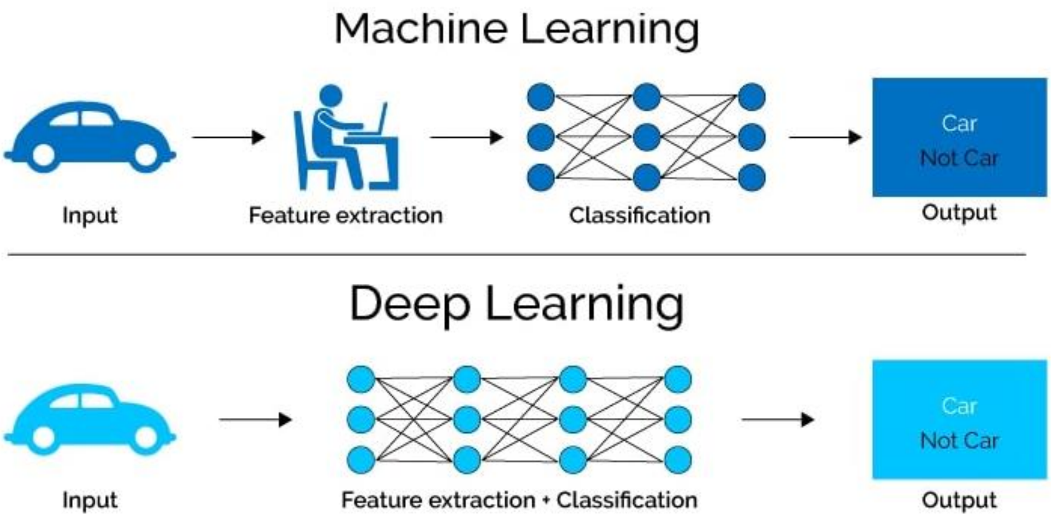


Figure 2. 3: Comparison of Machine Learning and Deep Learning

Deep learning is a subset of machine learning that utilizes deep neural networks to learn from data. It has gained tremendous popularity due to its high accuracy in handling large amounts of data. In recent years, the growth of big data has been exponential, and deep learning has emerged as a promising solution to deal with such a massive amount of unstructured data (Sharma, Sharma, & Jindal, 2021). Big data can be collected from a wide range of sources, such as social media, the internet, search engines, e-commerce platforms, and online movies. However, this data is often unstructured and voluminous, making extracting useful information challenging. Figure 2.3 demonstrates that deep learning algorithms have a unique hierarchical structure, which enables them to learn complex representations from raw data, eliminating the need for manual feature extraction. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two common types of deep learning models used to process unstructured data, such as images and text.

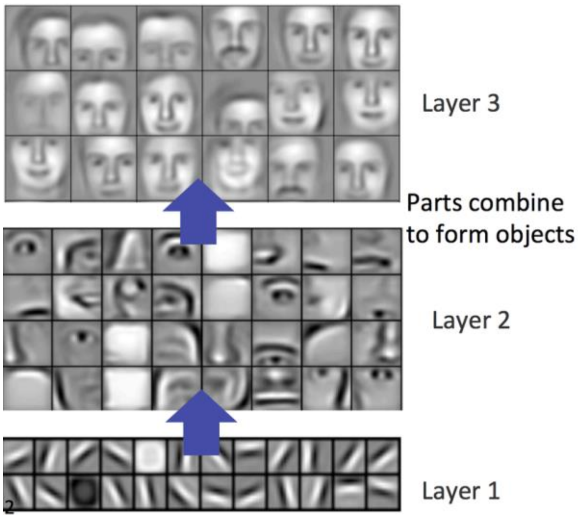


Figure 2. 4: Lower-level features progressively combine to form higher-level features (Asghar et al., 2019)

Deep learning models use a hierarchical structure of layers that progressively extract more complex features from the input data. In image recognition, for example, the system first processes the individual pixels of an image and then identifies edges and lines by detecting variations in the pixel intensity. These basic features are then combined in the subsequent layers to identify more complex shapes and patterns.

Based on Figure 2.4, The lower-level features extracted from the initial layers are then progressively combined in deeper layers to form higher-level features. For instance, in facial recognition, the system may start by recognizing the eyes, nose, and mouth in the early layers of the network; then, it may combine these lower-level features to identify higher-level features, such as the face's overall shape, the distance between the eyes, and the curvature of the lips.

The progressive combination of lower-level features to form higher-level features is a critical concept in deep learning because it allows the system to recognize more complex patterns and features in the data. The hierarchical structure of deep learning models enables them to identify abstract concepts, such as emotions or intentions, by combining lower-level features in increasingly sophisticated ways.

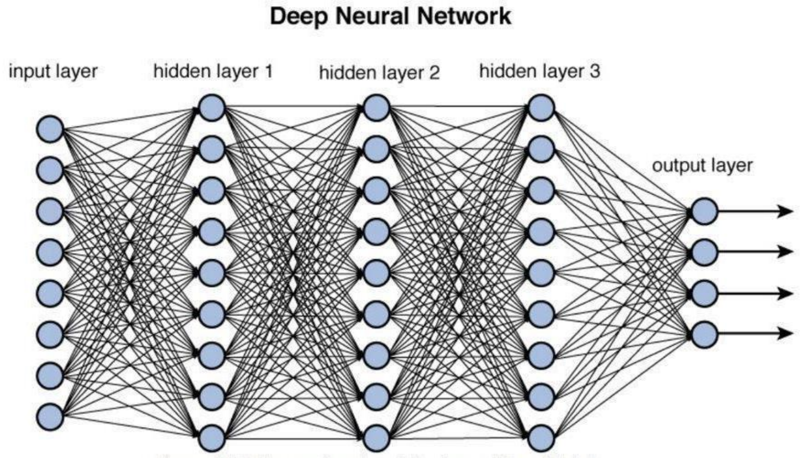


Figure 2. 5: Deep network architecture with multiple layer (Ravindra, 2018)

Deep learning architecture consists of multiple layers of artificial neural networks designed to simulate the human brain. First, the network receives input data, which is then processed through multiple layers of nodes, each with its activation function. The formula for each node is $Z = \sum_{i=1}^{m} W_i X_i + b$, where X represents the input data, W represents the weights between two adjoining unit layers, and b represents the bias, the minimal number required to pass the threshold. Next, the activation function is applied to Z, producing a non-linear output at each layer, which is then passed to the next layer in the network (Shrestha & Mahmood, 2019; IBM Cloud Education, 2020).

The process of computing output across the network is known as forward propagation, which generates predictions based on the learned features of the input data. Deep learning also employs backpropagation, an algorithm that uses gradient descent to adjust the weights and biases in the network when the prediction is incorrectly computed. This allows the function to move backwards through the layers and adjust the weights and biases to improve the model's accuracy (Shrestha & Mahmood, 2019).By using both forward and backpropagation, deep learning can generate predictions and fix errors, making the algorithm more accurate. It also allows the network to learn high-level features incrementally, which eliminates the need for feature engineers and results in higher accuracy. However, deep learning requires a massive quantity of data and processing power to achieve an acceptable degree of accuracy. Nonetheless, in today's big data and cloud computing era, it has become the primary option among others (Shrestha & Mahmood, 2019).

2.3 Image Processing Techniques

Image processing is spreading in various fields. Image processing is a typical technique for enhancing unprocessed photos obtained from diverse. It is a method for converting an image into digital form and performing specific actions on it in order to enhance the picture or extract useful information from it. It is a kind of signal distribution in which an image is an input, and the output is an image or attributes connected to an image. For the processing of images, mathematical techniques are used. Analog image processing and digital image processing are the two techniques used to process images.

2.3.1 Analog Image Processing

Electrical signals are used in this processing technique to alter the image as needed. Two-dimensional analogue signals may be processed analogy. This method involves converting the electrical signal to change the visuals. It is mainly used for photographic prints and hard copies for printing purposes. Contrarily, the kinds of pictures we view as humans are analogue ones. The brightness (or film density) and colour levels are seen in an analogue image. Typically, it is continuous and not divided into several little bits. Analog pictures are necessary for human vision.

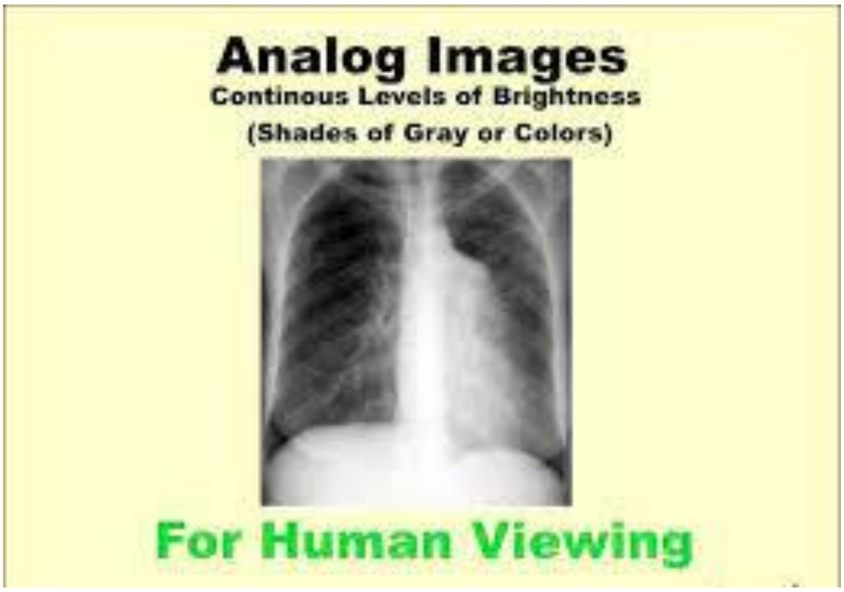


Figure 2. 6: Example of Analog Images

2.3.2 Digital Image Processing

Digital computers are used in this method to process photographs. Images are first digitalized through a scanner before undergoing further processing. To produce images with greater quality, digital image processing employs various methods, including data formatting, correction, and enhancement (Muaidi, 2014). Digital image processing primarily uses four operations: image preprocessing, image segmentation, feature extraction, and image classification.

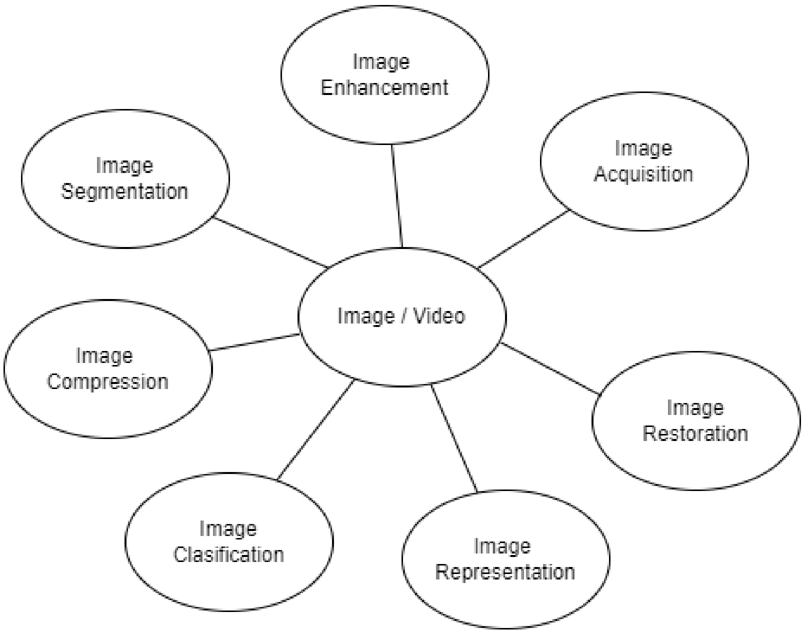


Figure 2. 7: Techniques of Image Processing

2.3.2.1 Image Segmentation

Segmentation is the division of a picture into different areas or components. When an image is segmented, it is broken into smaller pieces based on the user's needs or handled issue. It creates pixel divisions in the picture. Picture segmentation splits the image in a manner that makes it very precise. Segmentation aims to make an image's presentation more straightforward or evaluable by changing or simplifying it (Kaur, 2012). It results in a better-looking image. Image segmentation is done for image compression, object detection, and editing purposes. Methods of picture thresholding are used for image segmentation. Each pixel in the picture is given a name during segmentation so that pixels with the same labels may share specific attributes (Aly, bin Deris and Zaki, 2011). There are various image segmentation methods, as shown in the figure below.

