TÜRKİYE CUMHURİYETİ
ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL
ELECTRICAL AND ELECTRONIC ENGINEERING DEPARTMENT

MINIMIZING ASSEMBLY ERRORS DURING MASS PRODUCTION PROCESS IN AUTOMOTIVE INDUSTRY BY USING VISUAL PROCESSING METHODS

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M.Sc.

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ADANA, 2025

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

05/11/2025

[Signature]

Mehmet YAVUZ

ÖZET

GÖRSEL İŞLEME YÖNTEMLERİ KULLANARAK OTOMOTİV ENDÜSTRİSİ SERİ ÜRETİM HATLARINDAKİ MONTAJ HATALARINI MİNİMİZE ETMEK

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Danışman: Prof. Dr. Esen YILDIRIM
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Otomotiv endüstrisindeki seri üretim hatlarında prototip araçla birebir aynı aracın üretilmesi manuel olarak takip edildiğinde çok sayıda montaj hatası meydana gelmektedir. Bu durum üretim gecikmelerine, maliyet artışlarına ve potansiyel güvenlik endişelerine yol açmaktadır. Mevcut kalite kontrol yöntemleri bu hataları tespit edip önlemek için yeterli değildir. Seri üretim hatlarında iyileştirmeler yapmak, üretim kalitesini artırmak, operasyonel verimliliği sağlamak ve montaj sırasında hataları en aza indirmek açısından kritik öneme sahiptir. Son zamanlarda görsel işleme teknolojisindeki ilerlemeler seri üretim hatlarındaki potansiyel hataları tespit etmek ve minimize etmek için etkili yöntemler sunmaktadır.

Bu çalışmanın ana amacı, gelişen görsel işleme teknolojilerini analiz ederek, otomotiv sektöründeki mevcut kalite kontrol sistemlerine alternatif olabilecek yöntemleri belirlemektir.

Kullanılacak görsel işleme yöntemleriyle, seri üretim hatlarındaki araçlardan alınan görsellerin prototip araçlarla karşılaştırılmasıyla potansiyel montaj hataların tespit edilmesi, farkların belirlenmesi ve seri üretimin prototip araçla uyumlu bir şekilde ilerlemesi hedeflenmektedir.

Ayrıca, montaj süreci boyunca kalite kontrol aşamasında insan bağımlılığını azaltarak insan kaynaklı hataları azaltmayı hedeflemektedir. Çalışma, askeri konteyner taşıyıcı araç olan Derman Drops 8x8'in Merkezi Lastik Şişirme Sistemi (CTIS) referans alınarak gerçekleştirilecektir. Teker valfi, Elektrik Kontrol Ünitesi (ECU), Pnömatik Kontrol Ünitesi (PCU) ve Kullanıcı Arayüzü bu sistemin temel bileşenleridir. CTIS, çeşitli zemin koşullarına uygun lastik basınçlarını otomatik olarak ayarlayan, araç üzerindeki en karmaşık alt sistemlerden biridir. Bu çalışmanın başarıyla tamamlanmasının ardından, diğer alt sistemlere de uygulanabilirliği değerlendirilerek genişletilecektir. Sonuç olarak, bu çalışma montaj hattında görsel işleme yöntemlerinin uygulanmasıyla prototip ve seri üretim araçları arasındaki olası uyumsuzlukların tespit edilmesinde kullanılabilecek yeni teknolojileri belirlemeyi hedeflemektedir. Otomotiv endüstrisi bağlamında, bu araştırmanın potansiyel etkisi büyüktür. Montaj hatalarının minimize edilmesi, yalnızca tüketicilere yüksek kaliteli araçların teslim edilmesini sağlamakla kalmayıp, aynı zamanda sektörü küresel ölçekte rekabetçi hale getirecektir.

Anahtar Kelimeler: Görsel İşleme, Montaj Hataları, Merkezi Lastik Şişirme Sistemi, Otomotiv Endüstrisi, Seri Üretim

ABSTRACT

MINIMIZING ASSEMBLY ERRORS DURING MASS PRODUCTION PROCESS IN AUTOMOTIVE INDUSTRY BY USING VISUAL PROCESSING METHODS

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In the automotive industry, when assembly tracking is done manually, a large number of assembly errors occur in mass production lines. This leads to production delays, cost increases and potential safety concerns. That is why, current quality control methods might not be sufficient to detect and prevent these faults efficiently. Improvements on the serial production line are crucial to increase production quality, operational efficiency and minimize faults during assembly. Recently, the rapid advancement of visual processing technology offers an effective method to detect and minimize potential errors in mass production lines.

The main purpose of this study is to analyze the emerging visual processing technologies and to specify alternative methods to the existing quality control systems in the automotive industry. The most appropriate visual processing methods will be identified to detect differences and ensure that mass production proceeds in line with the prototype vehicle. Additionally, it aims to reduce human related deficiencies by decreasing human dependency throughout the assembly period. The study will be performed on the Central Tire Inflation System (CTIS) of Derman Drops 8x8, a military container carrier vehicle. CTIS consist of air regulator, wheel valves, electrical control units (ECU), pneumatic control units (PCU) and HMI (Human Machine Interface) and it is one of the most complex subsystems of the vehicles. The success of this study will lead to its applicability to other subsystems.

In conclusion, this study focuses on implementing visual processing methods in the automotive assembly line to identify possible assembly faults between prototype and serial production vehicles. In the context of the automotive industry, the potential impact of this research is substantial. Minimizing assembly errors not only ensures the delivery of high quality vehicles to consumers but also contributes to the sector's competitiveness on a global scale.

