DEVELOPMENT AND EVALUATION OF A DIGITAL SYSTEM FOR ASSEMBLY BOLT PATTERN TRACEABILITY AND POKA-YOKE

by

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Poświęcam tę pracę dla moich ukochanych rodziców. To dzięki wam, jestem tym kim jestem, i mam możliwość realizować moje marzenia. Dziękuje wam za waszą niekończącą się miłość, cierpliwość, i wsparcie. Za wasze poświęcenie i waszą ciężką prace! Kocham was niezmiernie.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AR – Augmented Reality

BOP – Bill of Process

CCD Camera- Charge-Coupled Device Camera

DEC – Digital Enterprise Center (Purdue University)

DES – Digital Enterprise System

ERP – Enterprise Resource Planning

HMD- Head Mounted Display (AR/VR)

IoT – Internet of Things

MES – Manufacturing Execution System

PLM – Product Lifecycle Management

STEP – Standardized Technology Evaluation Process

VR – Virtual Reality

ABSTRACT

The manufacturing industry has begun its transition into a digital age, where data-driven decisions aim to improve product quality, output, and efficiency. Decisions made based on manufacturing data can help identify key problem areas in an assembly line and mitigate any defects from progressing through to the next step in the assembly process. But what if the products' as manufactured data was inaccurate or didn't exist at all? Decisions based on incorrect data can lead to defective parts being passed as good parts, costing manufacturers millions of dollars in rework or recalls. When specifically referring to mechanically fastened assemblies, products that experience rotation, like an aircraft propeller, or compress to create a seal, like an oil pipe flange, all require specific torque pattern sequences to be followed during assembly. When incorrectly torqued, the parts can have catastrophic failures resulting in consumer injury or ecological contamination. This paper outlines the development and feasibility of a system and its components for tracking and error-proofing the assembly of bolted joints in an industrial environment.

Using a machine vision system, the system traces the tool location relative to the mechanical fastener and records which order the fasteners were torqued in, if an error is detected, the system does not allow the user to progress through the assembly process, notifying if an error is detected. The system leverages open source machine learning algorithms from TensorFlow2 and OpenCv, that allow efficient object detection model training. The proposed system was tested using a series of tests and evaluated using the STEP method. The data collected aims to understand the system's feasibility and effectiveness in an industrial setting.

The tests aim to understand the effectiveness of the system under standard and variable industrial work conditions. Using the STEP method and other statistical analysis, an evaluation matrix was completed, ranking the system's ability to successfully meet all predetermined benchmarks and successfully record the torque pattern used to assemble apart.

CHAPTER 1. INTRODUCTION

Mechanical fasteners have played crucial roles in many industries across the globe. Industries such as aerospace, automotive, and construction rely on the use of mechanical fasteners to assemble complex components safely and effectively (Roy, 2014). With complex products like airplanes, that can have millions of mechanical fasteners, assembling critical components in the engines, landing gear, wings, and fuselage, it is important to ensure all fasteners are assembled correctly (Anupindi & Lee, 2009). In recent years, both automotive and aviation industries are challenged with producing lighter and more fuel-efficient vehicles. Amongst material and design alterations, manufacturers have reduced the number of redundant fasteners to save on vehicle weight and fuel consumption (Mascarenas et al., 2009). With fewer redundancies, each fastened joint is critical to the success of the assembly.

With thousands of mechanical fasteners being used to assemble products, manufacturers must consider not only the material cost of each bolt but the handling cost as well. According to (Speck, 2015), the total fastening cost is equal to 20% fastener purchasing cost and 80% fastener installation cost. With such a high percentage of the total fastening cost being attributed to fastener installation, manufacturers must reduce the amount of unnecessary handling, rework, and inefficient inspection methods associated with high numbers of fasteners, which can result in higher manufacturing costs. In the oil industry, where millions of miles of pipes are joined together using both welded and bolted assemblies, an operator assembling a 24-bolt joint will count and mark each bolt number and interpret the bolt pattern required to assemble that joint (Brown, 2004). With such a high quantity of bolts and joints, unnecessary handling of fasteners and physically marking the torque patterns adds to the overall fastener cost.

Apart from manufacturing and handling costs, safety is of high importance when it comes to bolted assemblies. In cases where products with incorrectly assembled fasteners were sold to consumers, manufacturers lost millions of dollars due to product loss or recalls. In August of 2011, while conducting a relay mission in Afghanistan, an Airforce EQ-4B Global Hawk drone crashed due to an incorrectly fastened electronic connector. Fortunately, there was no loss of life due to the accident, but the accident resulted in an estimated loss of $72.8M to the Air Force. The cause of the accident was ruled to be a failure of the LRU-X-1 unit, which failed due to a partially loose connection. The JX connector that connected the LRU-X-1 unit was fastened using mechanical fasteners that were incorrectly assembled during routine maintenance. Upon further investigation, eight additional in-service aircrafts using LRU-X-1 units were inspected, and six out of the eight were incorrectly assembled. The maintenance personnel responsible for assembling the units were deemed adequately trained and merely overlooked the specific assembly requirement for the LRU-X-1 units, which demonstrates the need for Poka-Yoke systems to help reduce operator error (United States Air Force, 2012).

In the automotive industry, where millions of automobiles are made yearly, assembly line employees are pushed to scale up production and reduce costs without sacrificing quality. Although meticulous attention is paid to quality inspections of each automobile, mistakes, and errors are sometimes passed onto the consumer. In 2013, Toyota recalled 342,000 Tacoma pickup trucks and 310,000 FJ Cruisers that were found to have incorrectly torqued seat belt assemblies, according to Eisenstein, Toyota stated, “screws that attach the seat belt pre-tensioner to the seat belt retractor within the seat belt assembly for the driver and front passenger can become loose over time due to repeatedly and forcefully closing the access door” (Eisenstein, 2013; Toyota Motor Corporation, 2013). Toyota is not the only one; automakers such as Nissan, Mitsubishi, and Hyundai have also released recalls for incorrectly torqued bolts on safety equipment. In 2018 Nissan recalled certain Infinity SUVs with seatbelt assemblies that were cross-threaded (NHTSA, 2017). In 2020, Hyundai recalled their 2016 Genesis coupe vehicles that had improperly torqued bolt patterns on the driver's side airbag assembly and in 2015 recalled the same vehicle for improperly torqued bolts on suspension components (Hyundai Motor America, 2015; Szymkowski, 2020). Even with strict quality inspections, without data captured during the manufacturing process, it becomes difficult to trace and quickly identify a manufacturing defect, such as incorrectly tightened mechanical fasteners, before the product leaves the manufacturing facility.

Industries adopt different techniques to help ensure all bolts are correctly fastened and tightened. In the oil industry, workers assembling oil pipelines often mark each bolt with a number corresponding to its position in the torque pattern (Eccles & Bolt Science, 2014). But even with physically marked torque patterns on the bolts, oil pipes that were assembled by unqualified assemblers, or assemblers using improper torque patterns or torque values, are likely to leak and cause irreversible damage to the environment and property. Insufficient torque or incorrect torque patterns can lead to leaks due to buckled flanges and gaskets, causing millions of dollars in property damage (Brown et al., 2013). In 2003 alone, leaking bolted joints accounted for over $300M globally in property damages (Brown et al., 2007). Assemblies requiring a gasket or components that will be rotating at high rotational speed, like airplane rotor blades, are typically required to be assembled using a torque pattern to evenly spread forces on mating surfaces and gaskets. Using a torque pattern allows rotating components to remain balanced and concentric with the rotating axles and prevent warping.

As critical as mechanical fasteners are, it is still difficult to ensure, once the component is assembled, that proper torque patterns and values were used during assembly. For example, common torque inspection methods often fail to consider the environmental changes that could occur between initial assembly and inspection which could alter the torque reading during the inspection (Eccles & Bolt Science, 2014). This project proposes a new method for tracing as-manufactured data of mechanically fastened assemblies. The system ensures the proper torque pattern is used, the correct fastener classifications and quantities are used to assemble a product, and created a record of torque data that can be saved and referenced back.

1.1 Problem Statement

The improper torquing technique when assembling products can cause component failure or decreased product lifespan, resulting in added costs to the manufacturer. Industry solutions for ensuring the use of proper torque techniques are not effective in providing complete data traceability of as manufactured bolted joints, including torque patterns, torque values, and fasteners used.

1.2 The Significance of Research

The objective of this research is to develop and evaluate a system that aids in monitoring the assembly process of circular bolt patterns to ensure proper assembly technique is used and all fasteners are torqued within specifications. Current industry practices, that require operators to manually record as manufactured torque data, do not adequately gather fastener assembly data, potentially allowing incorrectly assembled components to pass through production (“Bolt Torque For Polyethylene Flanged Joints TN-38 2019,” 2019; Noble, 2012). Current industrial systems that automatically gather assembly process data focus on the tool and its location relative to the assembly space vs the tool location relative to the fastener that can cause errors if the part is shifted or incorrect fasteners are used.

As in the case of automotive manufacturers like Hyundai and Toyota, that both released recalls due to incorrectly torqued fasteners, not ensuring fasteners are assembled in the correct order, can cost manufacturers millions of dollars in recalls and rework (NADA, 2014). If an incorrectly assembled product passes through the assembly process, it is difficult to inspect if the proper torque pattern was used. Common methods such as the on-torque, off-torqued, or marked fastener methods do not consider the torque pattern used to assemble the product (Speck, 2015). Using manual, non-connected tools, manufacturers risk missing key data that can be used in tightening traceability and can lead to users manually entering incorrect data (Tohnichi, 2019). Even with the use of connected tools, the order in which the fasteners are assembled is difficult to record and relies on user-inputted data to record information such as torque pattern followed ("Bolt Torque For Polyethylene Flanged Joints TN-38 2019," 2019; Noble, 2012).

With this system, manufacturers can create a digital thread of information between the as-designed torque specifications and the as-manufactured torque data. Operators are guided through the torquing process, ensuring they are following proper torque patterns. Using a digital torque wrench, all torque values are recorded and assigned to the specific fastener. This aids in product traceability and helps manufacturers trace the overall torque pattern used and the torque value each fastener was assembled to. To develop this system, open-source machine learning algorithms were be modified to train the algorithm to detect mechanical fasteners. As a result, a database of two thousand fasteners containing their images and classification was created.

1.3 Research Question

This research aims to answer the following research questions:

1. How can we use a vision-based system, integrated with connected tools, to enforce the proper assembly of bolted joints?

1.4 Hypothesis

My hypotheses for this study are:

1.4.1 Fastener Classification

H0: The Proposed system correctly identifies fastener classification, in an industrial environment, using the shape and features of the fastener with a 90%.
H1: The proposed system incorrectly identifies fastener classification with a 90% confidence.
H2: The proposed system correctly identifies fastener classification under 90%

1.4.2 Fastener Detection

H0: The proposed system detects the presence of a fastener when a fastener is present and the absence of a fastener when a fastener is missing.
H1: The proposed system incorrectly detects the presence or absence of fasteners.

1.4.3 Fastener Torque Pattern

H0: The proposed system records the torque value correctly
H1: The torque pattern recorded by the system, does not reflect the torque value used to assemble the part.

1.4.4 Torque Value

H0: The system records the correct torque value for the appropriate fastener
H1: The torque values recorded do not reflect the actual torque values used.

1.5 Definitions

Key terms that are used throughout the study are defined below.

Augmented Reality (AR) Headset - An augmented reality headset is a device that overlays virtual computer-generated information onto the real-world environment without completely obstructing the users' vision(Borko Furht, 2011).

Mechanical Fastener – A Mechanical fastener is a device that joins objects together mechanically. The two types of mechanical fasteners are permanent and non-permanent. In the context of this research, only non-permanent mechanical fasteners such as machine screws and bolts were be used (Ala Hijazi, n.d.).

Product Lifecycle Management (PLM) – PLM is the concept and process of managing a product's lifecycle through each stage of the product's life from product design, manufacturing, distribution, and disposal. Saaksvuori and Immonen write, "Product lifecycle management (PLM) is a systematic, controlled concept for managing and developing products and product-related information" (Saaksvuori Antti & Immonen Anselmi, 2008).

Turnover - As used in a human resources context, turnover is used to describe the number of persons hired as replacement of existing employees that are leaving (Merriam-Webster, n.d.).

Virtual Reality (VR) Headset - A virtual reality headset or head-mounted display (HMD) is a wearable device that allows users to interact with simulated virtual environments. These environments are computer 3D generated. The devices use sensors such as gaze tracking and gyros to allow the user to control the virtual environment with physical movements. VR headsets typically obstruct the users' vision to fully immerse the user in the virtual environment (Rouse & Matthew, 2016).

LUX- LUX is a SI unit that is equivalent to one lumen per square meter (Merriam-Webster, n.d.).

1.6 Assumptions

The following assumptions are made as part of this study:

- Because this research focuses on the evaluation of the systems technology stack, it is assumed the usability of the system is comparable to that of a standard industrial application.
- Thermal environmental conditions throughout the study are the same and have a negligible impact on torque value.
- It is assumed that the fasteners used in the study are of the same quality and pass manufacturer quality inspections.
- A single-pass torquing procedure was followed and is assumed to be adequate in representing industrial torquing methods.
- The configuration of hardware is relative to the equivalency between pixels and inches.
- The sample test assembly used during data collection has a matte surface finish. It is assumed that the surface finish used during testing is adequate in understanding the system performance in an industrial environment.

1.7 Limitations

- Because the vision system is mounted from a top view, fastener types with distinct features on the bottom, such as countersunk screws, cannot be detected.
- The system only works with digitally connected tools, as the system relies on torque values as triggers for recording tool position relative to the fasteners.
- The system requires the use of a GPU to train the system. The speed of the GPU is a limitation of how fast training data can be processed and object detection can occur.

- A dataset of approximately 2000 images was used to train the object detection model with 3 classifications. A rule of thumb when training a model is to use a dataset with 1000 images per classification. Ideally, the dataset should contain 3000 images, but because of time constraints, only 2000 images were gathered.

1.8 Delimitations

- Common industrial fasteners with distinct top characteristics were only be used.
- A digitally connected tool was used with this system that allows for live data transfer.
- A high-end NVIDIA Quadro RTX 4000 graphics card was used to run the training. The graphics card has 8Gb of memory and 416 Gb/s of bandwidth.