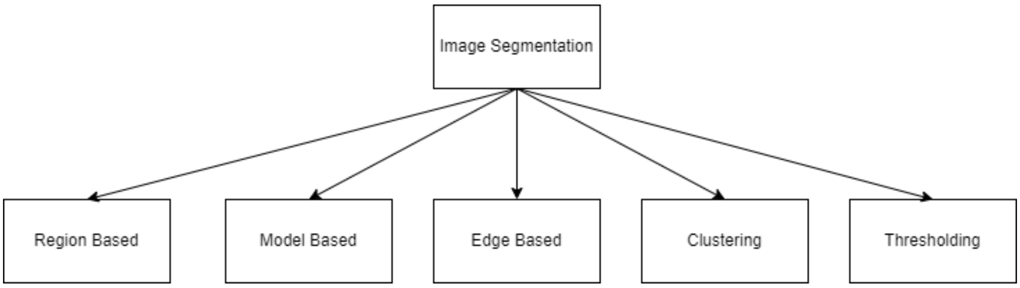


Figure 2. 8: Image Segmentation Techniques

2.3.2.1.1 Region

This segmentation approach combines certain segmentation items. This approach makes use of a segmentation methodology based on regions. The areas where segmentation must be done must be close to one another. It is sometimes referred to as segmentation based on resemblance. To do segmentation, the boundaries are identified. For processing purposes, at least one pixel is required for each step. A vector is then produced from the edge flow after the technique has affected the colour and texture of the picture. The edges are then subjected to further processing (Ma and Manjunath, no date).

2.3.2.1.2 Model

This method is based on the Markov random field. Inbuilt region constraints are utilised for colour segmentation. MRF and edge detection are combined to determine edge accuracy(Luo, Gray and Lee, 1998). This technique includes the relationships between coloured parts.

2.3.2.1.3 Edge

Edge detection is a different segmentation approach. The edges of the picture are identified in order to distinguish differences. Drawn edges are compared to other pixels in order to determine pixel values. It is not a requirement that edges identified by the edge detector technique be near one another. In this procedure, edges' information is first collected, then pixel labels are applied. This approach also retrieves data from the weak border (Li et al., 2010). Edges are another potential segmentation performer. There are some gaps among the edges since they are not entirely closed. Therefore, connecting is done to close the space between the edges (Shih and Cheng, 2004).

2.3.2.1.4 Clustering

Clustering is a different segmentation technique. In this method, an image is turned into a histogram. Clustering is then applied to it (Comaniciu and Meer, no date). An unsupervised method called fuzzy C is used to cluster the individual pixels to segment the colour image's pixels. This is used with regular pictures. If the picture is noisy, fragmentation will occur.

2.3.2.1.5 Thresholding

Thresholding is the most straightforward segmentation technique. With this method, each location where the two points are assigned to pixels transforms a grayscale picture into a binary image. These points fall below and are over the established threshold value. This approach employs a threshold value derived from the original picture's histogram. By looking for edges, the histogram's value is determined. Therefore, an exact threshold value depends on an accurate edge's detection. Comparing thresholding to other approaches requires fewer computations to accomplish segmentation. In a complicated context, this method does not provide the desired outcomes (Baradez et al., 2004).

2.3.2.2 Image Enhancement

Image enhancement raises the display quality of the image. When images are taken from different sources, there are occasions when the quality of the images is poor because of impediments. In order to boost the clarity of the images, image enhancement adjusts many aspects of the images. Modifying the aesthetic effect will also increase the information content of the images. This method is used for image analysis, feature extraction, and picture presentation. The algorithms utilised in this procedure are interactive and dependent on the applications. There are several approaches for enhancement, including histogram adjustment, noise filtering, and contrast stretching.

2.3.2.3 Image Acquisition

The picture acquisition step is the initial stage in any visualisation strategy.

Several techniques are applied to the picture once it is acquired. Image acquisition is a procedure used to obtain pictures from diverse sources. Real-time picture capture is the technique used most often. Using this technique, a pool of files is created and processed automatically—a method for acquiring images that generates 3D geometric data (Moustakides et al., no date).

2.3.2.4 Image Restoration

A damaged and noisy picture may be treated using an image restoration technique to create a perfect image (Pu-yin, 2004). As a result, restoration rebuilds photographs whose quality has been damaged by noise or a system fault. There are several reasons for deterioration, including air disturbance, sensor noise, and camera focus issues.

2.3.2.5 Image Representation

Image representation is the transformation of raw data so that computer processing may be applied to it. In essence, two categories of approaches are used to portray the images—depiction of boundaries and representation of regions. Boundary representations show how the image is internally shaped. It follows that the primary goal of the boundary representation approach is to show the form of the item, whether it has a corner, a rounded edge, or any other shape. When internal attributes are the primary interest, regions are represented (Kuriakose and P, no date).

2.3.2.6 Image Classification

Images are classified in order to extract the information, labels, and pixels from the images. It takes a lot of photos of the same things to conduct classification. An efficient sort requires a suitable classification system and a sufficient number of training examples. In essence, the categorisation system is designed to meet user needs (Lu and Weng, 2007). Several categorisation methods are available, including fuzzy logic, expert systems, and artificial neural networks—several categorisation systems, including per pixel, sub-pixel, and field. The most commonly used categorisation approach is per-pixel. Techniques for sub-pixel algorithms are flexible for pixel problems. These provide a greater degree of precision. The best choice is to classify data according to fields for satisfactory three-dimensional resolution.

2.3.2.7 Image Compression

Image compression refers to the data in digital pictures being compressed. (Sachin, 2011).Image compression removes data duplication, allowing for efficient storage and transmission. Lossy or lossless compression of images is possible. Data quality in lossless compression is maintained both during and after reduction. The quality of the data degrades after using lossy compression methods. Medical imaging, the content of technical drawings, and other applications often employ lossless compression. In contexts where a little loss of quality is acceptable, lossy techniques are utilised to achieve a significant bit rate decrease. JPEG compresses photos in full colour or grayscale and is the most commonly used compression method (Wallace, 1992). The picture is divided into blocks of eight by eight using this technique. These blocks are split such that no overlaps may arise between them.

2.4 Machine Vision in Application Field

Machine vision, also known as computer vision, refers to the use of computer algorithms and models to interpret, analyse and understand visual information from the world around us. Machine vision is widely applied in various fields such as medical imaging, robotics, autonomous vehicles, and surveillance systems (Chen et al., 2018). Machine vision is a subfield of artificial intelligence and a broad technology field that incorporates pictures. Its goal is to create an artificial intelligence system that extracts "valuable information" from images or multi-dimensional data by researching related ideas and technologies. Figure below shows the industry machine vision system.

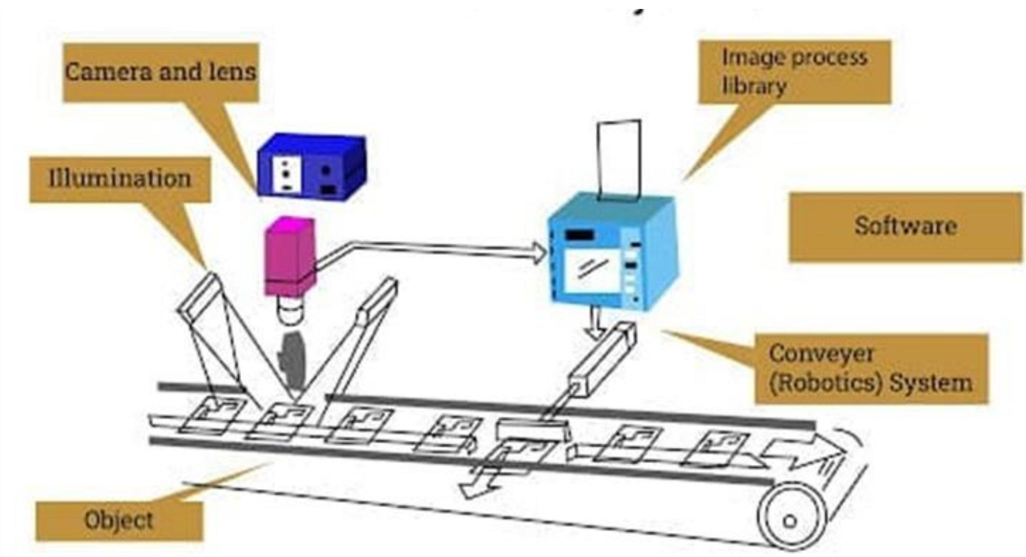


Figure 2. 9: Industry Machine Vision System

In terms of applications, machine vision research includes:

- Automated workpiece identification and recognition.
- Automatic food categorization (Bao, 2021).
- Autonomous unmanned vehicle navigation.
- Obstacle avoidance systems

It also involves monitoring forest fires and places that are prone to floods. Feature extraction of shoe textures based on machine vision; robots that draw lines and glue the look of shoes; deep learning and neural network algorithms based on machine vision; and other surveillance methods are examples (Guo et al., 2018). Low-level and high-level vision are the two levels of machine vision from the standpoint of the processing process. Edge detection, feature extraction, picture segmentation, and other operations are included at the bottom level, while feature matching and three-dimensional modelling are included at the high level of vision (Jiang and Chan, no date).

From a methodological standpoint, machine vision may also be split into active and passive categories. The distinction between the two is that the dynamic is less readily influenced by ambient light, allowing it to better comprehend and adapt to its surroundings (Arabnia, Deligiannidis and Tinetti, 2019).Additionally, there are techniques based on models and characteristics, each of which has benefits and drawbacks.

From a broad perspective, computer vision is another name for machine vision. This is due to similarities in the two fields of investigation. The main distinction between the two is that computer vision is heavily used in robots. The discipline of industrial inspection makes more use of machine vision. Additionally, machine vision concentrates more on the application level, whereas computer vision concentrates more on the academic research level. Complex challenges like occlusion, noise, and illumination must be considered when using machine vision. Effective image processing techniques like noise reduction and smoothing must also be taken into account at the same time.

2.5 Traditional Object Measurement Techniques

2.5.1 Overview of Traditional Object Measurement Techniques

Traditional object measurement techniques involve using manual measurement tools such as rulers, callipers, and micrometres to obtain precise measurements of an object's dimensions and features (Dong et al., 2018). These techniques are widely used in various industries, including manufacturing, engineering, and architecture, to ensure the accuracy and quality of products and designs.

However, traditional object measurement techniques have several limitations. They are often time-consuming and require skilled operators to perform accurate measurements (Wang et al., 2018). They also need to improve their ability to measure complex geometries and features, such as free-form surfaces and internal structures.

Despite these limitations, advancements in traditional object measurement techniques have been made in recent years. For example, new software and algorithms have been developed to improve the accuracy and efficiency of photogrammetry and other traditional techniques (Dong et al., 2018). Additionally, the integration of traditional measurement techniques with other technologies, such as machine learning and computer vision, has enabled the measurement of more complex geometries and features (Bhowmick et al., 2020).

2.5.2 Limitations of Traditional Object Measurement Techniques

Despite the advantages of traditional object measurement techniques, some notable limitations must be considered. One of the major limitations is that traditional techniques are often time-consuming and require manual effort, especially for complex objects. This can result in errors and measurement inconsistencies, leading to inaccurate data (Hsieh, 2017). Furthermore, traditional techniques may need to be able to measure objects that are too large or too small or have complex shapes. For example, measuring the surface area of a human body using traditional techniques would be challenging due to its complex shape and irregular surface (Li et al., 2019).