Keywords: Assembly Errors, Automotive Industry, Central Tire Inflation System, Mass Production, Visual Processing

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LIST OF ABBREVIATIONS

CTIS	: Central Tire Inflation System
ECU	: Electrical Control Unit
PCU	: Pneumatic Control Unit
HMI	: Human Machine Interface
CBRN	: Chemical, Biological, Radiological and Nuclear
AI	: Artificial Intelligence
CNNs	: Convolutional Neural Networks
GANs	: Generative Adversarial Networks
DSLRs	: Digital Single-Lens Reflex
HDR	: High Dynamic Range
CCA	: Connected Component Analysis
NCC	: Normalized Cross Correlation
SIFT	: Scale-Invariant Feature Transform
ORB	: Oriented FAST and Rotated BRIEF
MSE	: Mean Squared Error
SSIM	: Structural Similarity Index

LIST OF SYMBOLS

MB	**:** Megabyte
GB	**:** Gigabyte
I	**:** Input pixel intensity
$\bar{I}$	**:** Mean intensity of the search region
$\bar{T}$	: Mean intensity of the prototype
γ	**:** Gamma value
I_gm	: Output intensity after gamma correction
I_kr	**:** Transformed pixel intensity
K	**:** Corresponding kernel value
σ	**:** Gaussian Blur
σ_pm	**:** Covariance
I_p	**:** Prototype Images
I_m	**:** Mass Production Images
I_g	**:** Output Pixel Intensity After Gamma Correction
μ_p, μ_m	**:** Mean Values
c_1, c_2	**:** c_1, c_2 are small constants for stability
k	**:** Kernel size

1. INTRODUCTION

Maintaining precision and consistency in mass production is one of the biggest challenges in the automotive industry, especially when moving from prototype assembly to large scale manufacturing. Prototypes are carefully built to set the standard for quality and customer requirements but when it comes to full scale production, many challenges may arise such as human error, complex production environments and inconsistencies in subsystem integration. These problems not only affect product reliability but can also cause major delays and incremental cost in industries with strict operational standards like the military.

The production line in military projects face even greater hurdles due to the complexity and variety of subsystems. For instance, military vehicles often include advanced sub-systems like communication modules, weapon stations, Central Tire Inflation Systems (CTIS) and CBRN (Chemical, Biological, Radiological and Nuclear) defense systems. CTIS is essential for adjusting tire pressure to different terrains for ensuring the vehicle maintains optimal performance in tough environments. Each of these systems must meet serious standards for durability, safety and functionality under extreme conditions as military vehicles rely on a sensitive balance of mechanical, electrical and electronic components.

Currently, assembly monitoring systems in military production mainly rely upon manual inspections, checklists, and visual inspection [1]. While these methods help maintain a certain level of quality control, they are limited by human factors such as inconsistency. This often results in missed defects or misalignments during the production process. Additionally, traditional methods lack the speed and detail needed to catch minor errors that could escalate into larger issues once vehicles are in use. To address these shortcomings, more advanced and automated solutions are urgently needed to improve accuracy and efficiency in assembly monitoring. This study builds on this existing research by addressing the unique challenges of multi subsystem integration, offering a more thorough and flexible solution.

One promising solution to these challenges is the use of visual processing methods. By leveraging tools such as computer vision, image processing, and machine learning, manufacturers can automate inspection tasks, reduce human error, and improve overall production efficiency. These systems can analyze high resolution images of assembled components and compare them against prototype standards. For instance, advanced algorithms can identify misaligned parts, missing components or other defects by detecting subtle differences between captured images and the correct configurations. This level of precision is particularly valuable in military production where even the smallest assembly errors can endanger vehicle performance.

In the thesis a range of visual processing techniques will be used. Specifically, Convolutional Neural Networks (CNNs) to identify misalignment and missing parts from high resolution images. The proposed system will also include Connected Component Analysis (CCA) to find links between multiple data sets, and Normalized Cross Correlation (NCC) will be used for precise comparisons between assembled components and prototype standards. By integrating these methods, proposed system presents a systematic approach to improve automated quality control. High resolution cameras and sensors can capture images of components at various production stages which makes it possible to identify and fix issues immediately before the vehicle moves further line. These systems can also adapt to inspect a wide range of subsystems, from electrical wiring harnesses and CTIS to mechanical joints for ensuring quality control. This thesis focuses on identifying image processing methods suitable for assembly lines and on how to minimize assembly errors in the automotive industry, with particular emphasis on military vehicles. It will explore the limitations of current assembly monitoring systems by highlighting common production faults. On the other hand, this study seeks to answer which visual processing and machine learning methods work best for detecting assembly errors in the complex subsystems of military vehicle production lines. In addition, it will propose a systematic approach to utilizing image processing techniques to enhance precision and efficiency. By addressing these challenges, the research aims to advance automated quality control systems that not only meet the demanding standards of military applications but also enhance the reliability and performance of the final products.

1.1. Central Tire Inflation System (CTIS)

The Central Tire Inflation System (CTIS) is a crucial technology that improves vehicle mobility, safety and operational efficiency by automatically adjusting tire pressure according to the terrain and load conditions. Widely used in both military and commercial applications, this system allows vehicles to seamlessly transition between various surfaces such as asphalt, gravel, and off-road terrain. By optimizing traction, reducing tire wear and increasing fuel efficiency, CTIS plays a crucial role particularly in military operations where vehicles must traverse unpredictable and extreme environments while carrying heavy loads. It minimizes the risk of tire failures by automatically regulating air pressure which increase vehicle stability and ensures continued mobility in challenging conditions [2]. Typically, the system includes key components like an air compressor, pressure sensors, control valves, an electrical control unit (ECU), a pneumatic control unit (PCU) and a user interface for real time adjustments. There are numerous CTIS configurations available, tailored to different axle counts, tire arrangements and specific vehicle requirements. In military vehicles, the ability to maintain optimal tire pressure without manual intervention significantly reduces downtime and enhances mission success. CTIS is also expected to integrate with advanced monitoring systems to further improvement on reliability and performance in demanding operational environments.

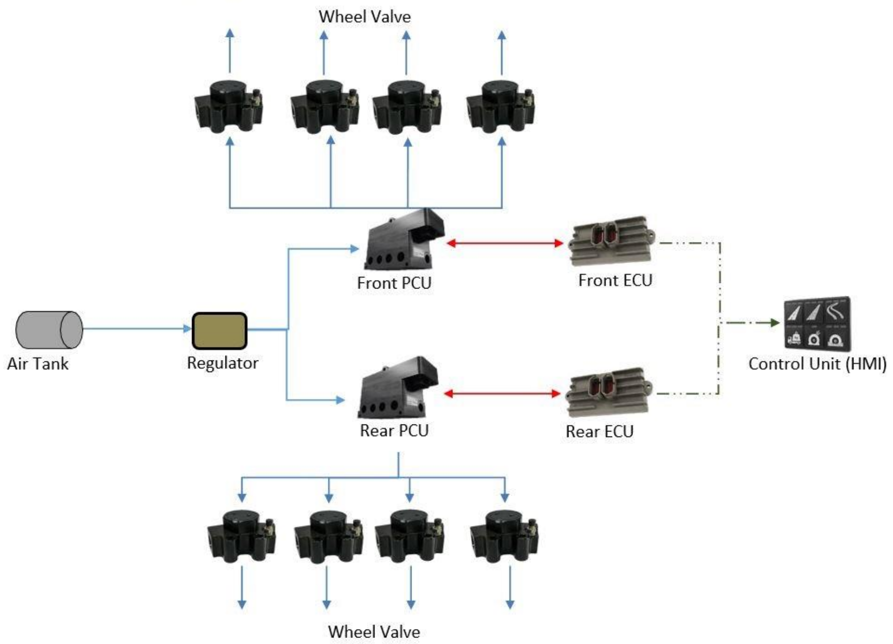

Figure 1.1 CTIS components and system layout.