1.9 Summary

It has been discussed that this study attempted to address the need for an industry-wide system to collect torque sequence data and ensure all proper torquing procedures are followed during the assembly of a bolted component. The study focuses on the ability to accurately gather the sequence in which a circular bolt pattern is assembled using a machine vision system and digitally-enabled torque tools. The application was tested and evaluated using various cycle tests, manipulating environmental conditions to benchmark the system's performance during standard work environments and variable environments. The following section reviews literature that pertains to the development and problem space of this study.

CHAPTER 2. REVIEW OF LITERATURE

With industrial applications going through a digital transformation, companies are requiring more data collection and connectivity between digital systems, physical tooling, and manufacturing processes. New methods of operator guidance and training are paving the way for manufacturers to combat increasing turnover rates and allow operators to follow interactive training systems that can record user growth and progress. Although some aspects of the manufacturing process are easily traceable through MES and ERP systems, evidence shows ensuring the correct torquing pattern is followed during faster assembly can be a challenge for manufactures and some still require manual data entry. Even Poka-Yoke methods, that previously used physical hardware to error-proof processes, are adapting digital vision systems to ensure proper part placement and quality.

2.1 Manufacturing Data Collection and Management

Lack of regulation and minimum operator requirements of bolted joints in the oil industry causes upwards of $100 million in damages and costs in any given year (Brown et al., 2007). Researchers are developing systems to help in training and creating a more effective and efficient assembly process of bolted joints. Apart from training and regulatory issues associated with bolted assemblies, records keeping and data management needs improvement. In industry, as bolts get torqued to a specified value, the operator logs that data into a management system, either electronic or paper-based. Oftentimes, these torque values can be inaccurate and, in some cases, multiple torque figures available for the same assembly (Noble, 2012). After a bolt is torqued and assembled, it is difficult to inspect the bolt's torque accurately as the torque value to loosen the bolt is initially different than the value used to torque the bolt. According to Eccles and Bolt Science, “Typically the torque needed to untighten a newly tightened fastener is around 10% to 30% less than the torque used to tighten it further” (Eccles & Bolt Science, 2014, p.112). An alternative method to the three most common torque auditing methods is the ‘On-Off-On’ proposed in the November 2016 issue of Fastener Fixing Magazine. The ‘On-Off-On’ method proves to be a more accurate test method when the fastener coefficient of friction is low. To use the method, a user would first measure the torque in the tightening direction, then measure the bolt in the untightening direction, and then retighten the bolt. Using this method as opposed to the other three provides more insight into the possible stresses the bolt is enduring and bolt load scatter is well between the limits of +/-17% to +/-33% (Eccles & Bolt Science, 2014)

2.2 Assembly Work Instruction and Guidance

The introduction of digitized work instructions has led many companies to shift their traditional paperwork instructions to a digitized copy. With digital work instructions, companies gain more control over the instructions used during production and reduce the environmental impact of paper waste. Standard static digital work instructions, although better than their paper counterparts, lack the flexibility and dynamic guidance that more complex assemblies require. With the wave of digital enterprise systems being researched under Industry 4.0, some researchers are researching the impacts of interactive model-based work instructions.

2.2.1 Virtual and Augmented Work Instructions

Research groups across industries are researching the integration of digital interactive animation-based work instruction into assembly guidance tasks. A research group at Purdue University has been working with integrating a Model-Based Work Instruction into assembly tasks as a substitute for static 2D work instructions. With the MBWI, users wear an augmented reality headset that guides the user through the assembly of mechanical and electronic components. With the use of spatial scanning, the researchers were able to map out the assembly stations, allowing them to accurately overlay holographic animations onto the real-world environment. When a user was ready to assemble a product, the headset would display arrows and textual instructions on which bin to pull components from and how to assemble the product. When a user completed a step, the system would compile the data collected during the step such as, cycle times, photographs of each step as it was completed, if the user skipped steps and how many times the user had to go back to the previous steps. Although the system is a guidance system more so than a data-gathering tool, useful information can be obtained on how the users interact with the tool. The research aims to conduct usability testing in an industrial setting comparing the effectiveness of such a system as compared to traditional paperwork instructions. Usability testing is scheduled for Fall 2020 (Hartman et al., 2019). A similar study reviewed by Chiarini and Kumar showcases an augmented reality system that guides the user through an assembly process by highlighting the process steps and tools using a green indicator. The system indicates which mechanical fastener is to be fastened next in the assembly process and which tool to use (Chiarini & Kumar, 2020).

2.3 Workforce training

In 2018, the US voluntary turnover rate was 27%, which is a 7.6% increase from the previous year. After studying employee turnover rates, the Work Institute estimates that by 2023, yearly 35% of employees will voluntarily leave their job and work elsewhere (Mahan et al., 2019) With a low retention rate and a decreasing pool of skilled workers, employers are faced with a challenge of finding new employees that are skilled and willing to work in the manufacturing industry. In a study conducted by Deloitte and The Manufacturing Institute, researchers found that by 2028, manufacturers will hire 4.6 million new employees (Deloitte, 2018). With such a large quantity of new hires and an existing high turnover rate, companies are searching for quicker and more efficient ways to train new hires. Not only is training for new employees important, but retraining for current employees is as well. As written by Newstrom and Davis, "...the use of knowledge and information dominates work and employs the largest proportion of the labor force. The distinguishing feature of a knowledge society is that it emphasizes intellectual work more than manual work--the mind more than the hands" (Newstrom & Davis, 1993; Sleight, 1993) Continuously developing employees' skill sets can bring a positive return on productivity and decreased manufacturing errors as well as increase employee retention rate (Mahan et al., 2019).

According to the 2016 Training Industry Report, put together by Training Magazine, industry spending expenditures on training totaled over seventy billion dollars. This included costs associated with equipment, training personal, and other services (Training Magazine, 2016). The cost was further broken down to individual training cost per employee and found the average training cost of an individual employee in a small company to be over one thousand dollars in 2016 (see figure 1) and take about 50 hours of training (See figure 2).

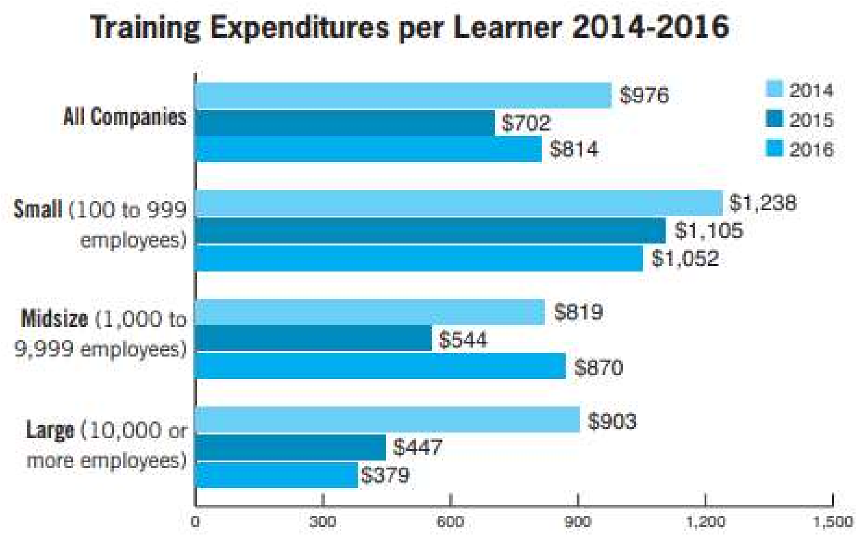


Figure 1. Graph depicting average training cost of an employee relative to company size (Training Magazine, 2016).

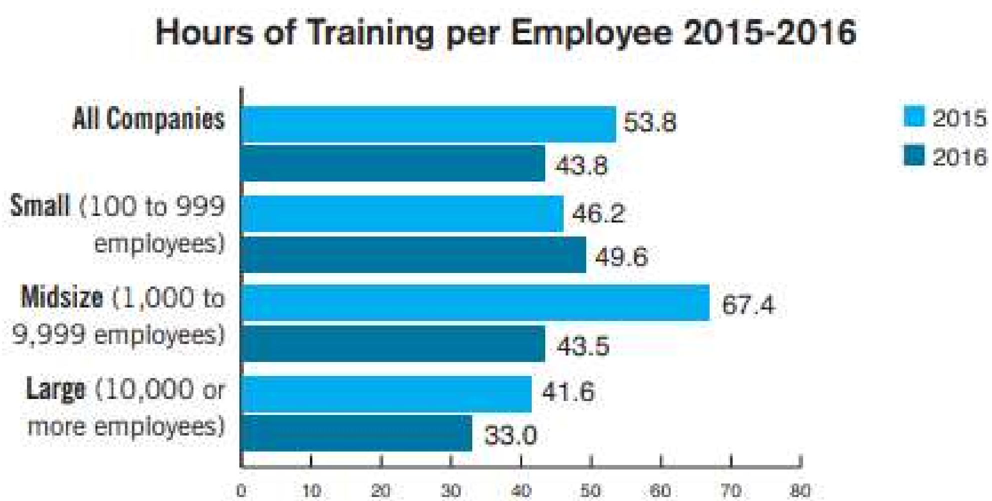


Figure 2. Graph depicting average training time of an employee relative to company size (Training Magazine, 2016)

Even with the rapid growth of digital tools in the industrial workplace, in 2016 41% of training was delivered in person in a classroom setting. While the traditional trend of in-person training is decreasing in favor of online training, particularly in larger companies, smaller and mid-sized companies continue to rely on classroom-style instructor-led delivery (Training Magazine, 2016).

2.3.1 Virtual Workforce Training

Traditionally, an average new hire at a manufacturing plant could expect around a week-long training. While the training methods may differ between companies, there is an industry-wide trend to conduct training using newer technology and mobile methods like augmented reality and online training sessions (Training Magazine, 2016). Because these virtual tools have become more accessible and affordable, companies have been working to integrate virtual and augmented reality headsets into new hire training. With these headsets, operators can experience immersive simulations and follow along with a guided tutorial on how a particular product is assembled in a physically safe environment.

In addition to assembly training, augmented systems have been used for maintainability analysis and training that allows users to practice performing maintenance tasks before conducting the potentially dangerous maintenance work (Qiu et al., 2013). When comparing two maintenance groups, one trained using immersive AR and the other trained using traditional non-immersive computer-based or videos, researchers found that the group that used AR training performed better (Gavish et al., 2015). However, the study did not compare the more traditional in-person training to AR training (Gonzalez-Franco et al., 2017) Researchers Gonzalez-Franco et al conducted a further comparison between AR and in-person training, comparing the usefulness of implementing AR technology over hands-on in-person training. Researchers chose a test fixture that was complex enough that would require previous training to assemble. They found that there was not a significant improvement in assembly success and knowledge levels acquired using AR training over in-person training (Gonzalez-Franco et al., 2017). With in-person training, not only is the company paying an employee to get trained, a trainer must also be present to conduct the training. With AR training, although maybe not a significant improvement is found in knowledge gain over in-person training, training an employee with AR does not require a company to hire or pay a trainer to conduct a weeklong in-person training.

2.3.2 Employee Qualifications

With mechanical fasteners playing a large role in industry, it is no surprise that researchers are working to not only optimize the fasteners themselves but also the process to install them. Because bolted joints and mechanical fasteners are viewed as a simple task, many supervisors and managers overlook proper assembler qualifications and requirements (Brown et al., 2013). Compared to welded joints, where operators must undergo recurring training and certifications, bolted joint assemblers have no required previous qualifications and are deemed qualified for the job simply if they can torque a bolt using a wrench. Welded joints on oil pipes are required to be conducted by a coded welder, joints are subject to nondestructive testing (NDT) verification, recorded and hydro tested. The same joint, only bolted, would require the assembler to be competent and the joint to be hydro tested. Torque data is recorded for the bolts, but they often prove to be inaccurate (Noble, 2012)

2.4 Poka-Yoke Systems

The use of Poka-Yoke gauges in manufacturing is not a new concept. Manufacturers have used these gauges as quick references for quality checks. Poka-Yoke, meaning mistake-proofing in Japanese, was coined as a term in the 1960s by Toyota engineer Shigeo Shingo (Dudek-Burlikowska & Szewieczek, 2009). The concept of Poka-Yoke is centered around eliminating manufacturing defects early on in the process. Traditionally Poka-Yoke methods, with reasonable effort, use physical features to prevent something to be put together incorrectly. One of the simpler examples of Poka-Yoke is an electrical outlet in a US home, where one prong is larger than the other and because of it, the plug will only go into the outlet in a particular orientation. Although Poka-Yokes are meant to eliminate mistakes, without proper training in identifying Poka-Yokes, users can still often find new ways. For example, the outlet, if the user attempts to insert the plug into the outlet in the wrong orientation and only attempts that orientation without flipping the plug over, the user may deem that plug defective and scrap it. Poka-Yokes are a great industry-wide used method, but as technology improves, new advances in Poka-Yoke systems help mistake-proofing more reliable and effective.

2.4.1 Poka-Yoke gauges

Oftentimes, Poka Yokes are built into manufacturing processes, adding explicit steps into workflows, instructing operators to use Poka Yoke gauges or devices to help remove the possibility of passing a defective part to the next stage of manufacturing. Poka Yokes are often included in jigs and fixtures, ensuring operators notice the presence, or lack thereof, any components like screws or springs and complete all required steps for assembly (Fisher, 1999). Poka-Yoke can be broken down into two approaches (See Figure 3), control method and warning method. The control method detects defects during production and prevents further product assembly by stopping all related production so the defect can be addressed. With the warning Poka Yokes, defects are detected, but rather than stopping production, a decision is made to adopt or reject the product. Warnings are given via visual or sound indicators to alert of a defect, but the process does not stop and the part can be removed from the production line if necessary (Dudek-Burlikowska & Szewieczek, 2009; Kurhade, 2015). Poka-Yoke defines a defect as either a defect that has already occurred (defect detection) or a defect that is about to occur (defect prevention) (Kurhade, 2015). In this research, a control method was be adopted, that prevented the operator from continuing the assembly of the part if the bolts are not torqued in the correct order.