Another area for improvement is the need for automation and digitalization in traditional techniques. These techniques often require manual measurement and recording of data, which can be time-consuming and prone to errors. In addition, traditional techniques may not be able to capture specific parameters such as surface texture or colour, which are essential in many applications, including medical imaging and quality control in manufacturing (Liu et al., 2020).

Finally, traditional techniques may not be able to provide real-time measurements, which is critical in many applications, such as robotics and automation. Real-time measurements can improve the accuracy and precision of measurements and reduce the risk of errors and accidents (Song et al., 2018).

Despite these limitations, traditional object measurement techniques remain essential for many applications. However, advancements in technology have led to the development of new and more sophisticated techniques, such as machine learning and computer vision-based methods, which can overcome some of these limitations and offer new opportunities for object measurement.

2.5.3 Advancements in Traditional Object Measurement Techniques

Traditional object measurement techniques have undergone various advancements over the years to address the limitations and challenge traditional methods face. One of the significant advancements is the use of computer-aided measurement techniques, which utilize sophisticated computer programs to improve the accuracy and precision of measurements. For example, coordinate measuring machines (CMM) use computer software to provide accurate and precise measurements of objects, which is impossible with traditional measurement techniques (Chen et al., 2018).

Another significant advancement in traditional object measurement techniques is the use of optical measurement techniques. These techniques use optical sensors, cameras, and light to capture the dimensions of objects accurately. One example of an optical measurement technique is structured light scanning, which uses a projector to project a light pattern onto the measured object. Then, the object's surface reflects the light to a camera, which captures the surface's dimensions and reconstructs the object's 3D model (Zhang et al., 2018).

Moreover, traditional object measurement techniques have also benefitted from integrating artificial intelligence and machine learning. Machine learning algorithms have been used to improve the accuracy of traditional measurement techniques by identifying and correcting measurement errors. For instance, machine learning algorithms can be trained to detect and correct systematic errors in coordinate measurements, which can improve the accuracy and precision of the measurements (Srinivasan & Kim, 2019).

In conclusion, the advancements in traditional object measurement techniques have significantly improved measurements' accuracy, precision, and efficiency. In addition, computer-aided measurement techniques, optical measurement techniques, and machine learning algorithms have revolutionized how objects are measured, enabling accurate and precise measurements in various industries such as manufacturing, engineering, and medical fields.

2.6 Review of Existing Object Measurement System

2.6.1 Object Measurement System with A4 paper (Murtaza,2020)

The system is designed to measure the size of objects using a standard A4 paper as a guide. A4 paper is widely used in offices and is easily accessible, making it a convenient reference object for object size measurement. The system uses computer vision techniques to detect and recognize the A4 paper in an image and then uses it to calculate the size of other objects in the same image.

Figure 2. 10: Measure object within an A4 paper

Method:

The A4 paper acts as a reference object, and its dimensions are known. Therefore, the camera captures the image of the objects placed in the designated region. The image is then processed using OpenCV to detect the edges of the A4 paper and calculate its size. Once the size of the A4 paper is determined, the width and height of the objects in the image can be calculated based on their relative sizes to the A4 paper.

Analysis:

The use of an A4 paper as a reference object provides a known size reference, which helps improve the accuracy of the measurements. This system is also easy to set up, as A4 papers are readily available and have standardized dimensions.

Limitations:

One of the limitations of this system is that it requires the objects to be placed in a designated region with the A4 paper. This may not be feasible in some situations, especially when measuring larger objects or in outdoor settings. Additionally, this system assumes that the A4 paper is correctly positioned and detected in the image. Therefore, any errors in the detection or placement of the A4 paper can affect the accuracy of the measurements.

Conclusion:

Overall, the object size measurement system using an A4 paper as a guide provides an accurate and easy-to-use solution for measuring the size of objects. However, it is important to consider the system's limitations when using it in various situations.

2.6.2 Object Measurement System with Reference Object (Adrian, 2016/2021)

The object measurement system from pyimagesearch using a reference object for static images is a computer vision-based system developed using the Python programming language and the OpenCV library. The system is designed to estimate the size of an object in a static image using a reference object. The reference object should be easily distinguishable from other objects in the image and its width and height should be known. The system works by first identifying the reference object in the image, extracting its dimensions, and then using those dimensions to calculate the size of other objects in the image.

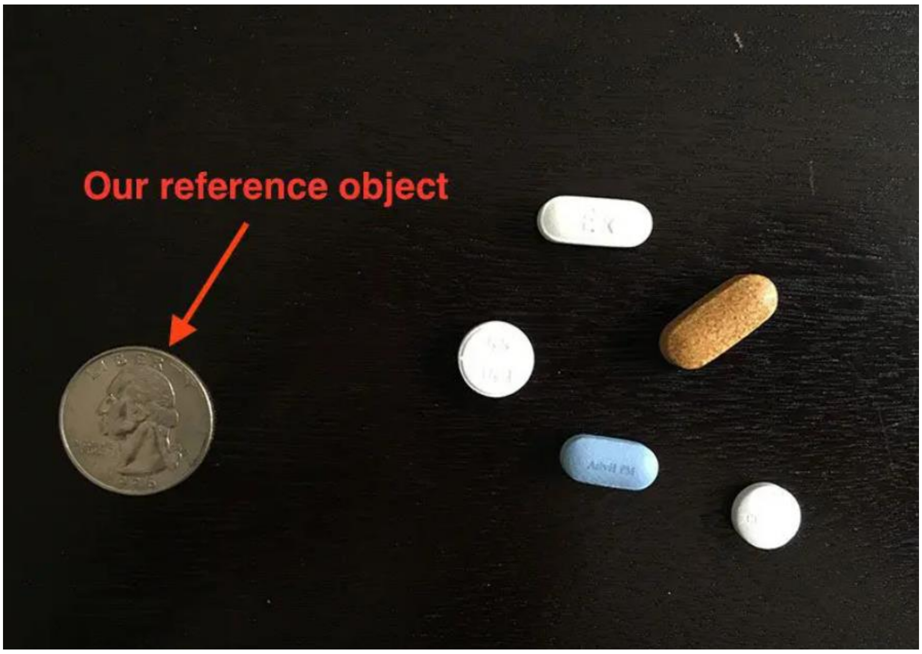


Figure 2. 11: Example of reference object placed in the image (Adrian,2021)

Method:

The system uses image-processing techniques to identify the reference object and extract its dimensions. The first step is to convert the image to a grayscale and apply a Gaussian blur to reduce noise. The next step is to apply edge detection using the Canny algorithm to detect the edges of objects in the image. The system then applies a series of morphological transformations, such as erosion and dilation, to remove noise and fill gaps in the edges.

Once the edges of the reference object have been identified, the system extracts its dimensions using contour detection. Contours are the boundaries of objects in an image and can be used to extract the dimensions of objects. The system sorts the contours from left to right and identifies the leftmost contour as the reference object. The width and height of the reference object are then extracted from the contour and stored.

With the dimensions of the reference object known, the system can then estimate the size of other objects in the image. The system does this by first identifying the contours of the objects in the image and then calculating their width and height using the dimensions of the reference object.

The reference object can use to define the pixel per metric, which define as:

pixels_per_metric = object_width / know_width

The below figure shows the output of the execution of the system

Figure 2. 12: Measuring object' size in an image with OpenCV and Python (Adrian,2021)

Analysis:

The object measurement system using a reference object for static images is an accurate and reliable system for estimating the size of objects in images. The system is easy to use and can be applied to a wide range of images, provided that a suitable reference object is available. The system works well with objects of different shapes and sizes, and the accuracy of the system is dependent on the accuracy of the dimensions of the reference object.

Limitations:

The object measurement system using a reference object for static images has a few limitations:

1. The system is designed for static images and cannot be applied to real-time or dynamic images.
2. The system's accuracy depends on the accuracy of the dimensions of the reference object, which can be difficult to obtain in some cases.
3. The system is designed for use with objects easily distinguishable from other objects in the image.

If objects in the image overlap or have similar shapes, the system may not be able to identify and measure them accurately.

Conclusion:

The object measurement system using a reference object for static images is a useful and reliable tool for estimating the size of objects in images. The system is accurate and easy to use and can be applied to a wide range of images, provided that a suitable reference object is available. The system has a few limitations, such as being designed for static images and requiring an accurate measurement of the reference object's dimensions, but overall, it is a powerful tool for object measurement in computer vision applications.

2.6.3 Object Measurement System with ArUco marker (Sergio, 2021)

This application is to study the implementation of measuring objects with the ArUco Marker. This review's significant finding is the application developed to identify the object in space and calculate pixels in centimetres with ArUco Marker, Python, and OpenCV. Camera posture estimation may be done using ArUco markers and binary square fiducial markers. Their key advantage is robust, quick, and straightforward detection. The ArUco module can identify these markers and their use in posture estimation and camera calibration. The figure below shows the ArUco markers with different matrix sizes (4x4, 5x5, 6x6, and 7x7 matrices).

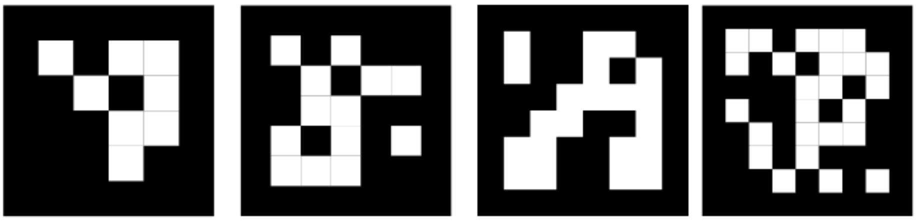


Figure 2. 13: Type of ArUco markers

In this system, the object's coordinate is first defined, and the dimension of the rectangle is shown in the pixel.

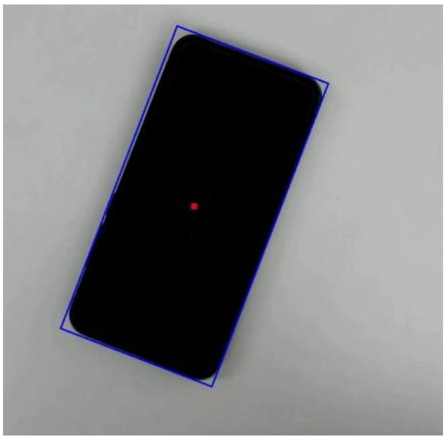


Figure 2. 14: Dimension of phone show in pixel

The actual data cannot be obtained by translating this measurement to centimetres since a reference for the dimensions is required. Thus, an ArUco Marker is used. Because it is a precise square measuring 5 cm x 5 cm, it has the great benefit of requiring no camera calibration. Beyond this, OpenCV understands that simple integration processes suffice. All that must be seen in the video are the marker and the items.

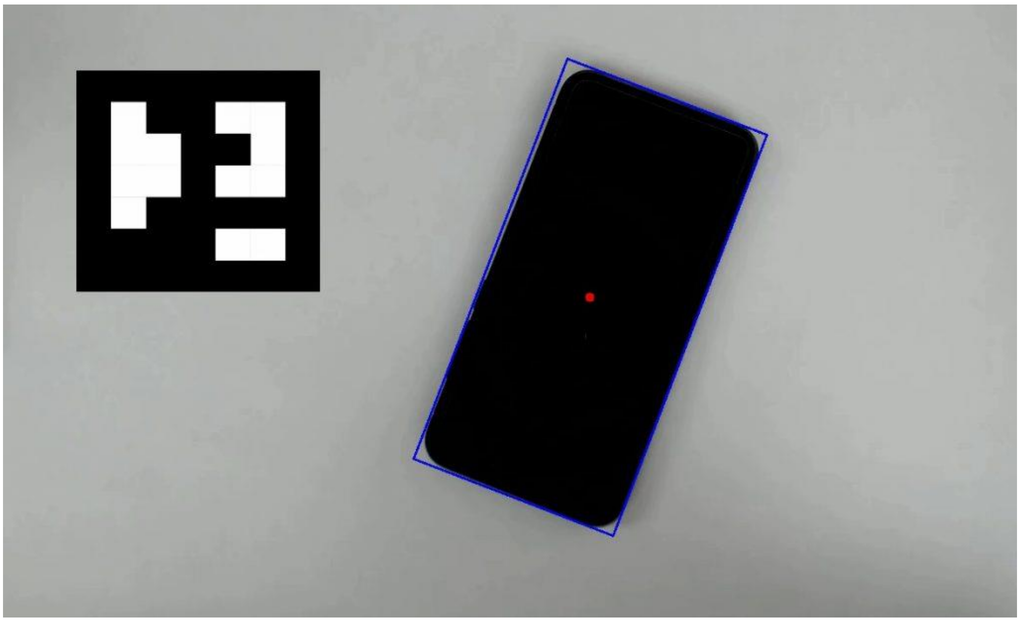


Figure 2. 15: Real-time image with ArUco Marker

Since the ArUco marker is a square with 5 cm on each side, the system measures a perimeter of 20 cm or around 560 pixels. The perimeter is then calculated using the points identified.