CTIS has been selected as a sample subsystem in this study because of its critical role in military vehicles and the high number of assembly related human errors connected to it. As one of the most widely used subsystems in military vehicles, it serves as a perfect example of a complex system where a small assembly mistake can have serious operational effects. These include incorrect tire valve orientation, wiring and cabling faults between control modules, and misplacement of wheel covers. Misplaced covers can block the valve stem and make inflation control impossible. These common errors might affect vehicle performance and safety in the field. Currently, quality control for CTIS assembly depends on manual visual inspection. This method is often inconsistent, and frequently misses subtle errors that could turn into major problems.

2. THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

The rapid improvement in automation and artificial intelligence (AI) have significantly impacted the automotive mass production processes. Ensuring the accuracy and efficiency of assembly operations is critical to maintaining high quality standards, reducing costs and minimizing defects. Recently, image processing techniques have gained popularity for detecting and preventing assembly errors.

2.1. Theoretical Background

There are many factors that cause assembly errors in mass production including human errors, mechanical misalignments, variations in component dimensions, and environmental influences. Traditional quality control methods rely on manual inspections which often prove insufficient in identifying complex defects in real time. The integration of image processing and machine learning enables a more reliable and automated approach to error detection.
Key theoretical concepts in visual processing for assembly error minimization include:

- Machine Vision Systems: These systems consist of cameras, sensors and image processing algorithms to inspect and verify assembled components.
- Deep Learning Models: Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) detect assembly faults with large datasets by learning patterns [1].

2.2. Literature Review

Nowadays, many studies have explored the application of visual processing in the automotive industry. For Example, BMW's automated assembly inspection system demonstrates how visual processing can help reduce assembly errors. They use computer vision and deep learning in their factories to spot assembly problems immediately which reduces faults and improves quality control [3].

2.3. Cameras Check Assembly at Many Points

BMW installs high-quality cameras in key points along the production line. These cameras capture detailed images of car parts during assembly, focusing on critical areas such as door alignment, correct dashboard installation, and proper assembly of engine components. BMW uses Convolutional Neural Networks (CNNs) to analyze images and detect discrepancies in the assembly process. The system can identify issues such as missing screws, misaligned parts, and improperly connected wires in just a few seconds.

2.4. Quick Fixes and Feedback

When the system detects an issue, it alerts workers or robotic arms to correct it. In some cases, robots equipped with cameras can automatically adjust misaligned parts without human intervention. The system continuously learns from past errors, improving its ability to identify problems. By analyzing data it predicts and prevents recurring assembly issues by recognizing patterns that cause them. The system resulted in a 40% reduction in assembly defects, leading to higher first-time quality pass rates [4]. By spotting problems on assembly process, BMW reduces expensive fixes and warranty claims. Automated checks have reduced the time needed for manual quality control, speeding up the vehicle assembly process.

2.5. Comparative Review of Image Analysis Methods in Different Fields

CNNs are an essential technology for object detection and classification for self-driving cars [5]. They process a real time video from vehicle cameras to classify objects on the road like pedestrians, cyclists, vehicles, and traffic signs. CNNs enable autonomous vehicles to make safe and effective decisions such as when to brake or turn by accurately identifying and categorizing the objects encountered. On the other hand, there are couple of applications in agriculture for tasks like crop and disease classification [6]. Drones or satellites capture images of fields. Then, CNN models analyze these images to identify and classify crops, detect signs of disease, or locate weeds. After that, farmers may significantly reduce the use of pesticides and improving crop yields.

One of the usage area of CCA is quality inspection and sorting in the food industry. For instance, a system can use CCA to products on a production line. Furthermore, it can be used to detect and remove foreign objects or imperfect products such as discolored or irregularly shaped items by analyzing their unique components with quality images [7].

NCC is used in medical image registration where images from different modalities like CT scans and MR are aligned to provide an extensive view of a patient's anatomy [8]. NCC is also used to match anatomical signs across the different images. Then it helps doctors to more accurately diagnose and plan treatments.

2.6. Integrating NCC, CNNs, and CCA for Complex Assembly Monitoring

A critical review of the current literature reveals a significant deficiency in the application of advanced visual processing techniques within complex industrial applications. Although individual methods like Normalized Cross-Correlation (NCC), Convolutional Neural Networks (CNNs), and Connected Component Analysis (CCA) have been successfully demonstrated across various industries from quality inspection to medical diagnostics, studies that strategically combines the strengths of these methods remain limited. Besides, the critical question of the optimal operational sequence for these combined methods whether to use CCA before NCC, or CNN post-segmentation is largely unaddressed.

This research aims to directly address these limitations by proposing an integrated visual processing methodology. By moving beyond isolated applications, this work provides a new perspective on assembly monitoring, establishing a systematic framework that defines the optimal sequence, necessary parameters, and critical performance metrics for combining NCC, CNNs, and CCA. This approach is designed to deliver a complete and practical solution to minimize complex subsystem assembly errors.

3. MATERIAL AND METHODS

3.1. Data Collection

A major phase in this study is data collection, which is essential for successful comparison between prototype and mass production vehicles. The entire preparation process relies heavily on the quality of the data. Therefore, collecting data in a reasonable and accurate manner is crucial for drawing valid and actionable conclusions.