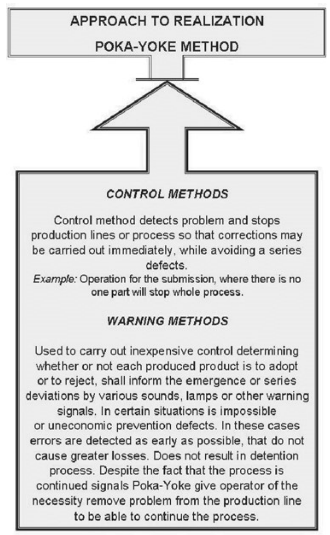


Figure 3. Two Poka Yoke Approaches (Dudek-Burlikowska & Szewieczek, 2009)

2.4.2 Machine vision inspection systems

Traditionally, Poka yokes are often simple mechanical devices, but with the industry shift towards Industry 4.0, Poka Yoke systems can now be more versatile. Vision systems can now be used to ensure proper product orientation, dimensions, and location. With machine vision, quality inspections during production can be automated, and in some cases, happen parallel with the assembly process, taking no additional time to inspect. A basic machine vision inspection system consists of a couple of integrated parts, a camera to capture the images, a computer/software to process them, and some monitor or headgear to display the results.

In a study conducted by Bin Li in 2018, geometric dimensions of the product were measured using a machine vision system to determine if the product met design specifications (Li, 2018). A CCD camera was used to capture the images of shaft parts. To analyze the images, Open CV and VC++ were used. These two libraries are common open source libraries that include many prewritten image analysis scripts that can be used with Python or C# coding languages. The researcher primarily focused on the libraries' edge detection functionality to allow him to recognize where the part edge started and be able to measure the distance between the desired edges using image pixels. Before the measurement can be made, the image needed to be preprocessed by converting it to grayscale and eliminating any noise. Because the image received was a 32-bit-RGB image possibly containing 224 different colors, the image is turned to grayscale where the edge of the feature can be expressed by the contrast and change of grayscale when the part edge ends and the background begins. Li then uses grayscale processing to create a grayscale histogram and using an algorithm, manipulate the image to make darker details that are not as defined in grayscale, clearer. To eliminate noise in the image, Li uses wavelet, which uses "multi-scale decomposition, multiscale denoising, and wavelet inverse transform. The wavelet transform is used to reconstruct the noisy signal, which can remove Gaussian noise and salt-and-pepper noise in the signal" (Li, 2018) With noise removed and a higher signal to noise ratio achieved, Li used the least-squares linear regression and spatial moment sub-pixel localization algorithm to accurate sub-pixel straight edge detection (Li, 2018). This algorithm can be particularly useful when dealing with recognizing simple straight edges, such as those of hex bolts, and be able to recognize, in sub-pixel accuracy, where the bolt outline is within the image.

In another study, researchers Leonard Rusli and Anthony Luscher developed a machine vision system to recognize fasteners for assembly verification (Rusli & Luscher, 2018). The system composed of a DC electric torque wrench, a small image camera mounted directly on the torque tool, and image recognition software from National Instruments. To identify bolt locations, the software analyzes images taken during the assembly of each bolts' surroundings.

The images are then compared to existing images of each bolts' surroundings and an algorithm creates matched patterns. Researchers concluded that the system was able to positively record the assembly process of fasteners and identify the fastener location in an assembly. A numerical threshold was set for the confidence score, this is threshold was used to determine if the image taken matched the already known background images(Rusli & Luscher, 2018).

2.4.3 Assembly Torque Tools.

A few different solutions for bolt assembly traceability are available from various suppliers, but these solutions are often permanently mounted to the work station and are cumbersome to use. Atlas Copco offers a torque tool position arm called Industrial Location Guidance (Atlas Copco, n.d.). This tool is a permanently mounted gantry arm system that a torque tool is mounted to (See Figure 4). The arms axis has servo encoders to recognize the arm position. After calibrating the tool location relative to the assembly part, the arms can record where the torque tool is assembling a fastener (Atlas Copco, n.d.). Using a permanently mounted arm restricts the tool's functionality and ability to adapt the workstation if the factory layout were to change. In addition, the tool cannot be used in field maintenance or assembly, like that of a pipeline.

Figure 4. Atlas Copco Articulated Arm with Positioning Hardware (Atlas Copco, n.d.).

Industrial wireless tools that trace torque procedures focus on the location of the tool within the workspace and not the fastener like in this proposed system. Atlas Copco uses an indoor GPS located tool, called the Tool Location System, that operates if the tool is located in the “correct area of the plant and on the right product” (*Tool Location System*, n.d.). The Tool Location System locks the torque tool out if it detects the tool is not at the product location. The system located the tool relative to a receiver and the part must be within the preset parameters relative to the receiver to be assembled. Although good for larger-scale operations, the system does not have the accuracy to detect if the operator is torquing an incorrect faster within the correct part.

2.5 Literature Review Summary

As detailed in chapter 2, the manufacturing industry has come a significant way in adapting digital thread concepts into their assembly processes. Adapting industry 4.0 concepts of data collection and as manufactured product traceability, manufacturers can gather more detailed information as to how their process work and where inefficiencies and defects lie. Research revolving around augmented reality training is helping industry shorten operator training times, by allowing a more hands-on training approach. Employee qualification training, although lacking, has a promising future when coupled with industry 4.0 technology, allowing operators to be trained on the fly and their progress tracked through vision and augmented reality guidance systems. Concepts of Poka-Yoke that have been around for decades are now being coupled with machine vision systems to ensure operators are following appropriate procedures and preventing defects from progressing in an assembly line. Assembly tool technology has also seen a growth in data connectivity, allowing tools to be tracked using arm-mounted encoders. Although tool location data is captured using the arm, arm-based tools lack flexibility. Though tool connectivity has improved, manufactures are still relying on manual entry methods for data collection that are prone to operator error and are inefficient. New systems, such as the one outlined in this study, aim to eliminate the need for operator data entry and create an autonomous or semi-autonomous loop of as manufactured data and product information.

CHAPTER 3. FRAMEWORK AND METHODOLOGY

The research goals, as stated previously are (1) to develop a flexible and cost-effective system that monitors and records the assembly process of a circular bolted assembly and (2) guide the user through the torque pattern of the assembly using a computer-generated torque pattern. The system, as specified in Table. 1, is comprised of a high definition vision camera, a wireless digital torque wrench, and a display. The outlined research was conducted at the Digital Enterprise Center (DEC) and Intelligent Manufacturing Testbed (IMT) at Purdue University.

Table 1. Equipment Specifications

Equipment List	Equipment to be used
Torque Wrench	TOHNICHI CEM/CTB Bluetooth Model Torque Wrench
Computer	Dell Desktop with Intel XEON processor
HD Camera	Mokose HD Camera 1080p @ 60FPS
Video Capture Card	Viixem 1080P @ 60FPS HDMI Capture Card
Assembly Guidance	Computer Monitor

To develop the application, a modified open-source Tensorflow2 machine learning algorithm was used to teach a detection model. The model is then be compared and used to search for bolt heads and patterns in a live camera feed. Tensorflow2 is an open-source machine learning platform that includes resources and libraries to develop machine learning and object detection algorithms (Géron, 2019). To train an object detection model, a directory of about two thousand images was obtained and saved to a local folder. Using an image annotation tool, such as LabelIMG, each image was annotated and classified as either a hex bolt, socket head cap screw, or button head cap screw (See Figure 6). Once annotated, the annotated file is converted to a tf.record file that was used to train using a pre-trained TensorFlow2 model. This resulted in a saved model that was used for object detection (See Figure 5).

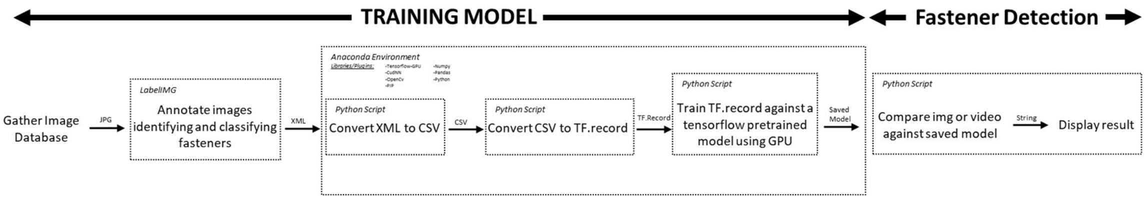


Figure 5. Development Workflow

Using an HD machine vision camera, the system compares the live feed to the saved model and determines the bolt location as well as the classification. In addition to bolt location and classification, the camera is used to detect torque wrench location relative to a bolt. The camera is mounted above the operator with a clear view of the assembly (See Figures 7 and 8). Connected to the PC via an HD capture card, the camera transfers live video images to be analyzed by Python script using a Python API called OpenCv.

Fastener Type	Head Shape
Hex Head	
Socket Head Cap Screw	
Button Head Screw	

Figure 6. Fastener Characteristics

3.1 Bolt Torque Detection

To detect if a particular bolt is being torqued, the program looks at three variables (See Table 2)

Table 2. System Variables and Measurement Methods

Variable	Measurement Method
Mechanical Fastener Location and Presence	Using Python code coupled with a camera, the algorithm recognized fasteners and recorded their presence or absence. Each bolt was virtually marked with a unique ID number that allowed the system to save the torque value for each bolt using the bolt's ID number.
Torque Pattern	The torque tool had a QR code located on the head of the tool. This allowed the vision system to recognize the tool and its X and Y coordinates. Using the tool location relative to the fastener, the system was able to identify the order in which the fasteners were torqued.
Torque Value	The torque value was wirelessly sent from the digital torque wrench to the computer and logged as the 'as manufactured' torque data. Using a USB Bluetooth dongle, the torque wrench transmitted a string containing the torque value, date/time, torque ID.
Fastener Type	Using Python code coupled with a camera, the algorithm recognized fastener types. Three faster types were used in this system: hex head, button head, and socket head.

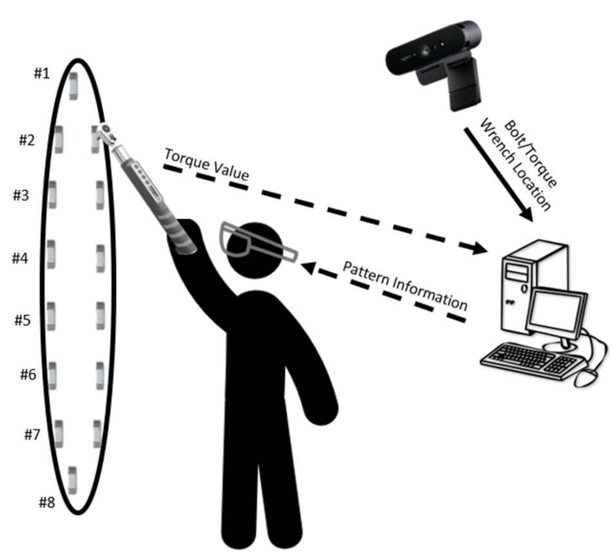


Figure 7. System Setup

To mark a bolt as torqued and complete, the program uses the three variables and compares them using IF Statements. Once detected, each fasteners' X and Y coordinate is recorded and saved as a variable. Similarly, the torque tool's location was tracked and saved only when the system received a torque value. If the location of the torque wrench was within a 40 pixels circular tolerance of a given bolt and a torque value was transmitted from the torque wrench, the program marked that bolt as torqued and assigned the torque value to that bolt (See Figure 8 and 10).

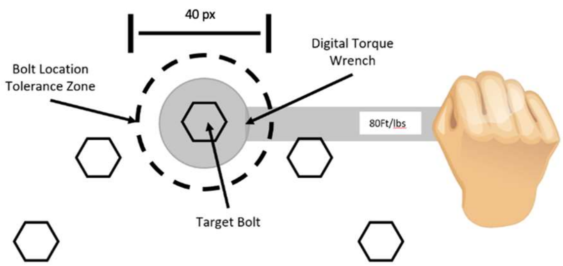


Figure 8. Program Bolt Validation

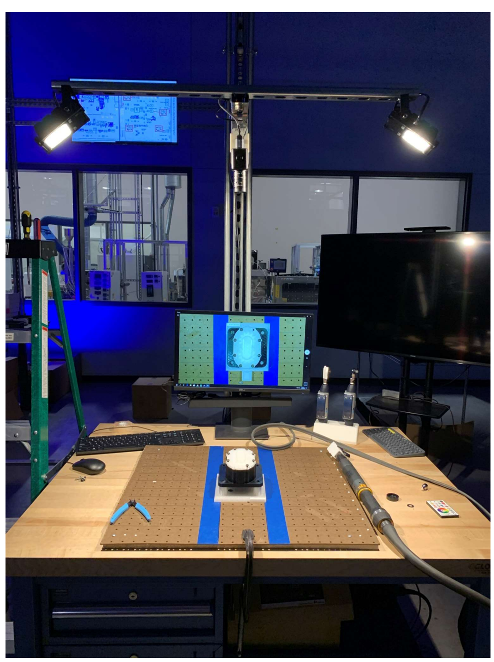


Figure 9. Assembly test setup with a camera hung over the assembly station.

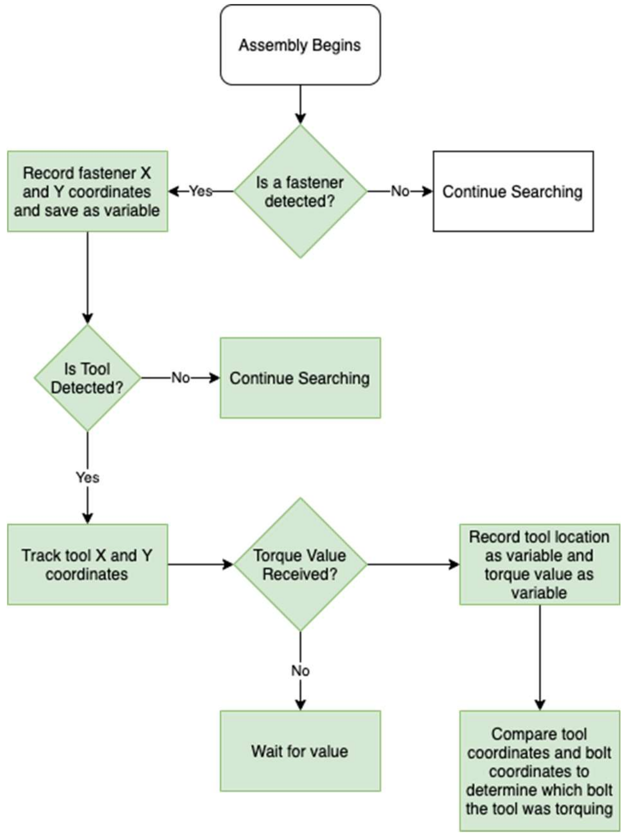


Figure 10. The above decision, flowchart shows the system variables and logic.