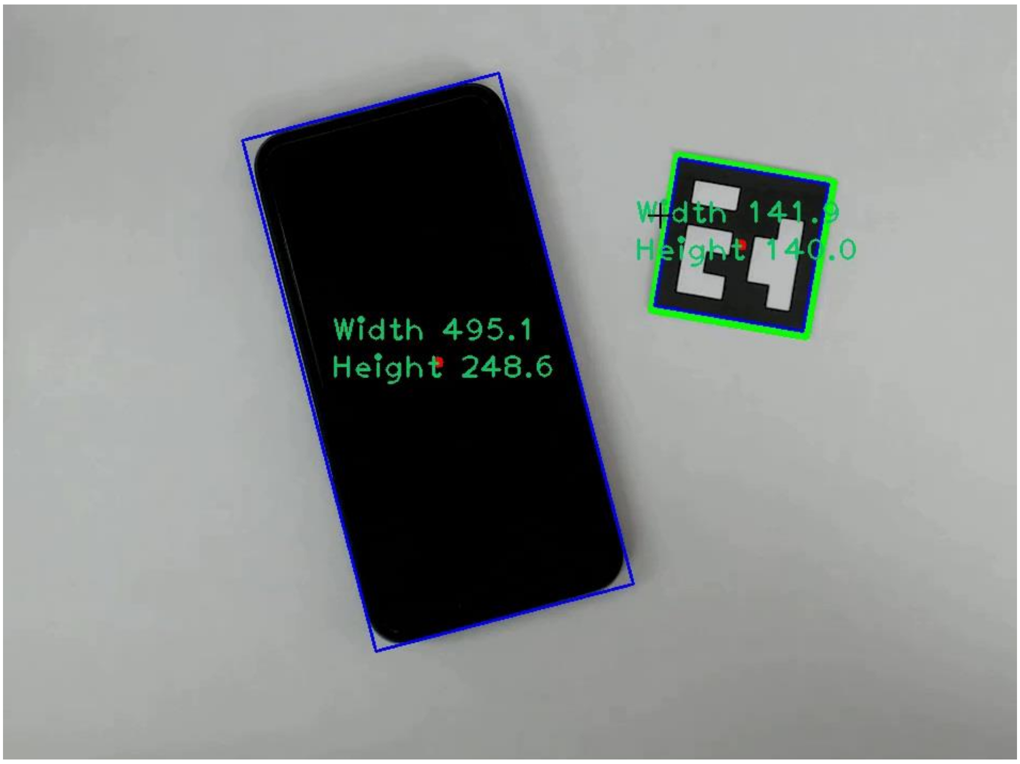


Figure 2. 16: Object's dimensions show with pixel

After applying the calculation, the result of the object's dimension with cm is shown in the application.

Figure 2. 17: Final result of the application

Analysis:

The object measurement result shown in this system is very close to the actual result, indicating the effectiveness of using the ArUco Marker as the reference object. ArUco Marker is a type of marker that can be easily detected by a computer vision system and provides reliable information on the size of the object being measured. The system uses OpenCV and Python programming language to detect the ArUco Marker and estimate the object's size based on its relative distance to the marker.

Limitations:

However, this system is relying solely on the ArUco Marker as the object reference. Therefore, the object cannot be measured when the system cannot detect the ArUco Marker. This is due to the lens distortion of the camera, which changes the object's size based on the perspective. Moreover, the system cannot adjust the threshold. This results in some parts of the object that cannot be measured or detected.

Conclusion:

In conclusion, the system presented in the study accurately measures object size using ArUco Marker as the reference object. However, the system has some limitations regarding its reliance on the ArUco Marker and the inability to adjust the threshold. These limitations may affect the accuracy of the measurement in some cases. Nonetheless, the system provides a helpful tool for object measurement applications, especially when the ArUco Marker can be easily detected and used as a reference object. Further development of the system may improve its accuracy and overcome some limitations.

CHAPTER 3

METHODOLOGY AND WORKPLANE

3.1 Workflow

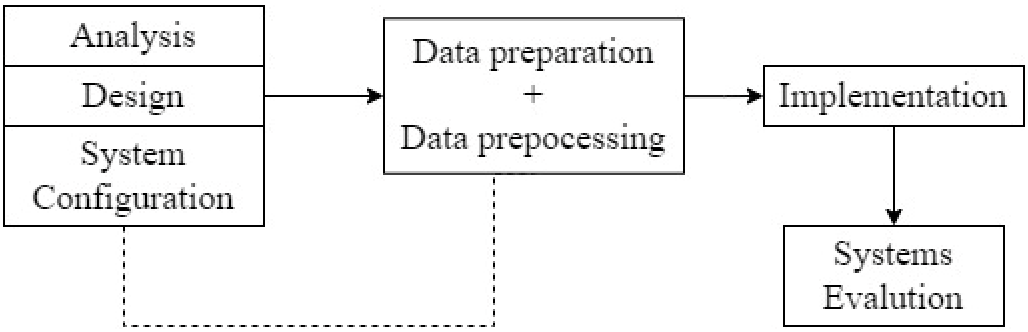


Figure 3. 1: Workflow implemented in this research

As illustrated in Figure 3.1, the workflow being employed in this project to guide the design and implementation of an object measurement system that accurately measures the size of objects in a static image. The first step of the process involves analyzing and evaluating existing object measurement systems to identify their limitations. Based on the analysis, the initial version of the system is designed. The system design consists of multiple iterations that involve developing and refining the system using a small dataset until it meets the project's requirements and resolves the limitations of existing systems. During each iteration, the system's accuracy, efficiency, and usability are evaluated, and adjustments are made as needed to improve the system's performance. The project's implementation phase involves building the system based on the final design, using appropriate programming languages and software libraries. The implementation phase also includes testing the system to ensure that it meets the project's requirements and functions as intended. The prototyping methodology, with its flexible and adaptable approach, allows for iterative development and refinement of the system. This ensures that the final system meets the project's requirements and addresses the limitations of existing systems. By utilizing this methodology, the project benefits from an efficient and effective design and implementation process.

3.2 Work Plan

A Gantt chart and a work breakdown structure outline the project's schedule and scope in the project plan. This ensures the project is finished within the given time and scope.

3.2.1 Work Breakdown Structure

A work breakdown structure is a means to divide a project into smaller segments based on what has to be done in project management and systems engineering. The work breakdown structure for this project is attached as Appendix A.

3.2.2 Gantt Chart

A Gantt chart represents how a project's activities and resources should be planned, handled, and monitored. It offers a list of features and progress bars for each task. The project manager-used chart is this one. The project's Gantt chart is shown in Appendix B.

3.3 System Analysis

Three existing object measurement systems are being analysed: a system without a reference object, a system with a reference object, and a system using Aruco Marker to collect and verify their limitations, as found in the literature review. This analysis is being used as the foundation for the design of the initial version of the system.


Figure 3. 2: System Setup & Device used

As depicted in Figure 3.2, an adjustable phone shooting bracket stand with a 6-inch desktop ring light is set up for the system analysis. The camera that is utilized for the object measurement system is a Leica camera from Huawei Mate 20 Pro, which consists of a triple-lens setup comprising 40 MP (wide), 8 MP (telephoto), and 20 MP (ultra-wide) sensors. The primary camera has a 7296 x 5472 pixels resolution and can capture high-quality images with accurate color reproduction and detail. The camera is positioned in a straight-up-and-down orientation to ensure consistent results. A white background is utilized since OpenCV is used in all of the systems, and therefore, it requires some contrast between the object and background so that OpenCV can recognize objects without needing to be pointed out. The IP Webcam Pro application is utilized as a connection between the system and the phone camera.

3.4 System Design

A proposed system has been developed to address the limitations of the existing object measurement systems, which do not rely on a reference object but instead use an initial frame configuration to achieve high accuracy. The proposed system will use a combination of computer vision techniques, such as feature detection and matching, to establish an initial frame representing the measured object. Once the frame is established, the proposed system will utilise machine learning algorithms to learn the object's size and shape, enabling it to measure the object accurately without the need for a reference object. To ensure flexibility, the proposed system has been designed to adapt to different object sizes, shapes, and environmental conditions. Furthermore, the system has been designed for robustness, capable of handling occlusions or poor lighting conditions using advanced image processing techniques. Finally, the proposed system has been designed for efficiency, with the ability to handle high-volume tasks and real-time measurement applications. By eliminating the need for a reference object and incorporating advanced computer vision techniques and machine learning algorithms, a highly accurate, flexible, robust, and efficient solution for object measurement can be provided in the organisation's operations using the proposed system.

3.5 System Configuration

Before measuring the object, the camera utilized in the proposed system must be calibrated. First, a calibration range is set with the maximum field of view from the centre of the frame to the farthest edge, which can be measured based on different units. For instance, if the objects are to be measured in cm, then the calibration range is set with the maximum field of view in cm units. Then, a ruler is placed under the camera, parallel with the red line, as depicted in Figure 3.3, in configuration mode.

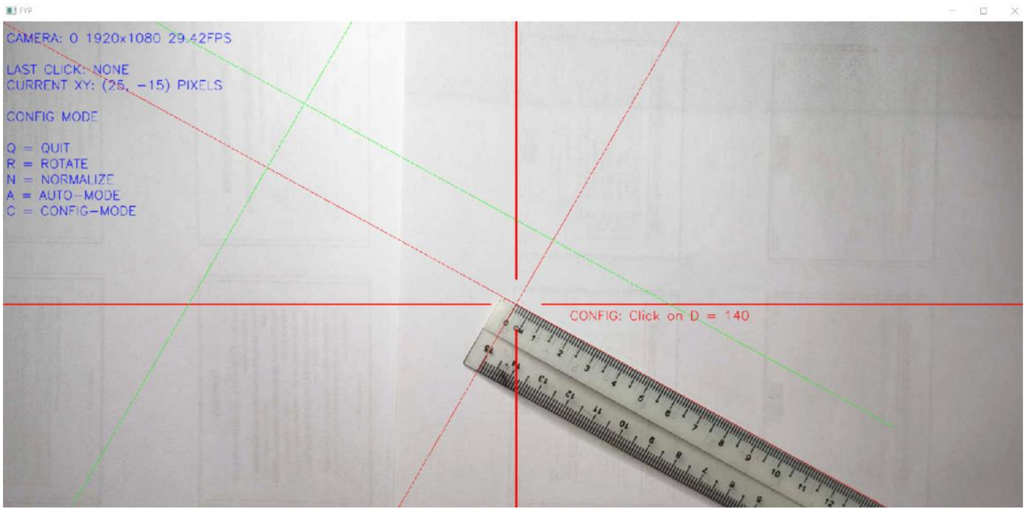


Figure 3. 3: Configuration Mode of Proposed System

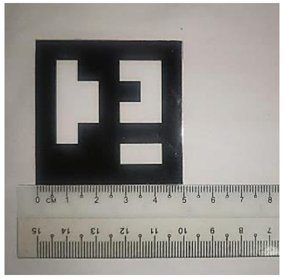
Every range of 5 of the calibration range is clicked until the maximum of the frame by the proposed calibration method, which is designed to solve the limitation of the existing system that heavily relies on the reference object.