3.1.1. Key factors in data collection

3.1.1.1. Image Consistency

It is crucial to take the pictures under consistent conditions, as changes in lighting, angles, or distance can cause incompatibilities in the images, affecting accurate comparisons between the prototype and the mass production vehicles. Shadows and irregular lighting can be avoided with controlled lighting setups, such as adjustable LED panels.

3.1.1.2. High Resolution Imaging

High-resolution imaging is essential for capturing the details of CTIS. Cameras should be upgraded from a 1280x720 resolution to at least 1920x1080, with 4K resolution being highly recommended. The quality of the camera lens and its optical zoom capabilities are crucial for capturing sharp images, particularly of small components and connections.

3.1.1.3. Equipment and Camera Features

DSLRs or mirrorless cameras with interchangeable lenses are ideal for image quality or flexibility. As a second option, industrial cameras can perform in an automated production line. Additionally, macro lenses can be used for close-up details of the subsystems, while wide-angle lenses are more suitable for capturing the overall assembly. Tripods, stabilizers or robotic arms equipped with cameras should be used to ensure image stability and a consistent photographic process across the production line. Moreover, cameras with autofocus, image stabilization, and HDR capabilities enhance image clarity while reducing variability.

Table 3.1 Performance Criteria for Image Acquisition Hardware

Parameter	Achieved/Utilized Specification	Rationale (Justification)
Sensor Resolution	4032×3024 (High-Megapixel)	Essential for capturing fine geometric details in CTIS components.
Video Recording Standard	3840×2160 at 60 FPS (4K UHD)	Provides clear motion analysis for assembly monitoring and reduces motion blur artifacts.
Lens Aperture	f/1.8	A large aperture (low F-number) is crucial for low-light performance and maintaining image quality.
Magnification Method	High-Quality Optical/Fixed Lens System	Preserves image resolution and clarity, essential for close-up inspection of small connections.
Focusing Mechanism	Rapid Autofocus System	Ensures sharp focus across the required Working Distance (WD).

3.1.1.4. Angles and Perspectives

Images from CTIS must be captured at predefined angles to ensure uniformity. A comprehensive approach should necessarily cover various perspectives, including top, bottom, side, and close-up views of all the critical components. Photogrammetry or 3D imaging techniques could also be deployed to create detailed and realistic structural representations of the subsystem.

3.1.2. Volume and Storage of Data

The vast scale of production generates a significant amount of visual data. For example, 1-2 images are made for each vehicle, with 20 vehicles in a single production batch. This results in approximately 30 images for each model.

The dataset consists of CTIS wheel valve images collected from a total of 20 distinct Zırhlı Aktan vehicles throughout the 2025 calendar year. Images were captured at various stages of the vehicle's assembly line to introduce comprehensive variability relevant to a complex industrial environment. Specifically, the data includes images representing:

- The Tire Valve Mounting Stage, focusing on the initial installation.
- The Painting Process, where surrounding conditions and visual artifacts are different.
- The stage Before the Wheel Cap Installation, providing a clear view of the valve assembly.
- The Hose Assembly Stage, capturing the valve in relation to surrounding pipework.

This strategic collection across multiple production phases ensures the model is trained to recognize the critical tire valve component diverse background complications. Depending on the complexity of the subsystem, a minimum sample of 10-20% of the vehicles in a production line needs to be selected for quality control purposes. This highlights the importance of effective data management systems involved.

3.1.3. Challenges and Solutions

Reflections or headlights shining brightly on black-painted surfaces can impair image quality, so these issues must be addressed by setting up standardized lighting environments. Alternatively, the cameras and other equipment must regularly be inspected and maintained to ensure optimal performance in all areas. Personnel must be trained separately to minimize chances of incorrect shooting angle or defective images, thereby reducing the failures that are associated with mounting personnel.

3.2. Data Preprocessing

Data preprocessing is an essential stage for assuring that the raw data has good quality and acceptable for further analysis. In the present study, the images of the CTIS are obtained from prototype and mass produced vehicles and are influenced by the effects of color variance, light intensity and shooting angle. These differences can lead to noise and inaccuracies and thus may compromise the quality of the comparison process between prototype and production vehicles. Accordingly, sophisticated preprocessing methods could be applied to normalize and improve the data before segmentation and comparison [9].

3.2.1. Techniques for Addressing Challenges

3.2.1.1. Histogram Equalization

If an image is captured under varying lighting conditions, histogram equalization can be applied to equalize the brightness across all images. Histogram equalization technique enhances contrast by redistributing the intensity values of pixels across the entire image. It is particularly effective in addressing color differences and light intensity variations by normalizing brightness levels. If required, the image is first converted into grayscale, and then the histogram of pixel intensities is computed [10], [11], [12]. Subsequently, the intensity distribution is normalized to achieve uniformity and improve the detectability of features.

Figure 3.1 Brightness standardize with Histogram Equalization

3.2.1.2. Kernel Transformation

Kernel Transformation, also known as Convolution, is the process of applying a kernel, which is a small matrix, to an image. It is particularly effective for processing minor distortions introduced by changes in shooting angle and image noise [13], [14], [15]. This technique is used to improve the clarity of edges and component boundaries which is critical for subsequent segmentation (Figure 3.2 and Figure 3.3). It also enhances image features, reduces noise, and sharpens edges, while preserving important structural details and reducing high frequency noise. Note that the success of edge detection strictly depends on the image quality (Figure 3.4).