A tolerance zone is determined by the size of the fastener. To calculate the appropriate tolerance, the diameter of the fastener is converted to pixels. To generalize the calculation of the tolerance zone, the tolerance zone formula was created (See Equation 1).

$$1\ pixel = 0.2646\ mm$$

$$Tolerance\ Zone = \frac{Fastener\ Diameter\ mm}{.2646\ mm}$$

Equation 1. Tolerance Formula

3.2 Mechanical Fastener Detection

A Python script was used to analyze the video image captured by the camera. To do so, an open-source object recognition/detection library, OpenCv, and TensorFlow APIs were used to recognize objects within the image frame. There are various image libraries available online that contain thousands of images of objects that can be used to train your machine vision algorithm to detect a specific object. Unfortunately, there are no libraries containing images of various mechanical fasteners, thus one had to be made from scratch. After collecting images and compiling an image library of about two thousand pictures, each image must be cleaned up and annotated to ensure accurate bolt recognition. LabelImg was used to annotate to cleanup and annotate bolt types and sizes.

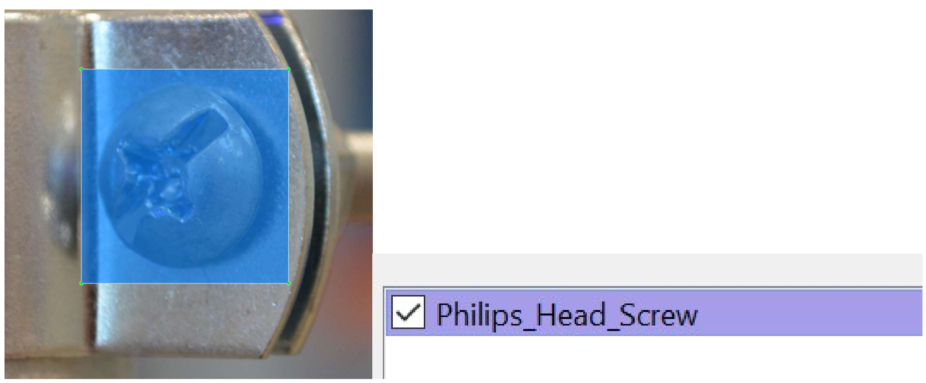


Figure 11. screenshot from LabelImg tool where images are annotated and the object of interest is selected. It is recommended when cropping the object of interest, to include some of the object’s surroundings to aid the algorithm in distinguishing between the object's contours and the background.

Once the image library is annotated, an XML file was generated with the associated images, their annotation, and the object of interest location selected in blue in LabelImg (See Figure 11). This XML file was then used in Tensorflow to teach the algorithm what object to detect. When running the script, a bounding box was be placed around the detected fastener, a confidence score was outputted, and the bolt classification displayed.

When the bounding box was generated around a detected fastener, the center of the box was used as the bolt's X and Y location. The midpoint formula (See Equation 2) was used to calculate the center of two diagonally opposite corners of the bounding box.

$$M = (\frac{X1+X2}{2}, \frac{Y1+Y2}{2})$$

Equation 2. Middle Point Formula

The center point X and Y coordinates were saved as a variable and be used to compare tool location.

3.2.1 Reducing Noise

To help reduce noise when capturing bolt locations, the image was preprocessed and OpenCV Denoising API was applied. Once the image of the API was applied, a correlation algorithm can be used to create a Grayscale processing map that maps the shades and values of gray to be used during denoising. This approach was used as an off-the-shelf noise-reducing API, but fortunately, the system performed with minimal image noise which did not trigger the software to use the Denoising API. The approach is similar to Li (2018), where then the image was being processed using the wavelet library in Python. Using wavelet, the script was able to remove Gaussian Noise, Salt-and-pepper noise, and conduct multi-scale decomposition (Li, 2018).

Environmental noise like vibration and lighting conditions were recorded using sensors. Two accelerometers, one placed on the workbench and the other placed on the camera, recorded the environmental vibration during assembly. To limit the amount of vibration noise experienced, the allowable vibration noise was be limited to 5 $\mathrm{mm/s^2}$, which is the recommended daily exposure limit for an employee as issued by the Parliament of the European Union. Although not officially a US regulation, this daily exposure limit has been accepted by researchers and medical professionals here in the US (Dong et al., 2006).

3.3 Tool Location Tracking

3.3.1 Torque Tool

To accurately transmit as manufactured torque values, a TOHNICHI digital wireless torque wrench was used. The TOHNICHI torque wrench, model CTB20N2X10D-G-BT, is capable of transmitting live torque values using a standard Bluetooth USB dongle. After the fastener was torqued, a string containing the torque value and tool location was transmitted. The python script then received the string from the serial port COM3 and stored it as a variable.

3.3.2 Torque Value

The torque wrench transmits a string of data to the PC containing data for each torque value taken. In the string, the torque wrench transmits, the data was structured as such: DATA HEADER, TORQUE ID NUMBER, TORQUE VALUE IN, DATE, TIME (See Figure 11). From the string, only the Torque ID and Torque Value are used. The values were then extracted from the string and saved as variables. The torque ID represents which number bolt is being torqued in that session and can be used to compare the bolt count that is registered by the camera.

Figure 12. Python output containing the decoded string with Torque ID, and Torque Value

Depending on the product configuration, the assembly may require different target torque values during product assembly. The system is capable of setting the tool's target torque value by transmitting a string of data to the torque tool, mitigating the possibility of operators incorrectly setting the target torque (See Figure 13).

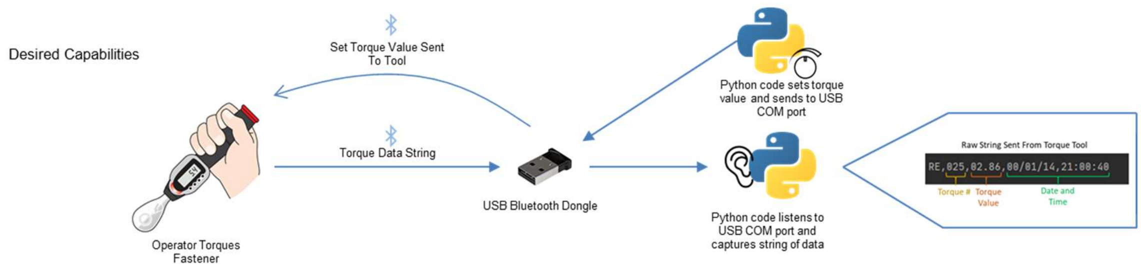


Figure 13. System torque data flow

3.3.3 Torque Tool Location

Using a camera and QR code attached to the torque wrench, the system was able to track where the torque wrench was located. The QR code was mounted on a 3D printed clip that is attached to the head of the torque wrench. The center of the QR code is concentric with the wrench's driver attachment, this gives a more accurate reading of which fastener the torque wrench is torquing. When the system detects the QR code, a blue bounding box is displayed and the center point of the box is used as the X and Y location (See Figure 15). To calculate the center of the box, Formula 1 was used again. The X and Y coordinate was outputted in Python. If a torque value is transmitted, the X and Y coordinates are then saved with the string transmitted from the torque value (See Figure 14).

```
879 926
```

```
1015 321 RE,025,02.86,00/01/14,21:00:40
```

Figure 14. Two Python outputs containing torque tool coordinates. Left, the system has not received a torque value from the tool and is only tracking location. Right, the system has received a torque value and the location where that torque value was taken.

Figure 15. System detecting torque tool using QR code attached to the torque wrench.

3.4 Assembly Guidance

To ensure the correct torque pattern was used, the program predetermined the torque sequence based on the assembly process specification. The assembly process specification sheet or commonly known as the bill of process (BOP) outlines the correct assembly steps including torque sequences and values (See Figure 16). The pattern and the next bolt in the sequence were displayed on the user's computer monitor allowing them to quickly reference which bolt was next. If the user strays away from the predefined sequence or does not tighten a bolt to a torque value that is within tolerance, the program displayed a message and does not proceed with the assembly guidance. Once the user torqued a bolt within tolerance, a green digit was displayed around the bolt indicating the bolt has been torqued and a yellow digit indicated the next bolt in the assembly process. All other bolts that need to be torqued, but have not been torqued yet had an orange digit on them.

```
        Installation (All Models)
        Apply liquid gasket sealer to pan surface, rear oil seal
retainer gasket and oil pump gasket. To install, reverse removal
procedure. Tighten oil pan bolts in sequence. See Fig. 15. See TORQUE
SPECIFICATIONS TABLE at end of article.
```

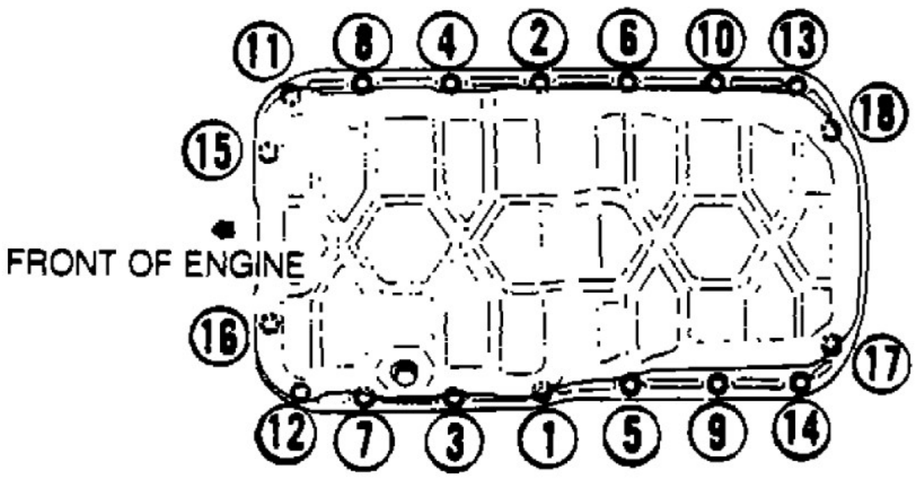


Figure 16. Shows excerpt from a bill of process for a 1991 Nissan Engine oil pan (*3.0l v6 - Vins [h,r] & 3.0l v6 Turbo - Vin [c] 1991*, 1991). The assembly method for oil pans has not changed since then, but torque patterns and values differ from model to model.

3.5 System Evaluation

The system was tested and benchmarked in a series of 30 cycles where individual system elements were evaluated in relation to varying environmental conditions. During each cycle, a test part was assembled using the system. As it pertains to this research, a cycle is defined as a complete assembly of a product from start to finish where the system successfully initiates tracking and finishes with a summarized report. To ensure reliable data, 30 cycles is regarded as an adequate number of cases (Hogg et al., 2003). The test part was an aluminum plate with 6 threaded holes in a circular bolt pattern. The part's surface was covered in a matte finish to reduce glare and potentially introduce error. 6 fasteners, two of each classification, were threaded into the thread holes in the plate (See Figure 17).

The system monitored the assembly process and reported a summary containing the system recorded data. This data was saved on a form in an excel spreadsheet (See Figure 17), where system and environmental parameters were recorded. After the data has been recorded, and an overall system evaluation was conducted using the STEP method. STEP is used commonly to evaluate technology stack capabilities and was developed by the MITRE Intelligence Community Test and Integration Center in 2004 (Brown, 2007). STEP identifies the technology's key objectives and based on system performance, each feature is either rated as 0, did not meet criteria, .5, met some criteria, and 1, met all criteria. Each feature is then weighted based on importance, and a total evaluation score for that cycle is calculated (see Figure 18). If an evaluation score of 1 was achieved for that cycle, the system was successfully able to identify fastener type with at least a 90% confidence, trace the order in which the fasteners were torqued without error, identify all fasteners are present, torque value is recorded matches the as assembled torque value.

				Specified Order
Researcher Name		Bolt 1 Type	Hex	1
Date		Bolt 2 Type	Hex	3
Time		Bolt 3 Type	Socket Head	5
		Bolt 4 Type	Socket Head	2
Cycle #		Bolt 5 Type	Button Head	4
		Bolt 6 Type	Button Head	6

During Cycle Operation

Environment			Comments
	Value	Unit	
Height of Camera above part		mm	
Lumens On Part Surface		lm	
Vibration (Workbench)		mm/s^2	Below Mark The Order Recorded By The System
Vibration (Camera)		mm/s^2	

Detection		
Bolt 1 Type		
Bolt 1 Confidence		%
Bolt 2 Type		
Bolt 2 Confidence		%
Bolt 3 Type		
Bolt 3 Confidence		%
Bolt 4 Type		
Bolt 4 Confidence		%
Bolt 5 Type		
Bolt 5 Confidence		%
Bolt 6 Type		
Bolt 6 Confidence		%

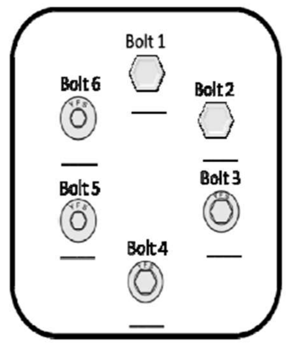


Figure 17. Cycle data form

Weighted Factors	How to Test	Weight	Proposed System Score	Comments
Fastener Presence Tracked	System will display a bounding block around the fastener, acknowledging it as detected	.1		
Fastener Torque Order Recorded	During and at the end of the assembly, the software will report the torque pattern followed.	.5		
Correct Fastener Types Detected	System will display what fasteners are detected. At least 95% Confidence is required.	.3		
Torque Value Recorded	System will record the torque value for each fastener and the value is within ±3nm	.1		
Total Score		1	0	

Score	Description
0	Factor Does NOT Meet Evaluation Criteria
0.5	Factor Partially Meets Evaluation Criteria
1	Factor DOES Meet ALL Evaluation Criteria

Standardized Technology Evaluation Process (STEP) method for technology evaluation

Figure 18. Matrix to evaluate overall system performance

The system was tested first under standard lighting and vibration conditions, defined by various institutions and accepted here in the US. OSHA outlines the amount of illumination an employee should work in as approximately 300 LUX (OSHA, 2010). Although no employee vibration limit is defined in the US, medical experts and researchers in the US accept a daily limit of vibration of 5mm/s² for an employee, which is defined by the European Union Parliament (Dong et al., 2006). With a max vibration limit of 5 mm/s², the testing location's baseline natural frequency of 0.005mm/s² was used as the minimal vibration limit. To test the effects of mid-range vibration (half of the allowable limit), 2.5 mm/s² was used as the moderate vibration level.