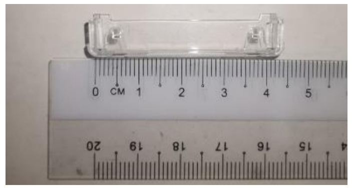
3.6 Data Collection

During the data collection phase of this project, a wide variety of objects with varying shapes, sizes, and colours are being utilized to ensure that the objective measurement system is robust and accurate. Objects of different shapes, such as circular, rectangular, and irregular shapes, are included in the dataset. The sizes of the objects range from small to large, covering a variety of dimensions, such as length, width, and height. Additionally, the colour of each object is being recorded, as it can impact the system's accuracy. To document the actual dimensions of each object, a table is used to record the measured dimensions of the objects along with their actual dimensions. The actual dimensions are measured using a reference tool, such as a ruler or calliper, and are recorded in the table for comparison with the measured dimensions obtained by the object measurement system. To ensure accuracy and reliability, proof of the actual dimension is also documented in the table, such as a reference from other resources or a photograph of the object being measured with the reference tool. For example, in order to prevent parallax error when measuring with a ruler, the actual object being measured must be viewed from a 90-degree angle to the ruler.

Table 3. 1: Object characteristic

No.	Object	Actual Dimensions	Shape	Color	Proof of Actual Dimensions
1	Malaysia Coin (50sen) 	22.65mm in diameter	Round	Gold	- https://www.bnm.gov.my/-/50-sen - Measured from vanier calippers: 
2	Malaysia Coin (10sen) 	18.80mm in diameter	Round	Silver	- https://www.bnm.gov.my/-/10-sen - Measured from vanier calippers: 
3	AAA battery	44.5mm in length	cylindrical	Black	- https://en.wikipedia.org/wiki/AAA_battery#:~:text=An%20AAA%20battery%20is%20a,0.8%20mm%20(0.031%20in)

					- Measured from vanier calippers: 
4	Aruco Marker 	5cm X 5cm	square	Black &White	- Measured from cm ruler: 
5	Tomato sauce packet	8.9 cm in length	rectangle	Orange	- Measured from cm ruler:

					
6	Power Bank 	14.1cm in height	rectangle	Black	- Measured from cm ruler: 
7	Razor cover 	4.2cm in length		Transparent	- Measured from cm ruler: 
8	Remote Controller	9cm in height	rectangle	White	- Measured from cm ruler:

					
9	Metal Screw 	40mm in length	silver		

3.7 Systems Evaluation

To ensure a fair evaluation and comparison of multiple systems, they must be tested based on the same physical setup. This requires that all systems are tested using the same equipment, materials, and conditions. The performance of each system is then evaluated based on various criteria, such as consistency and accuracy, flexibility, robustness, and efficiency. The Control Chart Method will also be used to evaluate the object dimension measurement system.

Accuracy & Consistency

Consistency is considered a crucial metric for evaluating the performance of an object measurement system. It is related to the degree of variation or dispersion in a set of measurements obtained from the system. A more consistent system is capable of producing measurements that are dependable and can be replicated with precision. Multiple measurements, ideally at least five, should be taken for each object to ensure that the measurements are consistent and reliable.

A consistent measurement system is desirable in any application that requires accurate and reliable measurement. When considering an object measurement system, consistency is particularly critical because measurement inconsistencies can result in significant errors in object dimensions. Therefore, it is essential to ensure that measurements are consistent and reliable.

Standard deviation is a widely used measure of consistency in a set of measurements. It is a statistical tool that quantifies the extent of variability or dispersion of data points in a dataset. A smaller standard deviation indicates that the measurements obtained from the system are more consistent and reliable.

The formula for standard deviation is:

$$\sigma = \sqrt{\sum \frac{(x_i - \mu)^2}{N-1}} \tag{3.1}$$

Where:

σ represents the standard deviation

Σ represents the sum of all individual measurements taken.

x_i represents each individual measurement value.

μ represents the mean, or average, of all measurements taken.

N represents the total number of measurements taken for a particular object.

The standard deviation is used to generate an error bar that visually represents the range of values within which the actual value of the measurement is likely to fall. The error bar is a graphical representation of the variability of the data and helps compare different measurements. It consists of a vertical line representing the mean measurement and horizontal lines extending from each side of the vertical line to indicate the range of values within one standard deviation of the mean. The error bar can also be extended to include multiple standard deviations, allowing for the visualization of a broader range of potential values. The width of the error bar represents the uncertainty associated with the measurement, with wider bars indicating greater uncertainty.

Accuracy, on the other hand, is measured by comparing the actual result, which is taken as the mean of the measurement results, to the expected result, which is the result of the actual measurement taken during the data collection. The accuracy formula is calculated using the error rate, which is expressed as a percentage of the difference between the actual and expected results, divided by the expected result, and multiplied by 100.The accuracy formula is:

$$Error\ Rate = \frac{|Expected\ Result - Actual\ Result_{(\mu)}|}{Expected\ Result} \times 100 \tag{3.2}$$

$$Accurancy = 100\% - Error\ Rate \tag{3.3}$$

Therefore, while accuracy is an important measure of a system's performance, it should be considered together with standard deviation to assess the consistency and reliability of the system in measuring object dimensions.

Flexibility (Size/Shape/Color)

Flexibility refers to the ability of a measurement system to accurately measure objects of different sizes, shapes, and colours. A flexible system can measure a wide range of objects, from small to large and from simple to complex shapes. In addition, it can accurately measure objects of different colours, including those with metallic finishes, iridescence, or transparency, and can compensate for ambient lighting that can affect the perceived colour of an object. This flexibility is important because it determines how versatile the system is and what kinds of applications it can be used for. For example, a flexible measurement system for quality control in manufacturing can measure the dimensions and colour of components, such as engine parts or electronic components, with a high degree of accuracy. To achieve this flexibility, measurement systems can use a variety of techniques, including contact and non-contact measurement, spectral measurement, and multi-sensor measurement. The ability of a measurement system to accurately measure objects of different sizes, shapes, and colours is crucial in a wide range of applications, including manufacturing, scientific research, and product inspection.

Robustness

Robustness measures a system's ability to maintain its performance under various challenging conditions, including environmental factors, variations in measurement parameters, and other sources of noise or interference. In the context of a measurement system, robustness is particularly important for ensuring that accurate and reliable measurements can be obtained in diverse operating environments. One critical factor that can affect the robustness of a measurement system is lighting conditions. Light sources can vary in intensity, colour, and directionality, which can impact the ability of the system to measure object dimensions and properties accurately. For example, a system that uses a camera to capture images of an object may be sensitive to changes in lighting conditions, which can affect the image quality and result in measurement errors. To address this, a robust measurement system should be designed to account for different lighting conditions and be able to adapt its measurements accordingly.

Efficiency (High-Volume Tasks)

Efficiency is an important consideration when evaluating measurement systems, as it refers to how fast and well a system can perform high-volume tasks. High-volume tasks, in this context, refer to the process of measuring many objects in a short time. In today's fast-paced world, efficiency is a key requirement for many applications, especially in manufacturing, where time is of the essence. An efficient measurement system can accurately measure objects quickly, thereby enabling the production process to be streamlined and optimized. Furthermore, measuring objects quickly and accurately is essential in ensuring that the manufacturing process is kept up, which can lead to delays and production backlogs. An efficient measurement system can minimize these risks by enabling measurements to be taken in a timely and precise manner, leading to faster production times and improved overall productivity.

3.8 Measurement System Acceptability

The Control Chart Method is used to evaluate the acceptability of the measurement systems. Control charts are a statistical tool that can be used to monitor and evaluate a process or system over time, and they are commonly used in quality control and manufacturing settings. By plotting the measured values over time on a control chart, it is possible to detect any shifts or changes in the process or system, which can indicate problems or changes in performance. For example, in evaluating an object measurement system, control charts can be used to track the measured dimensions over time and monitor the system's performance. In addition, the control chart can be used to establish control limits for both the X-bar and range portions, which can be used to determine whether the system is operating within acceptable levels of accuracy and consistency. If the measured dimensions fall outside the established control limits, it may indicate a problem with the measurement system, such as a calibration issue or a malfunctioning sensor.

Determine the Control Limits:

X bar chart:

$$UCL_{\bar{x}} = \bar{\bar{x}} + 3\frac{\hat{\sigma}}{\sqrt{n}} = \bar{\bar{x}} + A_2\bar{R} \quad (3.4)$$

$$LCL_{\bar{x}} = \bar{\bar{x}} - 3\frac{\hat{\sigma}}{\sqrt{n}} = \bar{\bar{x}} - A_2\bar{R} \quad (3.5)$$

R chart:

$$UCL_{\bar{R}} = D_4\bar{R} \quad (3.6)$$

$$LCL_{\bar{R}} = D_3\bar{R} \quad (3.7)$$

Where:

X is the individual value (data)

n is the sample size

X bar is the average reading in a sample

R is the Range, in other words, the difference between the largest and smallest value in each sample

R bar is the average of all the ranges.

UCL is the Upper control limit

LCL is a Lower control limit

Subgroup	X bar chart		Sigma estimate	R chart		S chart	
	A_2	A_3	d_2	D_3	D_4	B_3	B_4
2	1.880	2.659	1.128	-	3.267	-	3.267
3	1.023	1.954	1.693	-	2.574	-	2.568
4	0.729	1.628	2.059	-	2.282	-	2.266
5	0.577	1.427	2.326	-	2.114	-	2.089
6	0.483	1.287	2.534	-	2.004	0.030	1.970
7	0.419	1.182	2.704	0.076	1.924	0.118	1.882
8	0.373	1.099	2.847	0.136	1.864	0.185	1.815
9	0.337	1.032	2.970	0.184	1.816	0.239	1.761
10	0.308	0.975	3.078	0.223	1.777	0.284	1.716
11	0.285	0.927	3.173	0.256	1.744	0.321	1.679
12	0.266	0.886	3.258	0.283	1.717	0.354	1.646
13	0.249	0.850	3.336	0.307	1.693	0.382	1.618
14	0.235	0.817	3.407	0.328	1.672	0.406	1.594
15	0.223	0.789	3.472	0.347	1.653	0.428	1.572
16	0.212	0.763	3.532	0.363	1.637	0.448	1.552
17	0.203	0.739	3.588	0.378	1.622	0.466	1.534
18	0.194	0.718	3.640	0.391	1.608	0.482	1.518
19	0.187	0.698	3.689	0.403	1.597	0.497	1.503
20	0.180	0.680	3.735	0.415	1.585	0.510	1.490
21	0.173	0.663	3.778	0.425	1.575	0.523	1.477
22	0.167	0.647	3.819	0.434	1.566	0.534	1.466
23	0.162	0.633	3.858	0.443	1.557	0.545	1.455
24	0.157	0.619	3.895	0.451	1.548	0.555	1.445
25	0.153	0.606	3.931	0.459	1.541	0.565	1.435

Figure 3. 4: Control Chart Constants for X bar (Ted Hessing, n.d)

n	A_2	D_3	D_4	d_2
2	1.88	0	3.27	1.13
3	1.02	0	2.57	1.69
4	0.73	0	2.28	2.06
5	0.58	0	2.11	2.33
6	0.48	0	2.00	2.53
7	0.42	0.076	1.92	2.70

Figure 3. 5: Control Chart Constants Range chart (Ted Hessing, n.d)

I-MR control chart factors

n	2	3	4	5
A_2	1.88	1.02	0.73	0.58
D_4	3.27	2.57	2.28	2.11
D_3	0	0	0	0
E_2	2.66	1.77	1.46	1.29

Figure 3. 6: I-MR control chart factors (Ted Hessing, n.d)

From the X bar R chart, the average range helps to determine the total variance of observed product measurement.

$$\sigma_p^2 = (\frac{\bar{R}}{d_2})^2$$

The variance due to the measurement system needs to be estimated. A minimum of 20 values should be collected from the measurement system, and the variance σ_m^2 of the measurement system should be estimated using an appropriate control chart. Lastly, the variance due to the measurement system can be estimated by $\boldsymbol{\sigma_m^2/\sigma_p^2}$**.**

According to the Automotive Industry Action Group (AIAG), below are the guidelines for measurement system:

Table 3. 2: Guidelines using variance components

Percentage of process variation	**Acceptability**
Less than 10%	The measurement system is acceptable.
Between 10% and 30%	The measurement system is acceptable depending on the application, the cost of the

	measurement device, cost of repair, or other factors.
Greater than 30%	The measurement system is not acceptable and should be improved.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The purpose of this research is to evaluate for the object measurement system. Object measurement system without reference object, with reference object, with Aruco Marker and the proposed system with frame camera calibration method was selected. The results are analysed and discussed from the following perspectives:

1. Consistency & Accuracy
2. Flexibility
3. Robustness
4. Efficiency
5. System Acceptability
6. Summary of Results

4.2 Accuracy & Consistency Result

In this experiment, the system's accuracy and consistency were evaluated using five different objects, and each was measured five times. The aim was to obtain the average mean and compute the accuracy and standard deviation of the system's measurements. The results are presented in Table 4.1 and Figure 4.1 to demonstrate the variability of the measurements and the degree of uncertainty is indicated by the length of the error bars. The longer the error bars, the more uncertain the measurement, and the shorter the error bars, the more accurate and consistent the system's performance. These results provide insights into the reliability of the system and its potential for practical use in various applications.