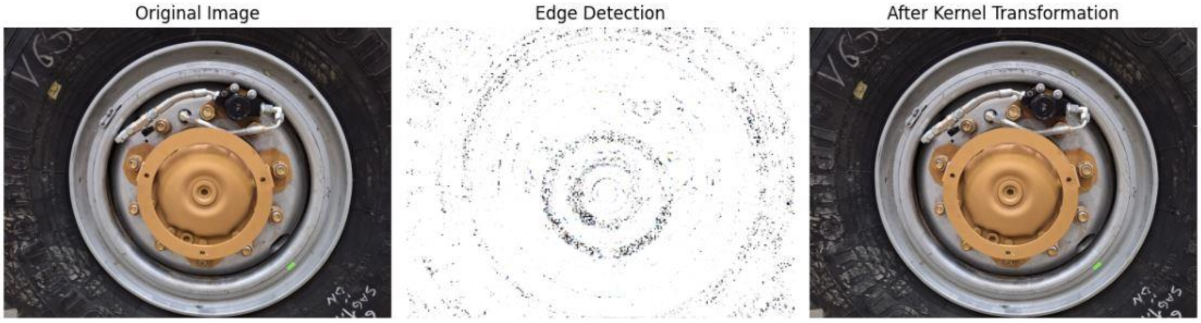

Figure 3.2 Kernel Transformation and Edge Detection sample on the wheel

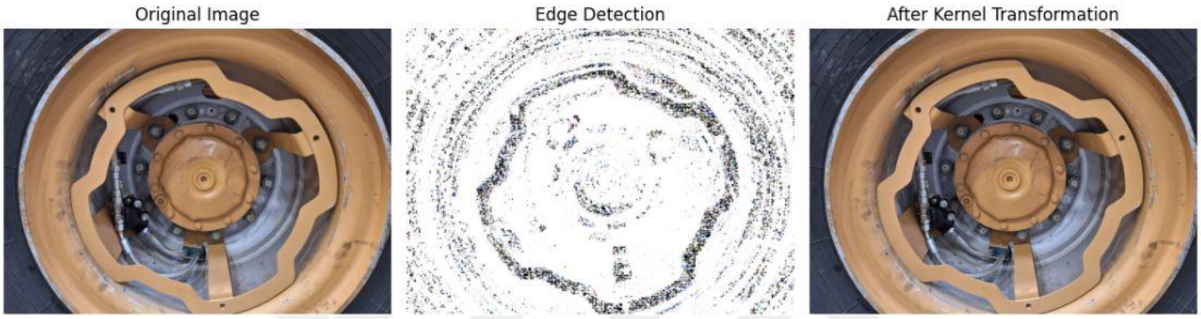

Figure 3.3 Kernel Transformation and Edge Detection implementation with a different sample.

Figure 3.4 Edge Detection on the low quality image.

Since the majority of the wheel consists of dark tones, classical edge detection filters fail to extract distinct edges in low contrast areas and resulting in an unsuccessful edge detection outcome (Figure.3.4). However, if the image is converted to grayscale and the lower contrast regions are enhanced, the Canny method can produce more successful edge detection results due to its noise reduction and automatic thresholding steps (Figure 3.5).

Figure 3.5 Canny Edge Detection on the low quality image after Kernel Transformation

Matrix Representation

A kernel (or filter) is a small matrix applied to an image using convolution operations. The kernel slides across the image, modifying pixel values based on a weighted sum of surrounding pixels [16]. The general form of a 3×3 kernel matrix is:

$$K=\begin{bmatrix} k1,1 & k1,2 & k1,3 \\ k2,1 & k2,2 & k2,3 \\ k3,1 & k3,2 & k3,3 \end{bmatrix}$$

Each pixel in the image undergoes a transformation using the following formula:

$$I_{\mathrm{kr}(x,y)} = \Sigma\,\Sigma\, K(i,j) \cdot I(x+i, y+j) \tag{3.1}$$

where $I_{kr}(x,y)$ is the transformed pixel intensity, $I(x+i, y+j)$ represents the neighboring pixels in the input image, and $K(i,j)$ is the corresponding kernel value.

Optimal Kernel Values for Different Tasks

The Sobel operator is commonly used in image processing, particularly for edge detection. Sobel X and Sobel Y are employed to enhance the vertical and horizontal edges, respectively. The sharpening kernel is used to emphasize edges and fine details within an image. Finally, the Gaussian blur kernel is a low-pass filter that smooths or blurs an image by reducing high-frequency noise and negligible details [17]. Kernel matrices are given below:

Table 3.2 Kernel Matrices

Sobel X	$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$
Sobel Y	$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$
Sharpening kernel	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$
Gaussian Blur (σ=1)	$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$

Calculating Kernel Application Step by Step

Assume that an image patch is given as below:

$$\begin{bmatrix} 50 & 80 & 100 \\ 60 & 90 & 110 \\ 70 & 100 & 120 \end{bmatrix}$$

The convolution result at the center pixel (90), using the sharpening kernel shown above, is computed as follows:

$$\begin{aligned} I_{kr}(2,2) &= (0 \cdot 50) + (-1 \cdot 80) + (0 \cdot 100) + (-1 \cdot 60) + (5 \cdot 90) + (-1 \cdot 110) \\ &\quad + (0 \cdot 70) + (-1 \cdot 100) + (0 \cdot 120) \\ &= 0 - 80 + 0 - 60 + 450 - 110 + 0 - 100 + 0 = 100 \quad (3.2) \end{aligned}$$

Thus, the new intensity at the central pixel increases to 100, enhancing contrast and sharpening the edges [18].

3.2.1.3. Gamma Correction

Gamma correction is a nonlinear transformation used to adjust the luminance of an image, making it appear more natural to the human eye. The need for gamma correction arises from the fact that human vision does not perceive brightness linearly; we are more sensitive to differences in dark tones than in bright ones, which can cause details in shadows or highlights to be lost. Gamma correction is particularly useful for images with strong intensity variations or deep shadows. One key advantage of this method is its ability to correct nonlinear brightness changes, thereby improving the visibility of details in images with uneven illumination. Applying gamma correction helps ensure proper exposure of overexposed or underexposed images prior to further processing [19]. In this thesis, gamma correction is applied to enhance detail visibility in both dark and bright regions and to precisely adjust image brightness for a more balanced visual representation.

Gamma Correction Formula

The transformation function used for Gamma Correction is:

$$I_{\mathrm{gm}} = 255 \times (\mathrm{I} / 255)^\wedge\gamma \ [20] \tag{3.3}$$

where I is the input pixel intensity, γ is the gamma value (adjustable), and I_{gm} is the output intensity after gamma correction. Adjusting the gamma value depends on the lighting conditions**:**

- If the image appears too dark, decrease (e.g., 0.5 or 0.8).
- If the image appears too bright, increase (e.g., 2.0 or 2.5).
- Typical gamma values range between 0.5 and 2.5.