Thus, for this research, a minimal illumination work environment was 300 LUX and a maxim vibration work environment was 5mm/s². After 30 cycles of evaluation under standard working conditions, three environmental conditions were manipulated, one at a time and each combination was cycled 30 times, see figure 19 for a list of test configurations.

Illumination (LUX)	Vibration Workbench (mm/s²)	Vibration Camera (mm/s²)
IL: 300	VWB: 0.005	VC: 0.005
IL: 500	VBW: 2.5	VC: 2.5
IL :700	VBW: 5	VC: 5

Number of Combinations	27
Number of Cycles per Combination	30
Total Number of Cycles	**810**

LIST
IL: 300 / VWB: 0.005 / VC: 0.005
IL: 300 / VWB: 0.005 / VC: 2.5
IL: 300 / VWB: 0.005 / VC: 5
IL: 300 / VBW: 2.5 / VC: 0.005
IL: 300 / VBW: 2.5 / VC: 2.5
IL: 300 / VBW: 2.5 / VC: 5
IL: 300 / VBW: 5 / VC: 0.005
IL: 300 / VBW: 5 / VC: 2.5
IL: 300 / VBW: 5 / VC: 5
IL: 500 / VWB: 0.005 / VC: 0.005
IL: 500 / VWB: 0.005 / VC: 2.5
IL: 500 / VWB: 0.005 / VC: 5
IL: 500 / VBW: 2.5 / VC: 0.005
IL: 500 / VBW: 2.5 / VC: 2.5
IL: 500 / VBW: 2.5 / VC: 5
IL: 500 / VBW: 5 / VC: 0.005
IL: 500 / VBW: 5 / VC: 2.5
IL: 500 / VBW: 5 / VC: 5
IL :700 / VWB: 0.005 / VC: 0.005
IL :700 / VWB: 0.005 / VC: 2.5
IL :700 / VWB: 0.005 / VC: 5
IL :700 / VBW: 2.5 / VC: 0.005
IL :700 / VBW: 2.5 / VC: 2.5
IL :700 / VBW: 2.5 / VC: 5
IL :700 / VBW: 5 / VC: 0.005
IL :700 / VBW: 5 / VC: 2.5
IL :700 / VBW: 5 / VC: 5

Figure 19. Combinations for manipulating environmental variables.

3.5.1 Evaluation Cycle

At the start of every cycle, the three environmental conditions were measured: the amount of light on the surface of the part, workbench vibration, and camera vibration. To measure illumination, a lumens sensor was placed on the surface of the workpiece and the LUX measurement was recorded. Two industrial accelerometers and a smartphone with an accelerometer app where be used to measure the environmental vibration noise affecting the camera and the workstation. One accelerometer was attached to the camera and another to the workstation near the workpiece and both vibration values were recorded before the start. The smartphone accelerator app was used as a redundancy. The environmental conditions were then manipulated to match the conditions specified for each particular cycle outlined in figure 18. Once manipulated, the illumination and vibration values were recorded and assembly began. A sample part was assembled using the system and at the end of the assembly, the system data was recorded in an excel spreadsheet mimicking the format of the form found in Figure 17. An overall system evaluation for that cycle was performed, and fasteners were slightly unscrewed. This cycle was repeated 29 additional times using the same environmental conditions. An outline of the cycle's flow can be seen in Figure 20.

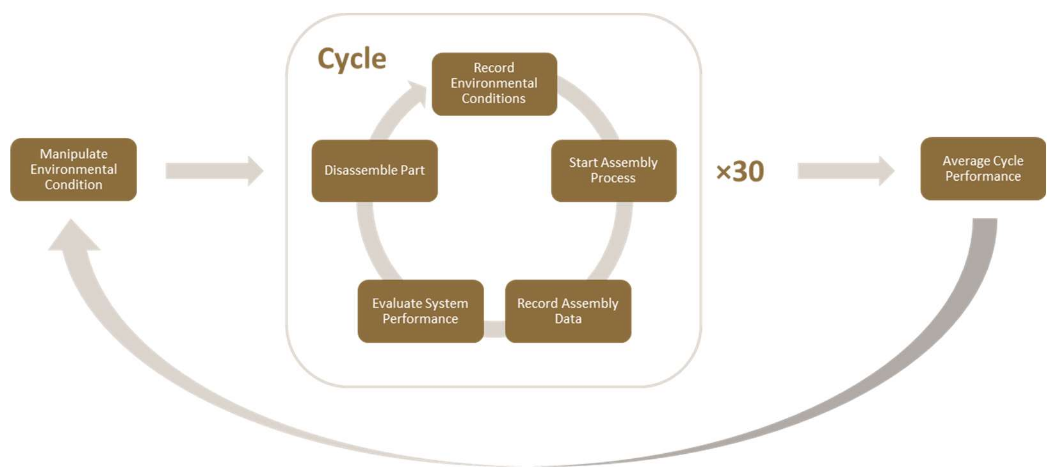


Figure 20. Data Collection Cycle Outline

3.5.2 Illumination Manipulation

At the beginning of every cycle, the illumination on the workpiece was recorded. As previously defined, a standard workplace illumination is approximately at least 300 LUX, which served as the minimum baseline benchmark for system performance. To manipulate the illumination on the part, variable LED work lamps were placed above to workstation, allowing to manipulation of the amount of light on the workpiece. Because the evaluation workspace is located in a naturally lit area that it is difficult to control the light, all testing was conducted after sunset and before sunrise using only the LED lamps as a true light source.

3.5.3 Vibration Manipulation

Similar to using a sensor to detect illumination, camera and workbench vibration readings were taken using accelerometers mounted to the camera and workbench. A baseline of 0.005 mm/s^2 was be used to evaluate the system at standard operating conditions. This baseline was the natural vibration of the work environment. Two variable speed motors producing vibration were fixed to the system, one to the workbench, and the other to the camera stand. To eliminate cross vibration between the camera and the workbench, the camera fixture was isolated from the workbench and mounted to the floor, while the workbench was placed on vibration dampening rubber pads. To further eliminate unwanted vibrational noise, the system was evaluated when no other nearby equipment was operating and producing vibration.

CHAPTER 4. RESULTS

This chapter will present the data collected during the validation testing of the developed system. The chapter overviews the environment in which the data collection took place, the effects of the manipulated environmental conditions and system performance, the results of the fastener detection, fastener torque patterns, and torque values. The chapter will conclude by summarizing the data collected.

4.1 Test Conditions

The evaluation of the system was conducted over a two-day period from March 21st to March 22nd, 2021. The equipment setup and evaluation of the system were performed at Purdue's Intelligent Manufacturing Testbed located at Indiana Manufacturing Institute. LED work lights and two vibration motors were used to emulate various industrial and manufacturing environments. The baseline illumination is set to 700 LUX and the baseline vibration for both workbench and camera are 0.005 mm/s² (See Table 3).

Table 3. Environmental variable levels

Severity Level	Illumination (LUX)	Workbench Vibration (mm/s²)	Camera Vibration (mm/s²)
Baseline	700	0.005	0.005
Moderate	500	2.5	2.5
Elevated	300	5	5

In this study, the effect of three environmental conditions on the system's performance was tested. The three environmental conditions tested are; the amount of illumination (LUX), environmental vibration experienced by the workpiece/workbench (mm/s²), and the environmental vibration experienced by the machine vision camera (mm/s^2). Each of the three environmental variables had a severity level of baseline, moderate, and elevated (See Table 3).

4.2 Industrial Environment Effects on System Performance

To arrange the environmental variables, permutations were used, as opposed to combinations. The permutations of the environmental conditions and severity levels resulted in 27 permutations (See **Error! Reference source not found.**). Each permutation was tested 30 times resulting in 810 cycles and 4855 data points. All 810 assemblies and data points were assembled and gathered by the researcher during the testing period.

Due to the number of tested variables, data collected, and setup time needed for each variable, the data was arranged using permutations instead of combinations. If combinations were used, a total of 84 combinations would be tested 30 times resulting in 2520 assemblies, which would not be feasible for this study.

Table 4. Table outlining the permutations of variables used in the study

Permutation Number	Illumination (LUX)	Workbench Vibration (mm/s^2)	Camera Vibration (mm/s^2)
1	700	0.005	0.005
2	700	0.005	2.500
3	700	0.005	5.000
4	700	2.500	0.005
5	700	2.500	2.500
6	700	2.500	5.000
7	700	5.000	0.005
8	700	5.000	2.500
9	700	5.000	5.000
10	500	0.005	0.005
11	500	0.005	2.500
12	500	0.005	5.000
13	500	2.500	0.005
14	500	2.500	2.500
15	500	2.500	5.000
16	500	5.000	0.005
17	500	5.000	2.500
18	500	5.000	5.000
19	300	0.005	0.005
20	300	0.005	2.500
21	300	0.005	5.000
22	300	2.500	0.005
23	300	2.500	2.500
24	300	2.500	5.000
25	300	5.000	0.005
26	300	5.000	2.500
27	300	5.000	5.000

Each permutations' mean was calculated and the varying levels of environmental conditions were analyzed. The relationship between the environmental conditions and system performance was examined using multiple linear regression (See Figure 21) in IBM's SPSS software.

Based on the coefficients and the significance value of each variable, out of the three environmental conditions, vibration experienced by the workbench and the vibration experienced by the camera were determined to be significant and had a negative relationship on the system's confidence.

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Vibration_CAM, Vibration_WB, LUX[b]	.	Enter

a. Dependent Variable: CI_Means

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.860[a]	.740	.706	7.595479415

a. Predictors: (Constant), Vibration_CAM, Vibration_WB, LUX

b. Dependent Variable: CI_Means

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3769.193	3	1256.398	21.778	.000[b]
	Residual	1326.900	23	57.691		
	Total	5096.093	26			

a. Dependent Variable: CI_Means

b. Predictors: (Constant), Vibration_CAM, Vibration_WB, LUX

(I)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	91.685	5.348		17.144	.000
	LUX	.004	.009	.050	.472	.642
	Vibration_WB	-1.901	.717	-.282	-2.652	.014
	Vibration_CAM	-5.463	.717	-.811	-7.621	.000

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	80.622	102.748
	LUX	-.014	.023
	Vibration_WB	-3.384	-.418
	Vibration_CAM	-6.946	-3.980

a. Dependent Variable: CI_Means

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	56.13280869	94.60302734	75.37405338	12.04030553	27
Residual	-15.5510025	9.713118553	.0000000000	7.143851777	27
Std. Predicted Value	-1.598	1.597	.000	1.000	27
Std. Residual	-2.047	1.279	.000	.941	27

a. Dependent Variable: CI_Means

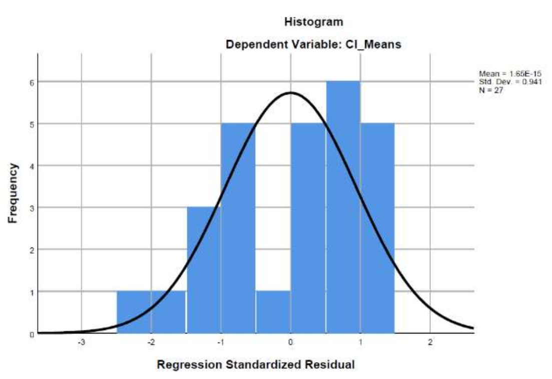
Figure 21. SPSS Output For Multiple Linear Regression
(I): Coefficients Output for Dataset

4.2.1 Relationship Between Environmental Variables and System Confidence

The linear regression coefficient was used to test the relationship of the independent variables (environmental variables) to the dependent variable (system confidence). From the SPSS outputs, we can see that the workbench vibration coefficient was calculated to be -1.901, while the camera vibration coefficient was -5.463. Both workbench vibration and camera vibration variables have a significance value <0.05. The illumination variable has a significance value of 0.642 (which is greater than 0.05), which shows that it does not significantly influence the system confidence. Although the environmental illumination did not show a significant influence on system performance, it shows that the system performed equally well across all lighting conditions. Because illumination did not have a significant influence on system confidence, we can derive the linear regression formula from our coefficient output from SPSS as:

$$-1.901(Vibration_{WB}) - 5.463(Vibration_{CAM}) + 91.685 = System\ Confidence$$

The SPSS outputs in Figure 22 show the residuals were normally distributed, and have an r^2 of .740, which shows there was a strong relationship between the variables and suggests that the regression equation explains most of the variation of the system confidence variable. With a higher r squared value, the results indicate that all variability is explained and the model first the data.



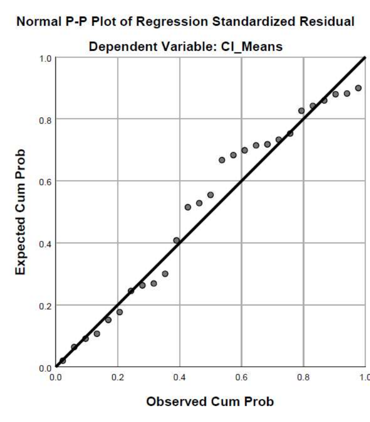


Figure 22. SPSS Regression Output Showing Data Normally Distributed

4.2.2 Statistical Significance

To calculate the statistical significance of the variables, and to determine if there was a statistically significant relationship between the environmental variables and the system confidence, the P-value for each variable was obtained. The resulting P-values for the environmental variables were; .642 for illumination, .014 for workbench vibration, and .000 for camera vibration (See Figure 21 Section I).

Both workbench vibration and camera are less than the significance level of 0.05, while the illumination variable was greater than the significance variable. This showed that the workbench vibration and the camera vibration resulted in statistically significant relationships, while the illumination did not result in statistically significant data.

4.3 Fastener Classification and System Confidence

The faster classification refers to the system's ability to detect if a fastener is present and what type of fastener it is. When detecting a fastener, the system provides a system confidence interval, in the form of a percentage, which represents how confident the system is of the detection and classification. In figure 23, all the permutations and their resulting average system confidence are shown.