Table 4. 1: Results of accuracy and Standard deviation of object measurement system

Object	System	Measurement (cm)					Average (cm)	Standard Deviation	Accuracy (%)
		1st	2nd	3rd	4th	5th			
Malaysia Coin (50sen)	Without reference object	5.40	5.30	5.50	5.40	5.30	5.38	0.07	0
	With reference object	2.20	2.10	2.20	2.30	2.20	2.20	0.06	83.02
	With Aruco marker	2.1	2.2	2.1	2.2	2.2	2.16	0.049	81.51
	Proposed System	2.65	2.65	2.6	2.7	2.64	2.648	0.03	99.92
Malaysia Coin (10sen)	Without reference object	4.7	4.8	4.7	4.7	4.6	4.7	0.06	0
	With reference object	2.2	2.1	2.1	2.2	2.3	2.18	0.07	84.04
	With Aruco marker	1.9	2.0	1.9	1.9	2.0	1.94	0.049	96.80
	Proposed System	1.87	1.91	1.87	1.87	1.87	1.878	0.016	99.89
AAA battery	Without reference object	9.2	9.2	9.3	9.4	9.5	9.32	0.117	0
	With reference object	4.3	4.4	4.1	4.2	4.5	4.3	0.14	96.63
	With Aruco marker	4.4	4.5	4.6	4.3	4.3	4.42	0.12	99.32
	Proposed System	4.43	4.45	4.45	4.43	4.43	4.438	0.0098	99.73

Aruco Marker	Without reference object	10.0	10.1	10.2	10.4	10.5	10.24	0.185	0
	With reference object	4.6	4.7	4.5	4.6	4.7	4.62	0.075	92.4
	With Aruco marker	4.8	4.9	4.8	4.9	4.9	4.86	0.049	97.2
	Proposed System	5.00	5.00	5.00	5.00	5.00	5.00	0	100
Tomato sauce packet	Without reference object	18.2	18.3	18.5	18.6	18.4	18.4	0.14	0
	With reference object	8.4	8.5	8.2	8.3	8.4	8.36	0.1	93.93
	With Aruco marker	8.7	8.8	8.6	8.5	8.6	8.64	0.1	97.08
	Proposed System	8.93	8.95	8.93	8.95	8.95	8.942	0.0098	99.53

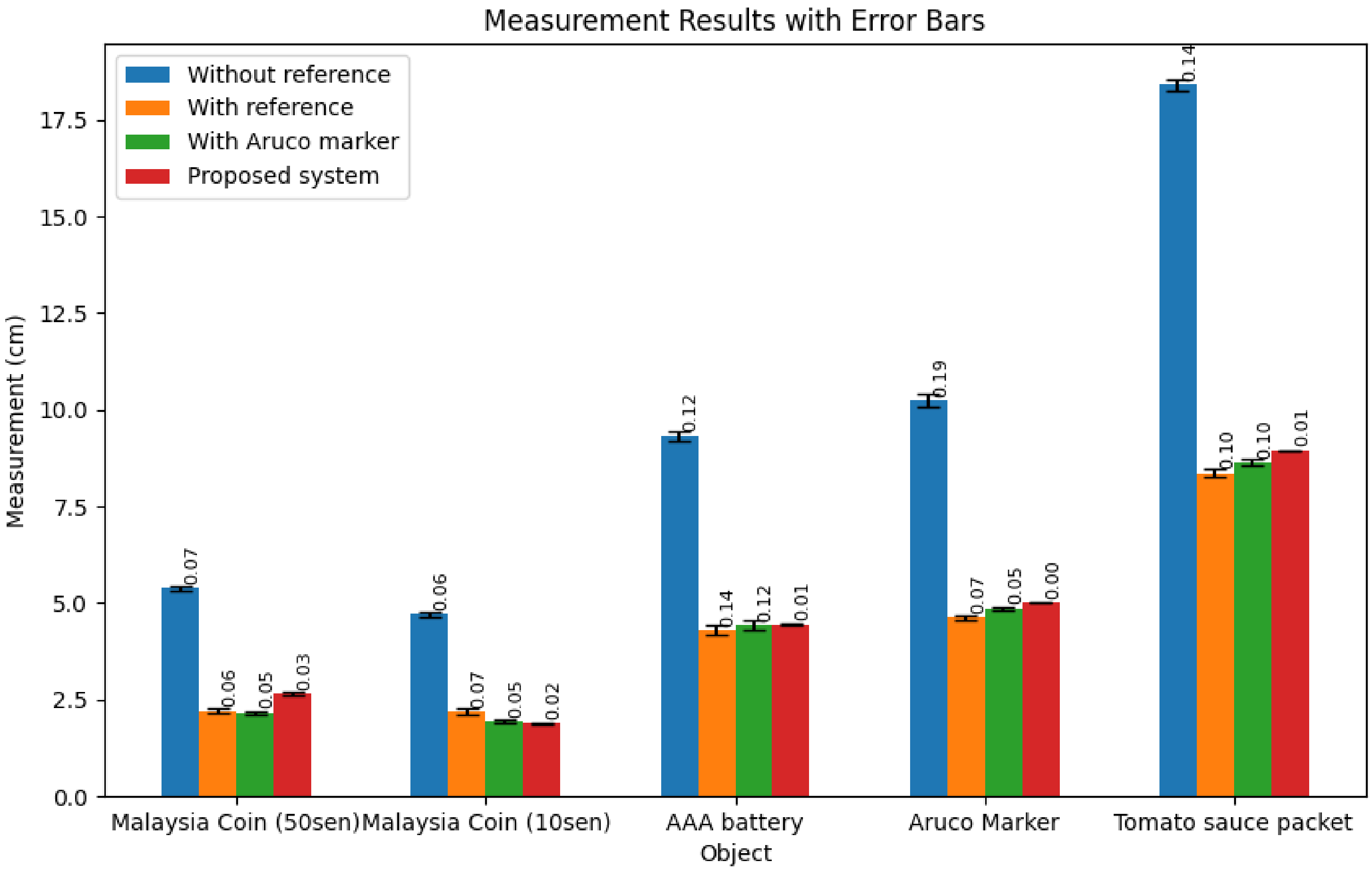


Figure 4. 1: Measurement result with Error Bars

Based on the results and error bars, it can be concluded that the proposed system is the most accurate and consistent among the tested systems. The system with a reference object and the system with Aruco Marker both show moderate performance, with their accuracy levels being similar. However, the system without a reference object is found to be inaccurate, with an accuracy level of 0, due to its lack of calibration. This system measures the width and height of objects in the image using the Euclidean distance between the midpoints of the bounding box. It does not use a reference object or calibration like the other systems, and instead relies on relative pixel distances within the image to measure the object. However, the accuracy of this system is affected by the variability of the measured results compared to the actual measurements, as it uses a pixel-to-metric conversion factor that is calculated by assuming that the object's width (or height) is known in centimetres. Therefore, this system cannot be used as a reference in future experiments.

4.3 Flexibility of the system

To evaluate the flexibility of the systems in measuring objects of varying size and colour, four objects were selected: a power bank with a length of 14.1 cm, a white remote controller with a height of 9 cm, a razor cover with a length of 4.2 cm with transparent colour and Malaysia Coin (10sen) with 1.88cm diameter. These objects were chosen to represent different sizes, and some of the colours could contrast more with the background. All three objects were placed under the same frame to evaluate the performance of the systems. It should be noted that since all the systems draw contours based on the detected object's maximum width and height, the shape was not considered in the results. Furthermore, due to the nature of the system used in this experiment, which does not utilize reference objects, the system could only measure one object at a time under one frame. Therefore, it is impossible to compare the measurements of different-sized objects under the same frame; thus, such measurements are not included in the results.

Table 4. 2 Results of accuracy of systems based on flexibility

Object	Size (cm)	Color	Measurement (cm) & Accuracy (%)		
			With reference object	With Aruco Marker	Proposed System
Power Bank	14.1	Black	13.5 (95.74)	14.2 (99.29)	14.0 (99.29)
Razor Cover	4.2	Transparent	-	4.2 (100)	4.2 (100)
Remote Controller	9.0	White	-	8.9 (98.89)	9.0 (100)
Malaysia Coin (10sen)	1.88	Silver	1.7 (90.43)	1.7 (90.43)	1.87 (99.47)

Table 4.2 shows the measurement and accuracy results of the three different systems in measuring four objects of varying sizes and colours. All three systems successfully measure the power bank, remote controller, and Malaysia coin, while the razor cover is only measurable by the Aruco Marker and proposed systems. This indicates that the proposed system and the Aruco Marker system are more flexible in detecting objects with transparent colours, while the system with reference objects could not measure it. Overall, the proposed system and the Aruco Marker system show higher flexibility in measuring objects of varying sizes and colours compared to the system with reference objects. Additionally, all three systems could accurately measure objects of varying sizes, such as the power bank and 10 Sen Malaysia coins, indicating that size is not a factor that significantly affects the accuracy of the systems. This suggests that the flexibility of the systems is not limited by the size of the objects being measured, and the proposed system and Aruco Marker system are still more flexible in detecting objects with varying colours, especially the colour not very contrasting with the background.

4.4 Robustness of the system

In order to assess the robustness of the system for measuring a single object, the experiment was conducted under various lighting conditions. These conditions ranged from very low lighting to low, normal, and high lighting conditions. By testing the system's performance under these different conditions for the same object, we aimed to determine how well the system can adapt to changes in lighting and maintain its accuracy and consistency. The results of this experiment, which only focused on the measurement of a single object, are presented in Table 4.3, along with an analysis of the system’s robustness in each lighting condition. The tomato package source with a length of 8.9 cm was selected as the object of measurement.

Table 4. 3 Result of System accuracy based on different lighting condition

Lighting Condition	**System**	**Measurement (cm)**					**Average (cm)**	**Accuracy (%)**
		1st	**2nd**	**3rd**	**4th**	**5th**		
Very Low	With reference object	-	-	-	-	-	-	-
	With Aruco marker	-	-	-	-	-	-	-
	Proposed System	8.8	8.7	8.7	8.8	8.8	8.76	98.43
Low	With reference object	8.4	8.2	8.4	8.3	8.5	8.36	93.93
	With Aruco marker	8.7	8.5	8.6	8.5	8.6	8.58	96.40
	Proposed System	8.90	8.88	8.92	8.89	8.9	8.76	98.43
Normal	With reference object	8.4	8.2	8.4	8.3	8.5	8.36	93.93
	With Aruco marker	8.7	8.5	8.6	8.5	8.6	8.58	96.40
	Proposed System	8.90	8.88	8.92	8.89	8.9	8.76	98.43
High	With reference object	-	-	-	-	-	-	-
	With Aruco marker	8.7	8.5	8.6	8.5	8.6	8.58	96.40
	Proposed System	8.90	8.88	8.92	8.89	8.9	8.76	98.43

Based on the experimental results, only the proposed system is able to detect the object under very low lighting condition. This was due to a function in the proposed system that can adjust the normalization of the frame, thereby increasing the frame's brightness and enabling detection under extremely low lighting conditions. On the other hand, under high lighting conditions, the reference object system fails to detect the object due to excessive light reflection, leading to a problem whereby the system captures too many measurements of the object. Overall, the results provide valuable insights into the robustness of the systems under different lighting conditions, highlighting the strengths and weaknesses of each system.