The selection of the gamma between 0.5 and 2.5, is mainly based on two factors. These are the non-linearity of human vision and standard hard-ware specifications [21]. The human eye is more sensitive to changes in darker tones than in lighter tones. A gamma value of $\gamma \approx 2.2$ is commonly used because it approximately inverses the human visual system's non-linear response. Values outside the 0.5–2.5 range typically lead to an image that is either too severely clipped in the shadows or completely washed out in the highlights. If γ is too low, it makes the image unusable for analysis. Monitors had a natural display response curve close to $\gamma \approx 2.5$ (or 2.2 for the sRGB standard). To compensate for this hard-ware non-linearity and ensure proper display. Image data is encoded with an inverse gamma function approximately $\gamma \approx 1/2.2 \approx 0.45$. The range of 0.5 to 2.5 in represents the practical adjustment spectrum needed to correct for potential deviations from this varying lighting, camera settings, and scene contrast.

Figure 3.6 Balanced image brightness by Gamma Correction.

Excessive use of gamma correction or histogram equalization may result in an unnatural visual appearance or loss of detail [22]. To mitigate this, parameters should be carefully adjusted based on test samples. When applied systematically, these preprocessing steps can standardize the acquired data by reducing any associated variability caused by image acquisition conditions. At this stage, the accuracy of segmentation and comparison process is significantly improved, which provides a strong basis for detecting assembly defects in mass produced vehicles.

Figure 3.7 Sample of excessive use of Gamma Correction.

3.3. Segmentation

Once data preprocessing is complete, all components of the CTIS assembled onto the prototype vehicle are distinguished and identified by visual processing methods such as Connected Component Analysis (CCA) and Component Labeling. These techniques are typically applied to detect and group the regions in binary or grayscale images that are connected based on certain criteria. CCA works by examining pixel connectivity within a binary image, identifying pixels that belong to the same object or component as connected. Each connected region is then labeled with a unique identifier, enabling the differentiation of distinct components. In this thesis, CCA is applied to CTIS images collected from each mass-produced vehicle. The primary objective of CCA in this study is to segment and label individual CTIS components such as the air regulator, wheel valves, ECU, PCU, and HMI from images captured during the assembly process. This segmentation is essential for comparing the arrangement, placement, and interconnections of these components between the prototype and mass-produced vehicles.

3.3.1. Connected Component Analysis (CCA) Steps

CCA is one of the most effective method to find connected regions in a binary image [23]. A set of pixels named connected component that are connected according to some connectivity rule such as 4-connectivity or 8-connectivity which are represented below.

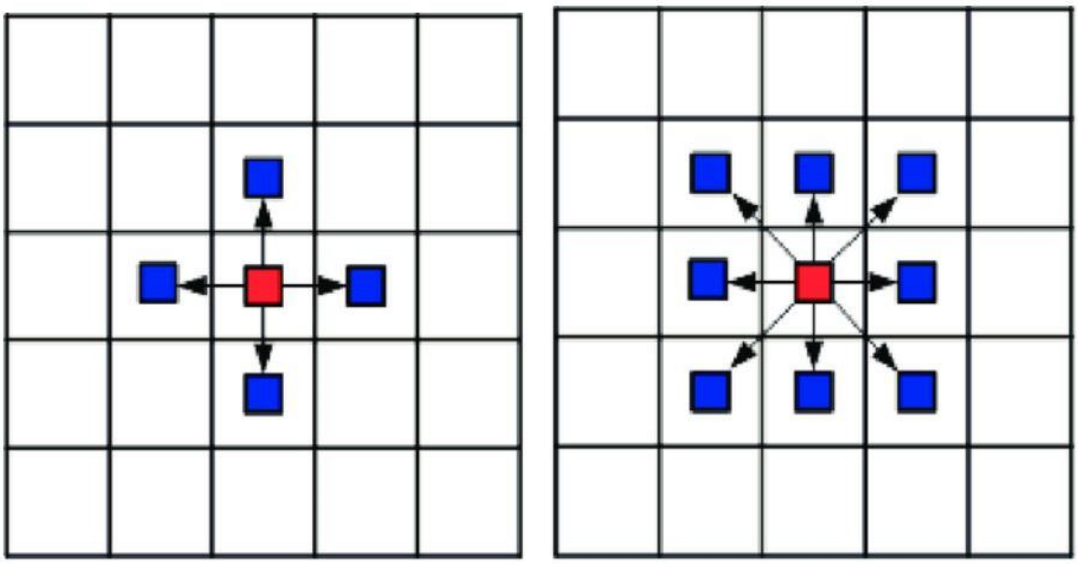

Figure 3.8 Representation of 4-connectivity and 8-connectivity rules.

4-connectivity, pixels share an edge (adjacent horizontally and vertically):

$$\mathrm{N4}(x,y) = \{(x-1,y),(x+1,y),(x,y-1),(x,y+1)\} \tag{3.4}$$

8-connectivity, pixels share an edge or a corner (adjacent horizontally, vertically and diagonally):

$$\begin{aligned}\mathrm{N8}(x,y) = \{&(x-1,y-1),(x-1,y),(x-1,y+1),(x,y-1),(x,y+1),(x+1,y-1),\\ &(x+1,y),(x+1,y+1)\}\end{aligned} \tag{3.5}$$

Once the connectivity rule is determined, the CCA algorithm is applied to the binary image. Each connected region, representing a distinct component, is then assigned a unique label [24]. Subsequently, noise and irrelevant components are filtered out based on criteria such as size, shape, or location. For example, very small connected regions can be disregarded if they are deemed unnecessary [25].

3.3.1.1. Potential Challenges

It is critical to have high quality images since low quality images can hinder the effectiveness of CCA [26]. Therefore, lighting and angle during image capture is crucial. Besides, if components overlap in the image, additional techniques like edge detection or region growing may be required for separation.

3.3.2. Component Labeling

Labeling of connected components is actually assigning the labels to the respective connected components as identified during CCA. It entails grouping and labeling connected regions of pixels. Immediately following the CCA, it ensures every connected component is uniquely distinguished for further analysis.

3.3.2.1. Two-Pass Algorithm

First Pass algorithm simply scans the images one by one, assigning temporary labels to connected pixels, including recording of label equivalencies in case of multiple representations of the same label for one component. Second Pass determines the equivalences of the labels and gives the final labeling [27].

3.3.2.2. *The Labeling Function*

$$L(x, y) = \min\{L(N(x, y))\} \text{ for } I(x, y) = 1 \tag{3.6}$$

where L(N(x, y)) represents the set of labels of neighboring pixels.