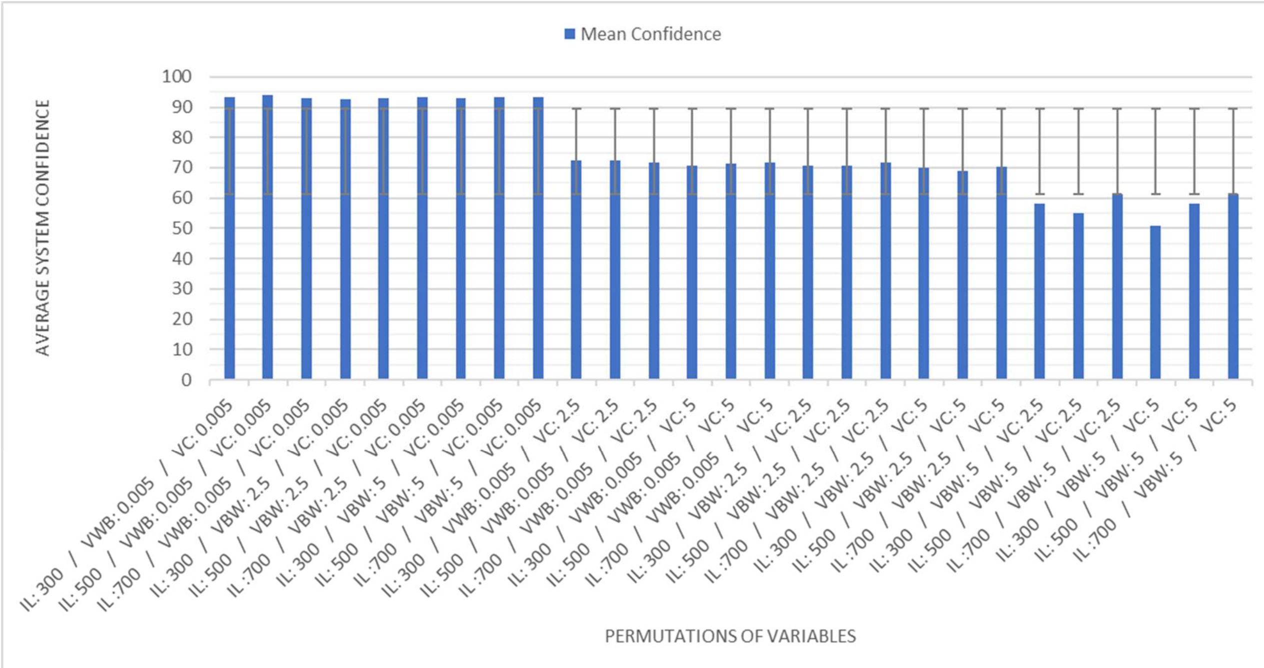


Figure 23. System Confidence per Variable Permutation

The average system confidence for all the permutations is 75.37% with a standard deviation of 18.932. The results can then be further broken down to understand how the different permutations influence system confidence.

4.3.1 Manipulated Illumination with Baseline Severity Vibration

The data can be further broken down to isolate illumination from vibration variables and understand the effects of the variables on the system confidence. In figure 23, when environmental vibration, specifically camera vibration, is introduced, the system confidence decreases significantly. Figure 24 shows the system confidence for varying illumination levels with baseline workbench and camera vibration levels.

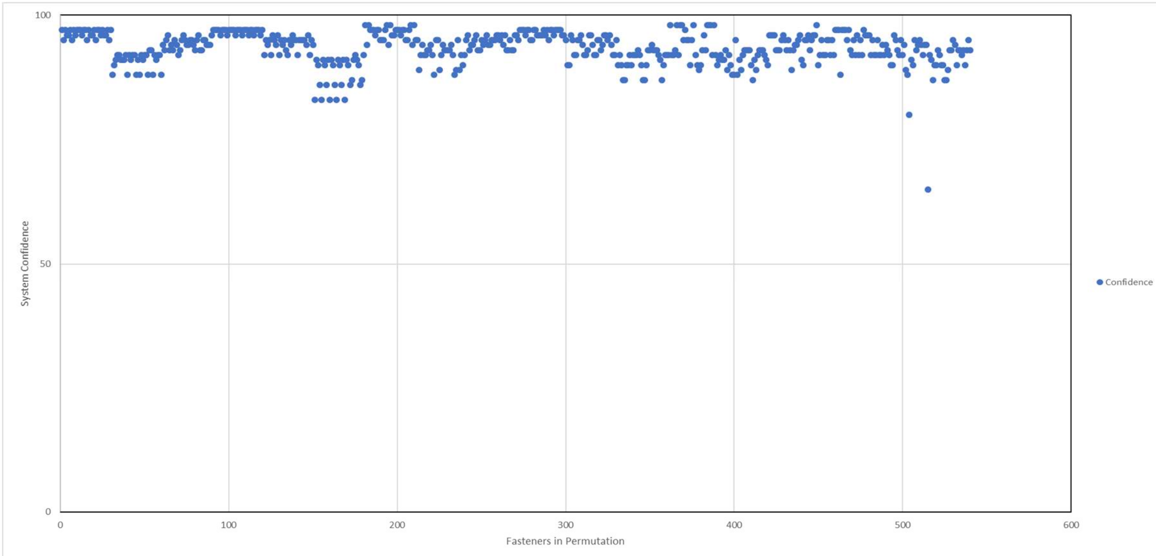


Figure 24. System Confidence for Fasteners During Permutations With Manipulated Lighting Conditions And Baseline Vibration Conditions

The average system confidence during all illumination with only baseline vibration resulted in a system confidence mean of 93.45% and a standard deviation of 3.24. The max confidence was 98% with a min of 65% (See Figure 25).

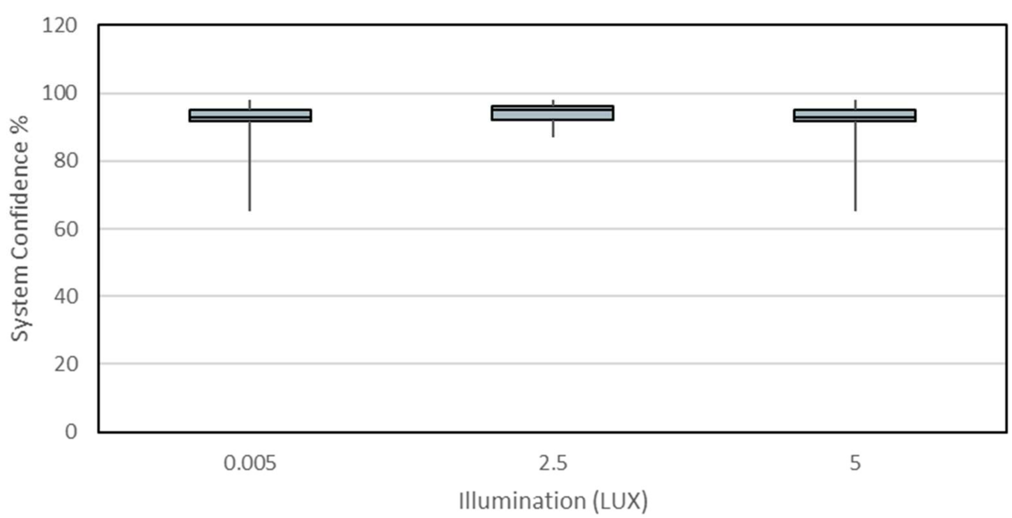


Figure 25. Box Plot Showing System Confidence for Illumination With Workbench Vibration and Camera Vibration at Baseline Severity.

4.3.2 Manipulated Illumination and Workstation Vibration with Baseline Severity Camera Vibration

In figure 23, the results show that the data remained consistent until camera vibration was introduced. To understand the environmental limits in which the system can perform, in the analysis below, camera vibration data was omitted, and only manipulated illumination and workbench vibration are shown with camera vibration set to baseline (See Figure 26).

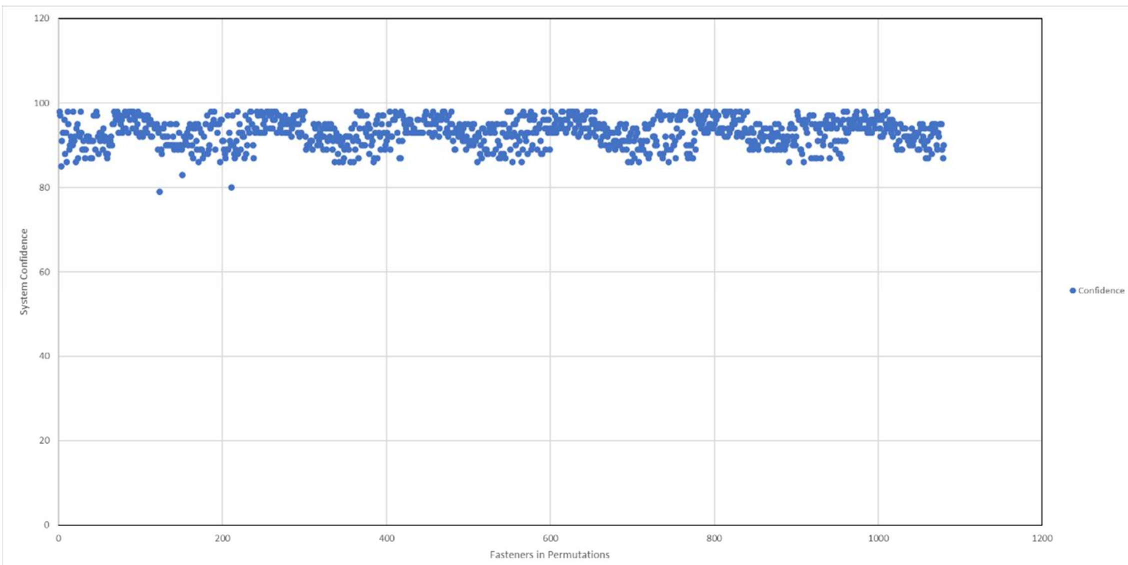


Figure 26. System Confidence For Fasteners During Permutations With Manipulated Lighting and Workbench Vibration Conditions And Baseline Camera Vibration Conditions

The average system confidence during all illumination and workbench vibrations with only baseline camera vibration resulted in a system confidence mean of 93.04% and a standard deviation of 3.18. The max confidence was 98% with a min of 79% (See Figure 30

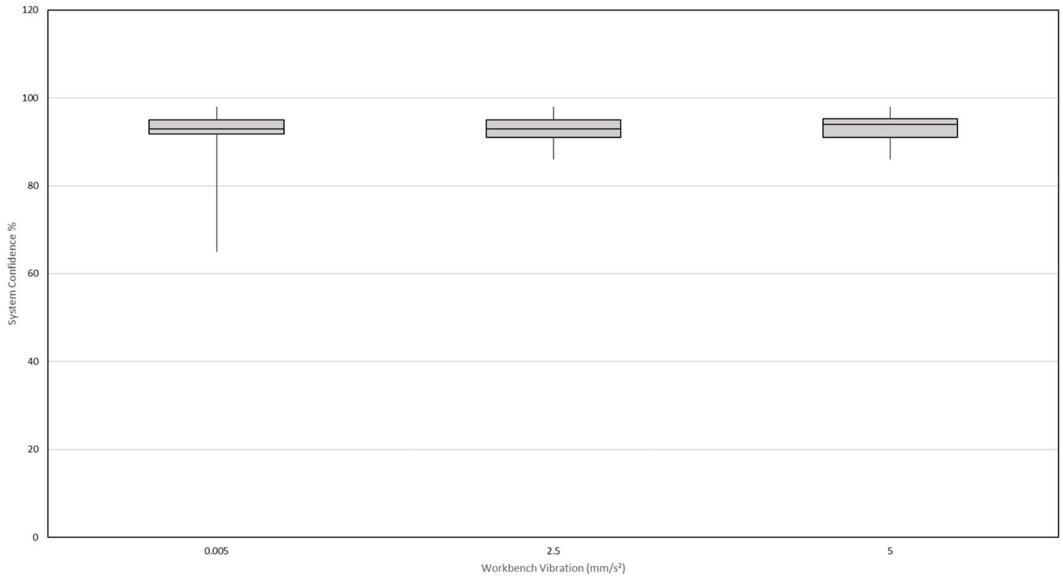


Figure 27. Box Plot Showing System Confidence for Workbench Vibration With Illumination and Camera Vibration at Baseline Severity.

4.3.3 Moderate and Elevated Camera Vibration Settings

When analyzing the system confidence of all the permutations, and when compared to the significantly low coefficient number for camera vibration, it is apparent that when camera vibration was introduced, system performance drastically decreased. To understand the extent to which the vibration affects the camera, only data containing moderate and elevated camera vibration is displayed in Figure 28. When collecting data, if the system was not able to detect a fastener, a confidence value of 0 was given. For the purpose of this analysis, the 0 value was omitted and only the confidence of the fasteners detected was included (See Figure 28).

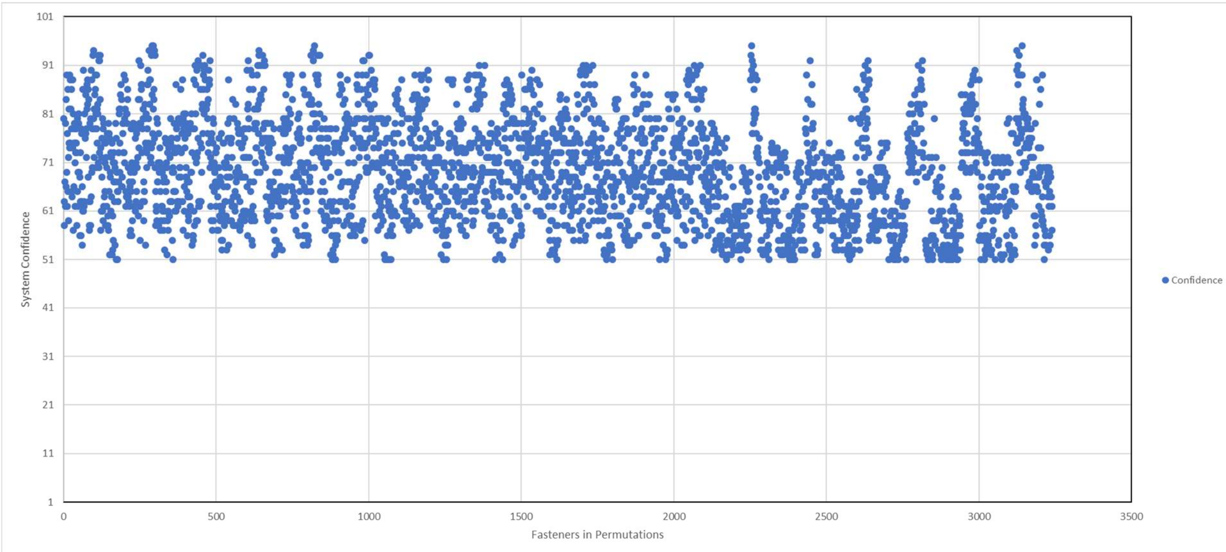


Figure 28. System Confidence for Fasteners During Permutations with Moderate and Elevated Camera Vibration

The average system confidence during all moderate and elevated camera vibrations resulted in a system confidence mean of 69.37% and a standard deviation of 10.34. The max confidence was 95% with a non-zero min of 51% (See Figure 29).