4.5 Efficiency of the system

This experiment aims to evaluate the efficiency of four different measurement systems in measuring Malaysia's 50 Sen coins. Efficiency is a crucial factor in the manufacturing industry, where time is of the essence, and high-volume tasks such as measuring a large number of objects need to be completed quickly and accurately. The systems being evaluated are a manual calliper, a system with a reference object, a system using an Aruco marker, and a proposed system. The 50 Sen coins were chosen as the objects of measurement due to their uniform size and shape, which allows for a fair comparison of the systems' performance. The results of this experiment provide insights into the efficiency of each system in measuring objects accurately and quickly, which can have significant implications for improving manufacturing processes.

Table 4. 4: Result of System performance in efficiency

Measurement System	**Average Time per Coin (seconds)**
Manual Calliper	11.3
System with Ref. Object	0.68
Aruco Marker System	0.75
Proposed System	0.64

Table 4.4 shows that the proposed system is the most efficient in terms of the average time per coin measured, with an average time of 0.64 seconds per coin. This is because the proposed system does not require a reference object and can measure multiple coins under one frame, enabling a larger volume of coins to be measured in a shorter amount of time.

The system with the reference object is also relatively efficient, with a total time of 34 seconds and an average time of 0.68 seconds per coin. This is because the reference object is small and does not take up much space, allowing more coins to be placed under the frame for measurement.

The Aruco marker system shows an average time of 0.75 seconds per coin. However, this system takes slightly more space under the frame, limiting the number of coins that can be placed for measurement, resulting in a longer time.

Finally, the manual calliper takes the longest average time of 11.3 seconds per coin. This is because it is a manual system and requires the measurement of each coin to be done one at a time, with the calliper having to be reset to zero for each measurement, leading to an average time per coin.

4.6 Measurement System Acceptability

This experiment aims to evaluate the acceptability of the measurement system for a proposed system. 20 samples of 4x40mm screws were measured to determine the system's performance. Control chart method was used to monitor the measured dimensions over time and to establish control limits for both the X-bar and range portions. The control limits were used to determine whether the system was operating within acceptable levels of accuracy and consistency. The results of this experiment evaluate the system's acceptability and identify any potential issues with the measurement system.

Table 4. 5 Result Measurement of X bar and Range R

Sample	Measurement values (mm)				X bar	Range R
	1st	**2nd**	**3rd**	**4th**		
1	39.94	40.12	40.03	40.14	40.0575	0.2
2	40.24	39.94	39.83	40.14	40.0375	0.41
3	39.75	39.94	40.03	39.85	39.8925	0.28

4	40.24	40.13	40.11	40.01	40.1225	0.23
5	40.05	40.23	40.13	39.94	40.0875	0.29
6	40.22	39.93	40.13	40.01	40.0725	0.29
7	39.83	40.03	40.22	40.13	40.0525	0.39
8	39.93	40.12	39.94	40.13	40.03	0.2
9	40.04	39.85	40.02	40.02	39.9825	0.19
10	39.93	40.13	40.02	39.84	39.98	0.29
11	40.12	40.01	40.22	40.02	40.0925	0.21
12	39.93	40.02	39.93	40.14	40.005	0.21
13	40.11	39.85	40.11	40.02	40.0225	0.26
14	40.02	40.22	40.13	40.12	40.1225	0.2
15	40.11	39.93	40.23	40.01	40.07	0.3
16	39.93	40.12	40.12	40.12	40.0725	0.19
17	40.02	39.85	40.02	40.02	39.9775	0.17
18	39.83	40.23	40.13	39.94	40.0325	0.4
19	40.12	40.01	40.22	40.02	40.0925	0.21
20	39.93	40.12	39.93	40.02	40	0.19
Total					800.8025	5.11
Average of X bar					40.04	
Range R						0.2555

Determine the control limit from equation 3.4 - 3.7:

X bar:

$UCL_{\bar{x}}$ = 40.04 + 0.729 * 0.2555 / sqrt (4) = 40.13

$LCL_{\bar{x}}$ = 40.04 - 0.729 * 0.2555 / sqrt (4) = 39.95

Range:

$UCL_{\bar{R}}$ = 2.27 * 0.2555 = 0.58

$LCL_{\bar{R}}$ = 0

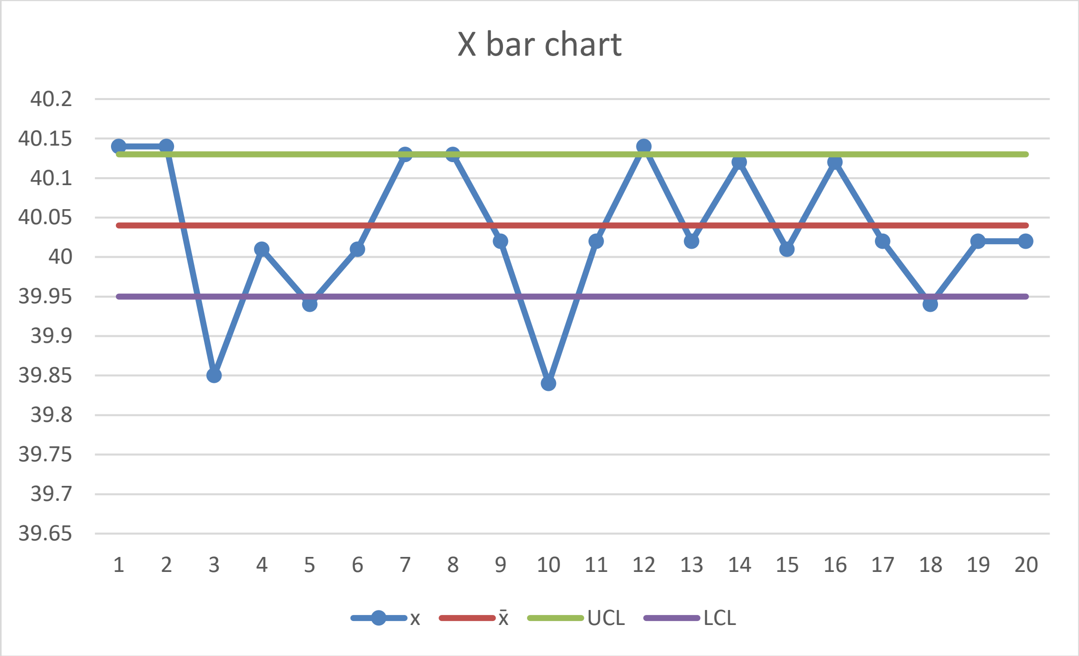


Figure 4. 2: X bar chart

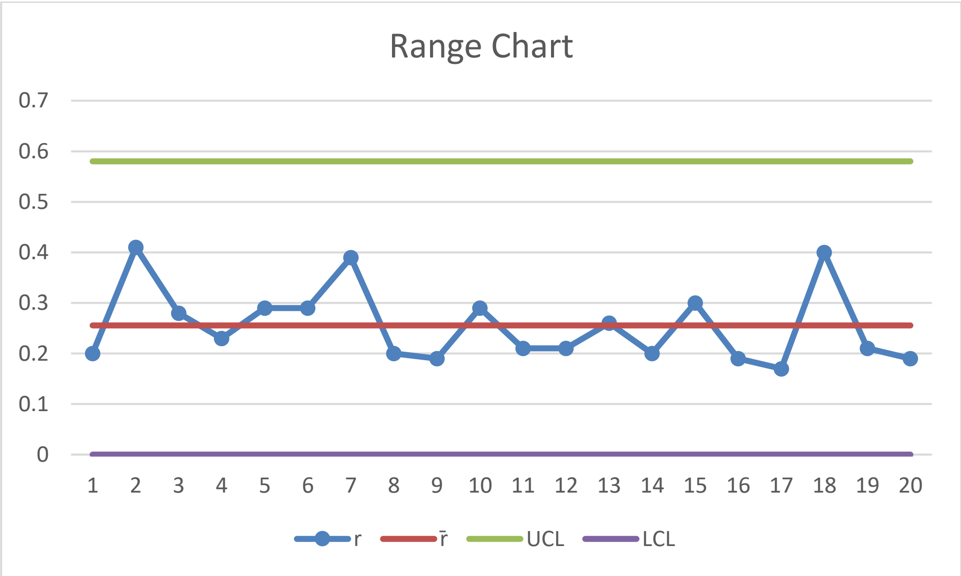


Figure 4. 3: Range chart

The X bar chart in Figure 4.5 shows that some of the points fall outside of the control limits, indicating the presence of special causes in the process. On the other hand, all the points in the Range chart in Figure 4.6 are within limits. Hence, the average range can be utilized to estimate the measurement system variation.

$\sigma_p^2 = (0.2555/2.059)^2 = 0.0154$

It is considered that the variation is solely due to the measurement system since the experiment evaluates the same sample repeatedly. The average of measurement X and moving Range values are computed and shown in Table 4.6.

Table 4. 6: Result of Measurement X and Moving Range

Sample	Measurement X (mm)	Moving Range (mm)
1	40	
2	40.03	0.03
3	39.93	0.1
4	40.02	0.09
5	40.01	0.01
6	40.05	0.04
7	40	0.05
8	39.99	0.01
9	40.05	0.06
10	39.98	0.07
11	40.02	0.04
12	39.96	0.06
13	40.03	0.07
14	40	0.03
15	40.05	0.05
16	39.96	0.09
17	40	0.04
18	39.97	0.03
19	40	0.03
20	39.99	0.01
Total	800.04	0.91
Average of X	40.002	
Average of MR		0.047894737

Determine the control limit from equation (3.4 - 3.7):

X Chart:

$UCL_{\bar{x}}$ = 40.002+ 2.66 * 0.04789= 40.13

$LCL_{\bar{x}}$ = 40.002– 2.66 * 0.04789= 39.87

Moving Range:

UCL_{MR} = 3.27 * 0.04789= 0.1566

LCL_{MR} = 0

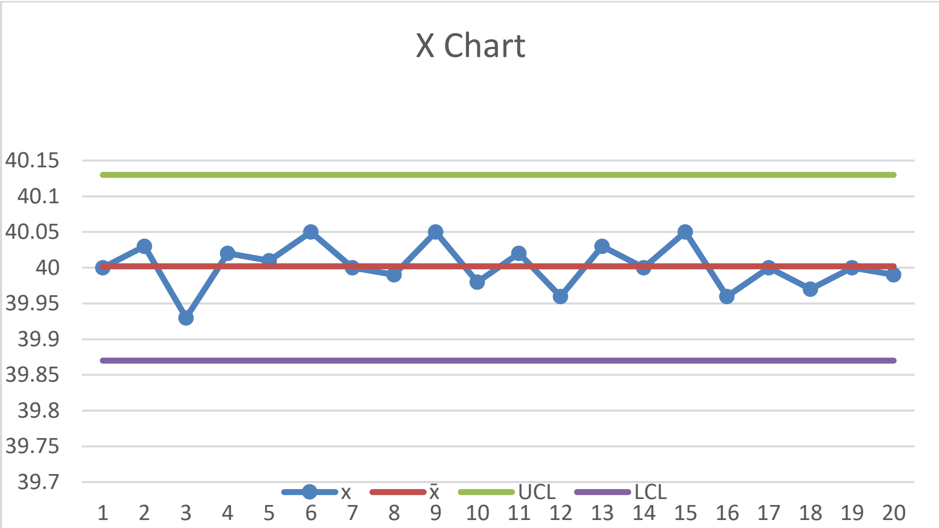


Figure 4. 4: X Chart

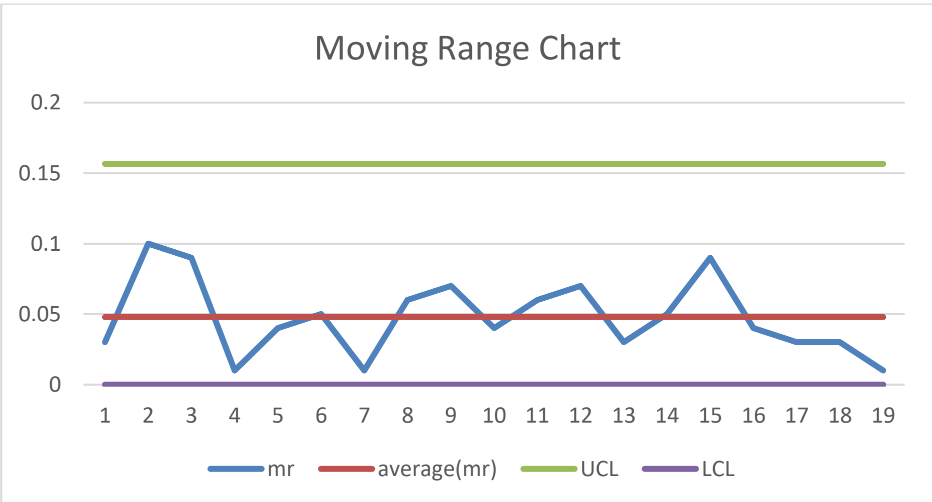


Figure 4. 5: Moving Range Chart

Based on the Figure 4.4 and 4.5, it can be seen that all the data points are within the control limits, indicating that the measurement system is stable and consistent.

Therefore, it can be concluded that the variation of the measurement system is acceptable and under control. The variance of the measurement system is
σ_m^2 = (0.04789/1.13)^2 = 0.001796

Total variance of the measurement = σ_m^2 / σ_p^2
(0.001796/0.0154) *100% = **11.66%**

∴ Based on the guidelines for measurement system (refer to Table 3. 2), The proposed system is acceptable depending on the application, the cost of the measurement device, cost of repair, or other factors.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

A study was conducted to evaluate the effectiveness of four different object measurement systems, including without a reference object, with a reference object, with an Aruco marker, and the proposed system that uses frame calibration. The evaluation criteria included consistency, accuracy, flexibility, robustness, and efficiency. The study successfully achieved all the set objectives and evaluated all four systems. Notably, the proposed system demonstrated superior performance in all aspects of evaluation, particularly in terms of accuracy.

Under normal conditions, the proposed system showed an average accuracy of 99.81%, the highest compared to the other systems. Furthermore, the proposed system was selected to test its acceptability and obtained a result of 11.66%. The acceptability of the system was determined based on the AIAG standard, which considers various factors such as the application, cost of the measurement device, and cost of repair. Therefore, based on these results, the proposed system is the most suitable for measuring the objects under consideration.

The proposed system also exhibited high levels of flexibility and robustness, enabling accurate measurements in various environments and conditions. Additionally, the system's efficiency was superior to the other systems evaluated in the study.

These findings have significant implications for industries that require accurate object measurements, such as manufacturing, construction, and engineering. By utilizing the proposed system, companies can benefit from improved accuracy and efficiency, which can lead to reduced costs and increased productivity. Overall, the study provides valuable insights into the effectiveness of different object measurement systems and highlights the advantages of utilizing the proposed system in real-world applications.

5.2 Limitation

5.2.1 Hardware requirement to achieve optimal performance

Due to the advanced algorithms and complex calculations the system requires, it may perform poorly on devices with low processing power or memory. This limitation highlights the need to consider the hardware requirements when implementing the proposed system and ensure that the device meets the minimum specifications to achieve optimal performance.

5.2.2 Measurement for non-uniform object

Another area for improvement of the proposed object measurement system is its inability to handle non-uniform objects accurately. While the system can accurately measure an object's length, width, and height, it struggles with irregularly shaped objects. This limitation suggests the need to improve the system's algorithms to accurately calculate the area of differently shaped objects and consider adding additional sensors or enhance the system algorithm to improve its accuracy.

5.3 Recommendations for future work

5.3.1 Improve the system with area measurement

To overcome the limitation of the proposed object measurement system in handling non-uniform object, future work could focus on improving the system's algorithms to include more sophisticated methods to calculate the area of irregularly shaped objects. This would require additional research and development to explore and integrate various mathematical models, machine learning algorithms, or computer vision techniques to improve the accuracy and consistency of the system's measurements.

5.3.2 Explore more object measurement system algorithm

Future work could focus on exploring and integrating more advanced algorithms for object measurement systems. This could involve research and development of new techniques for measuring various properties of objects, such as weight, volume, and density. Additionally, exploring the integration of emerging technologies such as augmented reality, machine learning, or robotics could improve the system's accuracy, flexibility, and efficiency and expand its potential applications.

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APPENDICES

APPENDIX A: Work Breakdown Structure

1.0 Project Initiation

- 1.1 Background Study
- 1.2 Identify and articulate the problem statement
- 1.3 Define Project Objective
- 1.4 Define Project Scope
- 1.5 Develop project Work Plan

2.0 Project Planning

- 2.1 Literature Review
  - 2.1.1 Review relevant concepts and theories
  - 2.1.2 Review and analyse relevant techniques or methods in the field
  - 2.1.3 Review existing systems or approaches
  - 2.1.4 Develop a propose system based on the literature review

3.0 Methodology and Work Plan

- 3.1 Describe the methodology or approach used in the study
- 3.2 Explain the work plan or timeline for the study
- 3.3 Outline the system analysis and design process
- 3.4 Explain the data collection process

4.0 Testing

- 4.1 Testing different object measurement system
  - 4.1.1 System without reference object
  - 4.1.2 System with reference object
  - 4.1.3 System with Aruco Marker
  - 4.1.4 Proposed System

5.0 Evaluation

- 5.1 Present and discuss the results of the study
- 5.2 Discuss the consistency, accuracy, flexibility, and robustness of the system or approach
- 5.3 Evaluate the efficiency of the system or approach

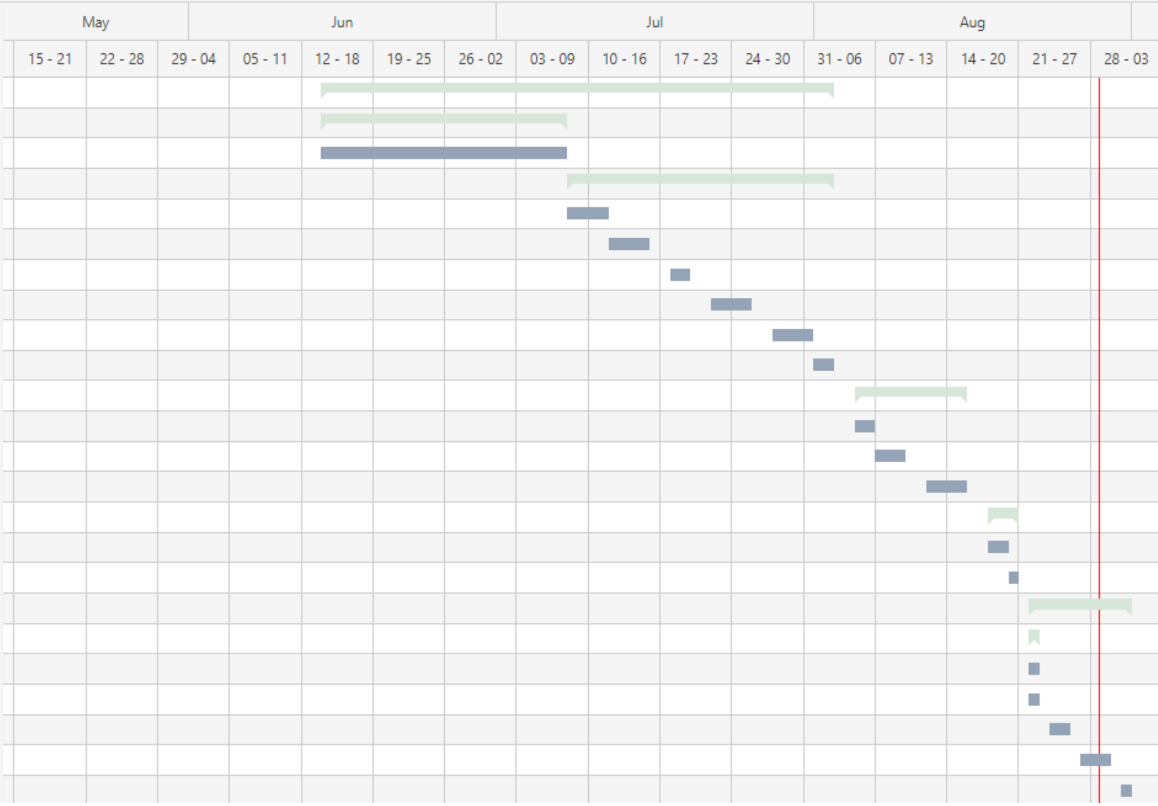
5.4 Discuss the measurement system acceptability criteria and results

6.0 Project Closure

6.1 Finalize the final report and presentation slides

APPENDIX B: Gantt Chart

ID	Title	Start Time	End Time
1	1.0 Project Initation	06/14/2022	08/03/2022
2	1.1 Requirement Gathering	06/14/2022	07/08/2022
3	1.1.1 Literature Review	06/14/2022	07/08/2022
4	1.2 Prepare Preliminary Report	07/08/2022	08/03/2022
5	1.2.1 Define Project Background	07/08/2022	07/12/2022
6	1.2.2 Define Project Problem Statement	07/12/2022	07/16/2022
7	1.2.3 Define Project Objective	07/18/2022	07/20/2022
8	1.2.4 Propose Solution	07/22/2022	07/26/2022
9	1.2.5 Propose Approach	07/28/2022	08/01/2022
10	1.2.6 Define Project Scope	08/01/2022	08/03/2022
11	2.0 Literature Review	08/05/2022	08/16/2022
12	2.1 Review the project concept and basic technique	08/05/2022	08/07/2022
13	2.2 Review and Analysis the relevant system	08/07/2022	08/10/2022
14	2.3 Compare SDLC model	08/12/2022	08/16/2022
15	3.0 Methodology and Work Plan	08/18/2022	08/21/2022
16	3.1 Define the Methodology use in the project	08/18/2022	08/20/2022
17	3.2 Define the Development tool for the project	08/20/2022	08/21/2022
18	4.0 Project Initial Specification	08/22/2022	09/01/2022
19	4.1 Define the system requirement	08/22/2022	08/23/2022
20	4.1.1 Define the functional requirement	08/22/2022	08/23/2022
21	4.1.2 Define the non-functional requirement	08/22/2022	08/23/2022
22	4.2 Design the use case diagram	08/24/2022	08/26/2022
23	4.3 Define the use case description	08/27/2022	08/30/2022
40	4.4 Propose user interface design	08/31/2022	09/01/2022



25	◢ 5.0 System Development	01/30/2023	02/28/2023
26	5.1 User Interface Development	01/30/2023	02/13/2023
27	5.2 Main System Development	02/15/2023	02/28/2023
33	◢ 6.0 System Testing	03/02/2023	03/17/2023
34	6.1 Unit Testing	03/02/2023	03/09/2023
35	6.2 User Acceptance Testing	03/10/2023	03/13/2023
36	6.3 Usability Testing	03/13/2023	03/17/2023
37	◢ 7.0 Project Closure	03/18/2023	03/26/2023
38	7.1 Final System Deployment	03/18/2023	03/25/2023
39	7.2 Finalize the final report and presentation slides	03/25/2023	04/16/2023