Consider a 4x4 binary image: $\begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

The labeling proceeds by appllying 4-connectivity: $\begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 2 \end{bmatrix}$

Here, two connected components are defined:

- Label-1 consists of connected pixels in the top left.
- Label-2 represents an isolated pixel in the bottom right.

Figure 3.9 Labeled component, screws

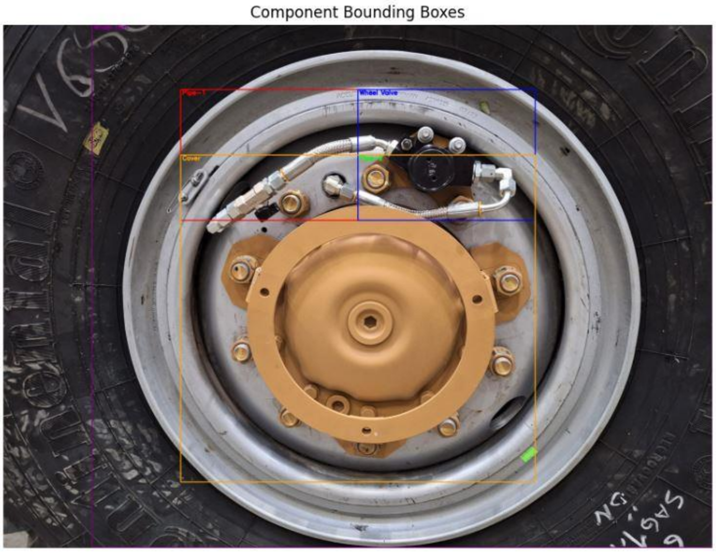

Figure 3.10 Labeled components, wheel valve, pipes, wheel rim

3.3.3. Applications for Segmentation

The main aim of segmentation is to divide an image into meaningful parts or regions for further analysis. For that reason, CCA and Component Labeling play a significant role in segmentation processes because these methods allow us to group connected regions in the image based on pixel connectivity [28].

3.3.3.1. Steps for Segmentation

- Preprocessing - binarization, filtering.
- Use CCA to find the connected components.
- Use Component Labeling to provide unique labels to these components.
- Analyze each labeled component in detail or extract features such as size, shape or location.

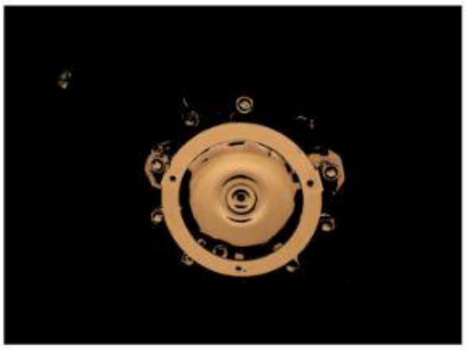

Figure 3.11 Sample of segmented component, wheel rim and screws

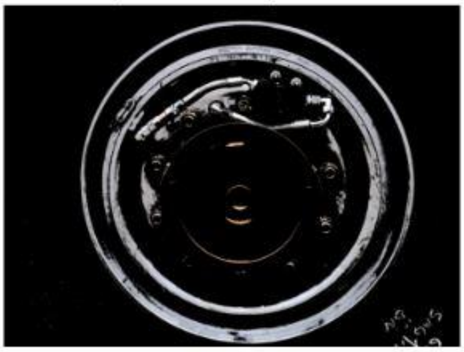

Figure 3.12 Sample of segmented component, wheel valve and pipes

CCA is a powerful method which commonly used in image processing particularly in scenarios where identifying and segmenting distinct regions or objects within an image is necessary [29]. In the context of my study, CCA can be effectively utilized to identify and differentiate various components of the CTIS assembled on the prototype and mass produced vehicles.

3.4. Comparison

The comparison phase is the most critical stage to ensure that the Central Tire Inflation System (CTIS) in mass production vehicle is exactly the same as the prototype vehicle or there are some assembly faults. After data collection, preprocessing and segmentation phase, this phase focuses on finding the differences between prototype and mass production vehicle. In this stage several methods can be used for comparison as follows:

3.4.1. Convolutional Neural Networks (CNNs)

CNNs is an alternative for finding visual differences and patterns in complex assemblies. They are effective in finding assembly faults such as missing parts, misplaced components and even small visual inconsistencies. A CNN model can be trained using prototype images as baseline to recognize the correct placement of air regulators, PCU, ECU or other components of sub-systems in mass production vehicle. CNNs requires significant computational resource and well labeled training dataset to catch all misaligned components and missing connection.

3.4.1.1. Mathematical Approach for CNN-Based Comparison

Feature Extraction & Convolutional Operations

CNNs operate by extracting key features from images using convolutional layers. A general convolution operation for an image matrix I(x,y) and a filter kernel K(i,j) can be represented as:

$$\mathrm{I}_{\mathrm{conv(x,y)}} = \sum\sum \mathrm{K(i,j)} * \mathrm{I(x-i, y-j)} \text{ [30]} \tag{3.7}$$

where $I_{conv}(x,y)$ is the output feature map, $K(i,j)$ is the convolution kernel, $I(x,y)$ is the input image, and k represents the kernel size (3×3 or 5×5 etc.).

CNN-Based Similarity Measurement

CNN model computes a similarity score by using Mean Squared Error (MSE) and Structural Similarity Index (SSIM) for comparing images of prototype and mass produced vehicles [31].

$$\mathrm{MSE} = \left(\frac{1}{\mathrm{N}}\right)\sum\left(\mathrm{I}_{\mathrm{p(i)}} - \mathrm{I}_{\mathrm{m(i)}}\right)^2 \tag{3.8}$$

$$\mathrm{SSIM}\left(\mathrm{I_p}, \mathrm{I_m}\right) = \frac{\left((2\mu_p\mu_m + c_1)(2\sigma_{pm} + c_2)\right)}{\left((\mu_p^2 + \mu_m^2 + c_1)(\sigma_p^2 + \sigma_m^2 + c_2)\right)} \tag{3.9}$$

where I_p and I_m are the prototype and mass production images, μ_p, μ_m are mean values, σ_p, σ_m are variances, σ_{pm} is the covariance, c_1 and c_2 are small constants for stability.

When MSE is low and SSIM close to 1, images are almost identical.