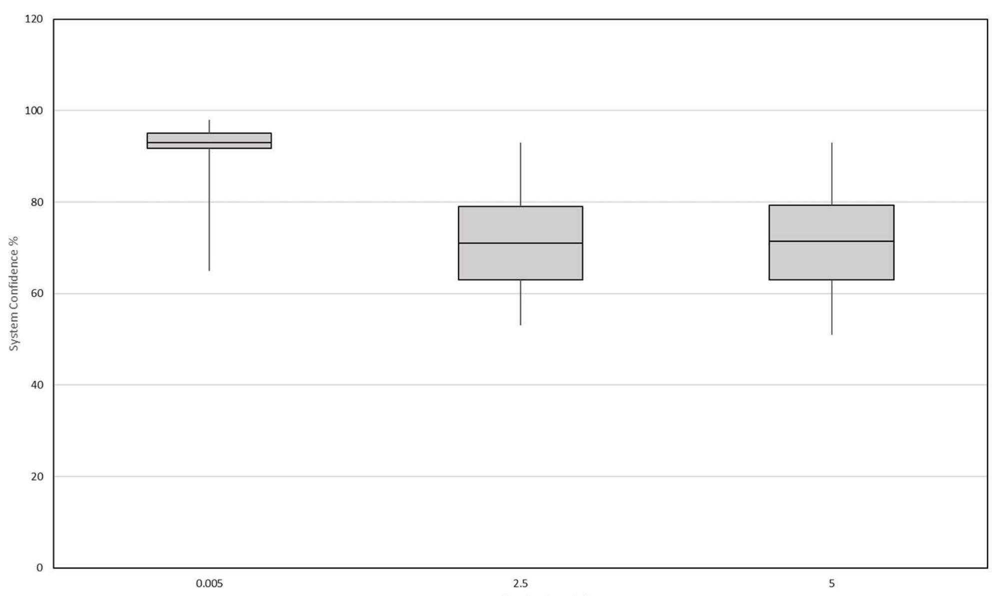


Figure 29. Box Plot Showing System Confidence for Camera Vibration With Illumination and Workbench Vibration at Baseline Severity.

4.4 Fastener Detection

To detect a fastener, the system streams a live feed using a vision camera located over the part. The software uses a Tensorflow2 and OpenCV-based algorithm to detect the fasteners within the steamed image. Once detected, the system counted the total quantity of fasteners and compared that to the nominal quantity of fasteners required to assemble the part. In the case of the test part, the total nominal quantity of fasteners was 6. During testing, the system would output how many fasteners were detected and if any fasteners are missing, and would display if any additional fasteners other than that required for the part were present.

4.4.1 Fastener Presence

If the system detected missing bolts, the system would not allow the user to proceed as an error was detected. This ensured all the fasteners were present during assembly, but in some cases, the system did not recognize fasteners that were meant to be detected. Table 5 shows the results of the total fasteners vs. missed fasters during testing. Out of 4860 fasteners assembled, the presence of 97% was accurately detected.

Table 5. Fastener Detection Summary

Total Amount of Fasteners Assembled	4860
Total Amount of Fasteners Un-Recognized/Missed	135
Percentage Accuratly Detected and Recognized	97%

4.4.2 Fastener Absence

In order to test if the system recognized the absence of a fastener, 103 random cycles were chosen to test the system's ability to recognize the absence of a fastener and prevent the system from progressing, ensuring the proper amount of fasteners are used. The system's missing fastener detection was tested by randomly covering one of the six fasteners in the assembly and recording the system output (See Figure 30). Out of 103 covered fasteners, the system recorded that a fastener was missing 103 times.

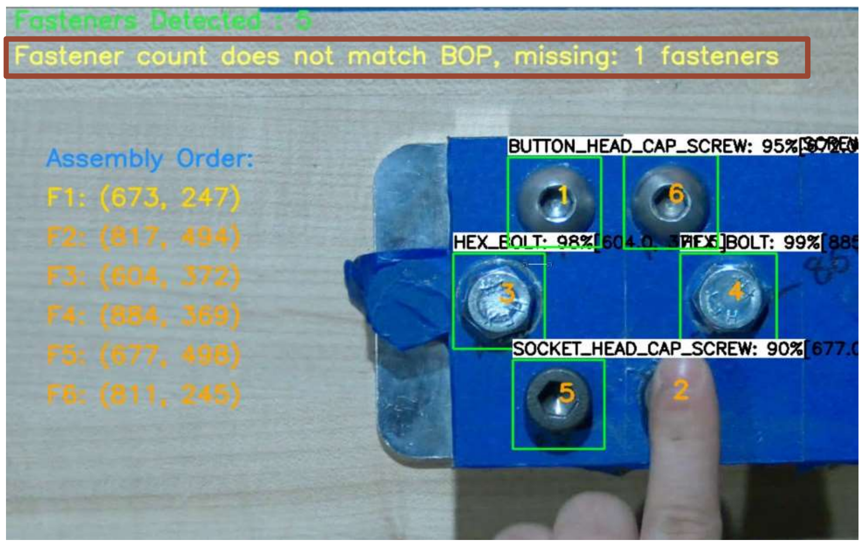


Figure 30. System Output Detecting Missing Fastener

4.5 Fastener Torque Pattern

The system recorded the pattern in which the fasteners were torqued. The system would confirm if the correct faster was torqued in the pattern and would prevent the system from proceeding if the incorrect faster was torqued in the pattern. The system tracked the tool's location using a QR code mounted on the head of the tool to ensure the correct torque pattern was used. Whenever a torque value was received, the system would compare the location of the tool with the location of where the fastener should be located. 810 cycles were each with 6 fasteners, the summary of the results of the pattern detection is shown in Table 6.

Table 6. Summary of Pattern Detection Including Camera Vibration

All Permutations	
Total Amount of Assemblies	810
Amount of Assemblies Pattern Correctly Recorded	270
Amount of Assemblies Pattern Incorrectly Recorded	540
Success Rate	33%

Because the system relied on the QR code to locate the tool, when camera vibration was introduced, the system could no longer track the QR code and failed to record the pattern. Before camera vibration was introduced, out of the 270 recorded cycles, all 270 patterns were correctly recorded (See Table 7).

Table 7. Summary of Pattern Detection Excluding Camera Vibration

Permutations Excluding Camera Vibration	
Total Amount of Assemblies	270
Amount of Assemblies Pattern Correctly Recorded	270
Amount of Assemblies Pattern Incorrectly Recorded	0
Success Rate	100%

The system's capability to detect incorrect torque patterns was tested by randomly selecting 50 assemblies to be torqued out of order. The assembly was attempted using the wrong torque pattern, and the system's ability to recognize that the error was recorded. Out of the 50 incorrect assembly attempts for all permutations including camera vibration, 29 were successfully caught as mistakes (See Table 8).

Table 8. Summary of System's Ability to Detect Incorrect Torque Pattern Including Camera Vibration

All Permutations	
Total Amount of Assemblies	810
Number of Incorrect Assembly Attempts	50
Number of Correctly Detected Inorrect Assembly Attempts	29
Success Rate	58%

Like before, the torque pattern recognition relies on the system's ability to track the tool's QR code and record tool location data. When camera vibration was introduced, the system could no longer accurately track the tool's location and the torque pattern recognition failed. With camera vibration at baseline, 21 incorrect assemblies were attempted, and 21 were successfully detected as incorrect and would not allow the user to proceed with the assembly process (See Table 9)

Table 9. Summary of System's Ability to Detect Incorrect Torque Pattern Excluding Camera Vibration

Permutations Excluding Camera Vibration	
Number of Incorrect Assembly Attempts	21
Number of Correctly Detected Inorrect Assembly Attempts	21
Success Rate	100%

4.6 Torque Value

In addition to using the torque value string sent by the tool as a trigger to record the location of the tool, the system recorded the torque value by decoding the string of data and saving the torque value. No specific torque value was used as the actual torque value does not matter in this study, but rather that the torque value used matches that of the torque value received by the system. In all 4860 fasteners torqued, the system received and recorded the value correctly 100% of the time.

4.7 STEP Analysis

After data collection was conducted, the STEP analysis method was used to evaluate if the system performs its key functions. This method is often used when comparing different systems with the same capability, for the purpose of this research, the STEP method outcomes were used to compare the system performance against itself in different environmental variables. After data collection, the STEP criteria were imported into an excel spreadsheet and each factor in the STEP evaluation was assigned a formula that would pull inferences from the recorded data using if statements.

Weighted Factors	How to Test	Weight	System Score Average	Comments
Fastener Presence Tracked	System will display a bounding block around the fastener, acknowledging it as detected	.1	.6247	When camera vibration introduced, some fasteners could not be detected
Fastener Order Pattern Recorded	During and at the end of the assembly, the software will report the torque pattern followed.	.5	.333	When camera vibration introduced, system could not track tool and could not record location
Correct Fastener Types Detected	System will display what fasteners are detected. At least 90% Confidence is required.	.3	.332	When camera vibration introduced, faster detection became unreliable
Tool Presence Tracked	System will display a bounding block around the tools QR coding	.1	.333	When camera vibration introduced, system could not track tool
Total Score		1	.3621	

Score	Description
0	Factor Does NOT Meet Evaluation Criteria
0.5	Factor Partially Meets Evaluation Criteria
1	Factor DOES Meet ALL Evaluation Criteria

Standardized Technology Evaluation Process (STEP) method for technology evaluation

Figure 31. STEP analysis matrix for recorded data

To score the fastener presence tracked if all fasteners were detected/classified the result was a score of 1, if any of the fasteners were not detected a particular cycle, that cycles score was 0.5. If non of the fasteners were detected for that particular cycle, the cycle's score was 0. The score was then multiplied by its weight. An average score of 0.625 was recorded using the STEP method when including all environmental conditions (See Figure 31). Excluding camera vibration, the average score was 0.996.

To score if the fastener order pattern was properly recorded, the formula for the score checked if the torque pattern was correctly recorded in the raw data. If correctly recorded, a score of 1 was given, if not a score of 0 was given. An average score of .333 was recorded using the STEP method when including all environmental conditions, including camera vibration (See Figure 31). Excluding camera vibration, the average score was 1.

To score if the correct fastener types were detected, the formula looked at the individual cycle's confidence score for every fastener in that cycle. If all the confidence scores for that cycle were greater than or equal to 90% then the resulting score is 1, if at least one of the fasteners' confidence scores were greater than or equal to 90%, then the resulting score was 0.5. If none of the fasteners' confidence scores were greater than or equal to 90%, then the score was 0. An average score of 0.332 was recorded using the STEP method when including all environmental conditions, including camera vibration (See Figure 31). Excluding camera vibration, the average score was 0.996.

To score if the system accurately tracked tool presence, the formula looks at the individual cycles torque pattern completion, if the torque pattern was completed, the system accurately tracked the QR code by displaying a bounding box around the code and a score of 1 is given. If not, then a score of 0 is given. An average score of .333 was recorded using the STEP method when including all environmental conditions, including camera vibration (See Figure 31). Excluding camera vibration, the result is an average score of 1.

The average total score, using the STEP methods weights was .3621 this includes all environmental conditions, including camera vibration. Excluding camera vibration, the average score was 0.999.

4.8 Chapter Summary

Chapter 4 presented the results gathered during the validation testing of the system to understand the feasibility of using this approach in an industrial environment. The environmental conditions were outlined and system performance and classification data were presented. The chapter also reviewed the summary and analysis of fastener detection data, fastener torque pattern data, and finally, torque value data. Lastly, the averaged results of the STEP analysis were presented.

CHAPTER 5. DISCUSSION

This chapter will provide a discussion of the results and a conclusion to the study. In this study, a digital system for tracking torqued assemblies was developed and the operational feasibility of the system in an industrial environment was tested. The system underwent 810 cycles, containing a total record of 4860 fasteners, where environmental conditions were varied to simulate an industrial environment. Three variables were examined; lighting, vibration experienced by the workbench/workpiece that was being worked on, and vibration experienced by the vision camera. This study concludes that it is feasible to use this approach to create a digital log of as manufactured torque data if the machine vision camera is isolated from environmental vibration.

5.1 Industrial Environment Effects on System Performance

The three environmental conditions are important to understand if the system is feasible in an industrial environment. A baseline industrial environment with good lighting conditions and low environmental vibration was used. Each variable was independently manipulated from a baseline to moderate and then to elevated and the system results were recorded. The relationship between the vibration experienced by the workbench and the vibration experienced by the camera was strong and negative at coefficients of -1.901 and -5.463 respectively. The more vibration either experienced, the less confident the system outputs were. The illumination variable in this study did not prove to have a significant effect on the system outcomes. This meant that at low or elevated levels of illumination, the system performed similarly to when used in a well-lit, baseline environment. This could be a result of the contours of the fasteners, as long as there was enough illumination to distinguish the contour of the fastener, the system would perform with at least a 90% confidence.

The system performed at an average of 93.4% confidence when no vibration was introduced to the system and performed at an average of 93.04% confidence when only workbench vibration was introduced at any level. But when machine vision camera vibration was introduced at any level, the system's average confidence dropped to 69.37%. This showed the system has the potential to operate at over 90% confidence in an industrial environment if the camera was isolated from environmental vibration. When Isolated from environmental vibration, we can confirm the null hypothesis that the proposed system correctly identifies fastener classification, in an industrial environment, using the shape and features of the fastener with a 90%.

5.2 Fastener Detection

To detect the presence or absence of a fastener, the system had to recognize what a fastener looked like and distinguish what type of fastener it was to understand if the fastener belonged in the assembly. To detect and classify the fasteners, a custom object detection model using Tensorflow2 and OpenCv was trained using a dataset of approximately 2000 pictures. The system would then analyze a live feed from the camera detecting which fasteners were detected and their locations. The system then counted the number of fasteners and if the number of detected fasteners did not match the number of needed fasteners for the assembly, the system would display the result and prevent the user from progressing through the assembly.

During testing, the system was able to correctly detect the presence of fasteners and correctly count the number of fasteners 97% of the time. The 3% of fasteners that were not detected when they should have been detected, were in cycles that experienced camera vibration.

In all other cycles, where camera vibration was not introduced, the system detected the presence of fasteners correctly 100% of the time. Additionally, the system was able to detect the absence of a fastener correctly 103 out of 103 times which confirms the null hypothesis that the proposed system detected the presence of a fastener when a fastener is present and the absence of a fastener when a fastener is missing. When detected, the system displayed a warning message and waited for the appropriate quantity of fasteners.

5.3 Torque Pattern

One of the key performance indicators for the approach is its ability to track the torque pattern used when assembling a part. During testing, 6 fasteners in a circular bolt pattern were torqued in a star pattern. During system calibration, the user identified the order in which the fasteners were assembled and the system recorded the nominal coordinates for those fasteners. To track the location of the tool, a QR located on the tool's head was tracked throughout the workbench. As an operator torqued a bolt and a torque value was received by the system, the location of the tool was recorded and compared to the calibrated location of the fastener that should be torqued in the assembly sequence. If the values are within 40 pixels in x and y, then the system records the fastener as torqued and the progress was saved.

Out of 810 cycles, the torque pattern for 270 was correctly recorded. The low success rate of the system can be attributed to camera vibration. When camera vibration was introduced at a moderate or elevated level, the system could not recognize the tool's QR code. Because the QR code was not recognized, when the torque value was received by the system, the tool's location was unknown, and the system could not confirm which fastener was being recorded. 270 assemblies were recorded excluding camera vibration, out of the 270, 270 were correctly recorded. With the exclusion of camera vibration, the null hypothesis, that the proposed system recorded the torque pattern correctly, can be confirmed.

The torque pattern followed in this study was a single pass torquing procedure. It was assumed in this study that this was an adequate torquing procedure due to time constraints, but commonly a multiple pass torquing procedure is followed to incrementally torque and retorque an assembly. The single-pass torquing procedure was adequate in understanding the system's capability in tracking a torque pattern, but depending on specific applications, the system would need to be modified to allow for multiple torque passes.

5.4 Torque Value

During testing, a torque value of between 1-18 nm was used. Because the study focused on the feasibility of using the system, an arbitrary torque value was used. The torque was sent to the computer as a string of data using Bluetooth. For the system to work, the tool would need to be digitally connected and have the ability to send a string of data containing the torque value used. The string was then captured by the python script and decoded. The torque value was saved along with what fastener was torqued. Out of the 4860 fasteners that were torqued during testing, all the torque values received and decoded by the system matched the as manufactured torque value, confirming the null hypothesis that the system records the correct torque value for the appropriate fastener.

The application currently records the torque value, but it does not compare if the as assembled torque value is within tolerance of the parts nominal torque value. When collecting data, the recorded torque value was compared to the actual as manufactured torque value. The two values were compared to check if they matched. Potential future works could include the addition of torque value tolerances to ensure the torque value is within tolerance of the nominal torque value.

5.5 STEP Analysis

The STEP process is commonly used to evaluate new technology stacks with similar capabilities against each other. The method proved a 0-1 score that weighs the system's key factors. In the case of this study, detection if a fastener was present or absent, torque pattern used during assembly, fastener detection and classification with a 90% confidence, and lastly, the recording of the torque value. After collecting data for every cycle, formulas for each variable in the STEP analysis were created. The formulas ran through all the data in Excel and made an inference based on the data. The average of the weighted scores was gathered and it was concluded that the system score of 0.3621 indicated the system performs poorly in all weighted factors and doe not meet most of the evaluation criteria. The method regards anything below a 0.5 score low in performance and not meeting most of the evaluation criteria. This low score was influenced by the camera vibration, and when camera vibration was illuminated, the system performs at an average total score of 0.9985, indicating good system performance and meeting all evaluation criteria.

5.6 Limitations

The first limitation of this system was the camera mounting position. Because the camera is mounted as a top view, only fasteners with distinctive top view features can be detected. For the system to successfully measure the fastener and tool location, the camera should view the part from the top, and any fasteners that have bottom features, like countersunk screws, cannot be distinguished from Philips head screws. This limitation was a result of the method used to train the machine vision model. When focusing on the classification of the fastener, the model was taught to only recognize the head of the fastener which resulted in the system only recognizing fasters with distinct top characteristics. To improve the capability and robustness of the system, the system can be taught to recognize top features and side features as well. The top features would be used to characterize the fastener, but the side features would be used the recognize the presence of a general fastener for foreign object detection.

The second limitation was the tool selection. Because the system uses the torque value sent by the tool as a trigger to record the location of the tool, only tools with that capability can be used. The tool can be a manual-style tool, like a click-style torque wrench, but it must have the capability to digitally transmit the torque value either through Bluetooth or tether. The tool must also be able to communicate with an open protocol.

The third limitation, one that surfaced during testing, was the need for the vision camera to be isolated from environmental vibration. Any vibration in the camera reduced system performance significantly and for the system to perform in an industrial setting, it would need to be isolated from vibration.

Another limitation was the need to train on a computer that uses a GPU. The training process when training the system to identify specific fasteners requires the use of a good performing GPU. If a GPU is not available, services like Google Collab allow you to use a web-based GPU for free to train your dataset.

Lastly, because of time constraints, it was not feasible to train the model using the general rule of thumb of 1000 images per classification. To train the model used in this study, approximately 2000 pictures were used. To use a picture for training was a labor-intensive task where a person has to physically annotate each image, outlining where in the image the object you want to detect was. Because of the lower sample size of images, I chose a confidence interval threshold of 90% rather than the common 95%. Although the system performed well, averaging over 90% with isolated camera vibration, system confidence could be improved if 3000 images were used to train the model versus the 2000 used. The exact difference in system confidence is unknown, but it can be assumed that system confidence would increase. For the purpose of this study, 2000 images were satisfactory.

5.7 System Robustness

5.7.1 Robustness Against Illumination

The feasibility of implementing this system in an industrial environment was tested by conducting a series of cycles. The effects of two environmental noise conditions were analyzed and it was found that the system performed well at all tested illumination conditions. This showed the system was robust against various industrial lighting conditions when using a part with a similar part surface finish. The sample part used during testing was an aluminum piece with a matte finish. Because the matte finish of the part could reflect or absorb light in a different way than other finishes, system confidence results may vary, and future studies can be conducted to understand the system's robustness using various industrial conditions and part surface finishes.

5.7.2 Robustness Against Vibration

The system's robustness against vibration can be divided between the systems robustness to workbench/workpiece vibration and systems robustness to camera vibration. The system proved to be robust against workbench vibration by performing consistently at over 90% system confidence at all severity levels of workbench vibration. On the other hand, the system did not prove to be robust when camera vibration above baseline was introduced. Due to the system's inability to track the tool's QR code, the system could not track the torque pattern and system confidence fell below the 90% threshold.

To improve the system's robustness against environmental vibration, the vision system would need to be dampened. Further research can be conducted on the best methods for dampening camera vibration and improving system performance. In this study, the camera was mechanically fixed to a piece of Unistrut that was mounted to the concrete slab floor of the testbed. It would be feasible to dampen the camera's vibration exposure by mounting the camera to a dampening base supported by elastic rubber pads. This would help isolate the camera from any environmental vibration transferred via the camera stand/support.

5.8 Improvements and Potential Use Cases

There are several possible improvements for this system to improve its confidence and reliability. Like previously mentioned, one improvement that would drastically improve system reliability is isolating the camera from external vibration. Although during testing, the system showed satisfactory confidence with baseline levels of vibration for the camera, if the system were to be implemented in an industrial setting, the camera would need to be isolated.

Additionally, to improve system confidence, a larger dataset of fasteners should be trained. More fastener classifications should be added to expand the capability of the system. Another improvement is the addition of training images of threads. Currently, because the system focuses on the head of the fastener, if a bolt is on its side, the system cannot detect it. If the system could recognize threads, it would make the foreign object detection capability more robust.

It was assumed that the system’s usability was comparable to that of a standard industrial application. Because this research focused on the feasibility of this approach, versus the usability of the system, the way the user interacted and received torque pattern guidance data was assumed to be comparable to other assembly guidance techniques. This application used computer-based AR technology to overlay data onto a live image feed that was displayed on a monitor. This approach to assembly guidance can be taken further and implemented using a head-mounted AR display that could overlay the assembly data directly in the user's view. The usability of using AR technology on the computer monitor versus the head-mounted display could be compared in future works.

There are several applications in which this system can be implemented and improved. Although the system focuses on the torque pattern of fasteners, it can be further modified to track the location of any digitally connected tool relative to an object of interest. The application can allow manufacturers to record as manufactured data for each fastener and ensuring the part was assembled using the specified torque patterns.

This system can be implemented in many industries ranging from automotive and aerospace assembling to oil transportation. Whenever a specific procedure was used, the system can track the tool and the fasteners being assembled. In addition to the core system capabilities, the research provided a robust database of images that can be used to train various fastener object detection models and used in other applications where the detection of fasteners is required.

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APPENDIX A TORQUE TOOL CALIBRATION

TOHNICHI

Certificate of Calibration
校 正 証 明 書

		Date of First Used:	/ /
Name:	TORQUE WRENCH	Serial No.:	702458L
Model:	CTB20N2X10D-G-BT	Accuracy ±(%):	1
Max. Capacity:	20.00	Temperature (°C):	20
Units:	N·m	Inspector:	H. INOUE
Date of Calibration: (Day/Month/Year)	24/03/2020		

Set Torque	Lower	Upper		Actual Readings				
4.00	3.961	4.040	CW	3.978	3.984	3.978	3.978	3.990
			CCW	3.970	3.980	3.986	3.984	3.978
12.00	11.882	12.121	CW	11.920	11.938	11.936	11.944	11.932
			CCW	11.980	11.972	11.984	11.984	11.982
20.00	19.802	20.202	CW	19.888	19.880	19.886	19.876	19.890
			CCW	19.968	19.990	19.978	19.978	19.980

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We certify that product identified above was calibrated using reference standard
That is traceable to the national standards specifications and according to TOHNICHI STANDARDS.
We have verified that these test results comply with product specifications.
Measured values are within tolerance according to ISO6789.

標準器 Standard Equipment	Model	Serial No.
トルクレンチテスタ TORQUE WRENCH TESTER	DOTE20N4	701346J

参照標準 Reference Standard	公的機関 Official Facility	製造番号 Serial No.
トルク基準機 DWTCM25 TORQUE CALIBRATION MACHINE	(株)ミツトヨ/(株)大正天びん製作所 MITUTOYO CORPORATION TAISHO BALANCE MFG.	706752B

株式会社 東日製作所

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00512

Head of Calibration

H. Tsuneyoshi

APPENDIX B AVERAGED TEST RESULTS PER PERMUTATION

Combinration	LUX	Vibration WB	Vibration CM	Cycles Ran	CI Means	sdev
IL: 300 / VWB: 0.005 / VC: 0.005	300	0.005	0.005	30	93.4555556	3.440349
IL: 300 / VWB: 0.005 / VC: 2.5	300	0.005	2.5	30	72.2444444	10.48576
IL: 300 / VWB: 0.005 / VC: 5	300	0.005	5	30	70.8222222	10.25439
IL: 300 / VBW: 2.5 / VC: 0.005	300	2.5	0.005	30	92.5555556	3.422277
IL: 300 / VBW: 2.5 / VC: 2.5	300	2.5	2.5	30	70.5722222	9.322904
IL: 300 / VBW: 2.5 / VC: 5	300	2.5	5	30	69.8833333	9.917129
IL: 300 / VBW: 5 / VC: 0.005	300	5	0.005	30	93.1333333	3.109546
IL: 300 / VBW: 5 / VC: 2.5	300	5	2.5	30	58.25	21.79228
IL: 300 / VBW: 5 / VC: 5	300	5	5	30	50.8994413	25.80651
IL: 500 / VWB: 0.005 / VC: 0.005	500	0.005	0.005	30	94.05	2.598399
IL: 500 / VWB: 0.005 / VC: 2.5	500	0.005	2.5	30	72.3166667	10.134
IL: 500 / VWB: 0.005 / VC: 5	500	0.005	5	30	71.2	10.6101
IL: 500 / VBW: 2.5 / VC: 0.005	500	2.5	0.005	30	92.9722222	3.420984
IL: 500 / VBW: 2.5 / VC: 2.5	500	2.5	2.5	30	70.5777778	9.346798
IL: 500 / VBW: 2.5 / VC: 5	500	2.5	5	30	68.8666667	9.195214
IL: 500 / VBW: 5 / VC: 0.005	500	5	0.005	30	93.1777778	3.121659
IL: 500 / VBW: 5 / VC: 2.5	500	5	2.5	30	55.0833333	23.62483
IL: 500 / VBW: 5 / VC: 5	500	5	5	30	58.0277778	24.16619
IL :700 / VWB: 0.005 / VC: 0.005	700	0.005	0.005	30	92.8388889	3.51241
IL :700 / VWB: 0.005 / VC: 2.5	700	0.005	2.5	30	71.55	10.14326
IL :700 / VWB: 0.005 / VC: 5	700	0.005	5	30	71.6222222	3.51241
IL :700 / VBW: 2.5 / VC: 0.005	700	2.5	0.005	30	93.1444444	3.012307
IL :700 / VBW: 2.5 / VC: 2.5	700	2.5	2.5	30	71.5611111	9.502816
IL :700 / VBW: 2.5 / VC: 5	700	2.5	5	30	70.1944444	22.77704
IL :700 / VBW: 5 / VC: 0.005	700	5	0.005	30	93.2944444	2.957232
IL :700 / VBW: 5 / VC: 2.5	700	5	2.5	30	61.3611111	18.97242
IL :700 / VBW: 5 / VC: 5	700	5	5	30	61.4444444	23.34421