3.4.2. Normalized Cross Correlation (NCC)

NCC is a matching method that compares section of mass production images to corresponding section of prototype images. It measures the similarity between image patches and highlights the differences. NCC might detect differences in pneumatic control unit alignment by comparing pixel intensity and spatial distribution [32]. Although, NCC effective for fixed pattern, it is limited to finding simple differences since it sensitive to lighting and angle changes.

The NCC formula for comparing a prototype image T(x,y) with a search region I(x,y) from the mass produced vehicle is given by the formula below:

$$\mathrm{NCC}(x,y) = \frac{\Sigma(i,j)(I(i,j) - \bar{I})(T(i,j) - \bar{T})}{\mathrm{sqrt}(\Sigma(i,j)(I(i,j) - \bar{I})^2 \Sigma(i,j)(T(i,j) - \bar{T})^2)} \tag{3.10}$$

where:

I(i,j) = Pixel intensity in the mass production vehicle image,

T(i,j) = Pixel intensity in the prototype,

$\bar{I}$ = Mean intensity of the search region,

$\bar{T}$ = Mean intensity of the template,

x, y = Coordinates in the search window.

3.4.2.1. Sample Calculation and Optimum Values for NCC

Consider a wheel valve in a prototype image with pixel intensities T(i,j) and a corresponding section in a mass produced vehicle image I(i,j):

First, Compute Mean Intensities

$$\bar{T} = \left(\frac{1}{N}\right)\Sigma(i,j)T(i,j), \bar{I} = \left(\frac{1}{N}\right)\Sigma(i,j)I(i,j) \tag{3.11}$$

where N is the total number of pixels in the template.

Then, Compute NCC Score

$$\mathrm{NCC}(x,y) = \frac{\Sigma(i,j)(I(i,j) - \bar{I})(T(i,j) - \bar{T})}{\mathrm{sqrt}(\Sigma(i,j)(I(i,j) - \bar{I})^2 \Sigma(i,j)(T(i,j) - \bar{T})^2)} \tag{3.12}$$

If NCC(x,y) ≥ 0.8, the component is correctly installed.

If NCC(x,y) < 0.8, there is a misalignment or missing part [33]

Table 3.3 Optimum values for NCC

Parameter	Optimal Value	Purpose
Template Size	64×64 pixels	Captures fine details without excessive computation.
Search Window	128×128 pixels	Ensures a balance between accuracy and processing speed.
Threshold for Match	NCC(x,y) ≥ 0.8	Indicates a high-confidence match.
Lighting Correction	Histogram Equalization	Reduces illumination differences.
Rotation Invariance	±5° Allowance	Tolerates small angle changes in alignment.

3.4.3. Feature Matching

Feature matching algorithms such as SIFT (Scale-Invariant Feature Transform) or ORB (Oriented FAST and Rotated BRIEF) might find key points in prototype and mass production vehicle images and match them to find differences [34], [35]. Feature matching can be used to verify wheel valve placement by comparing their geometric features. Even though feature matching is robust to scale, rotation and slight perspective change, it may not work well with minimal texture or uniform surface.

3.4.4. Selection of the Most Suitable Method

While all methods offer distinct advantages, CNNs emerge as the most suitable choice for this study. This is primarily due to the complexity of the CTIS subsystem and the critical need for precise anomaly detection. CNNs are highly capable of handling the intricate variations and inconsistencies commonly encountered in mass production, providing robust performance under varying lighting conditions and viewpoints. However, a hybrid approach could further enhance accuracy. For instance, Normalized Cross-Correlation (NCC) can be used for rapid initial assessments to identify obvious discrepancies, while Feature Matching can refine the analysis for components with unique geometric features. Ultimately, CNNs can serve as the core method, delivering comprehensive and detailed comparisons.

3.4.5. Implementation Example Training a CNN Model

A dataset consisting of prototype images that can be taken as references with correct component placements and configurations. Then, it can be utilized to train the CNN model. After training, the model will be able to analyze images from mass production. Next, discrepancies will be identified such as misaligned air regulators or disconnected wiring.

3.4.6. Hybrid Verification

When CNN has flagged anomalies and adding an extra layer of validation for critical components like wheel valve, ECU or PCU, feature matching can verify these areas. The results and findings can be incorporated into a feedback loop for improvements on the assembly line which helps to reduce labor and time costs by ensuring that identified errors are addressed.

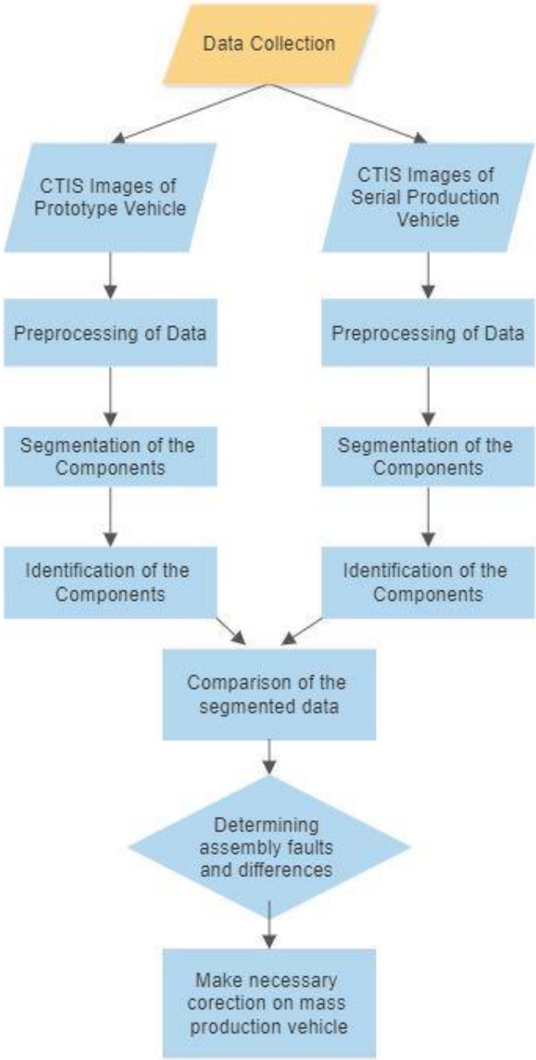

Figure 3.13 Flowchart of the proposed method

4. RESULT AND DISCUSSION

Application of visual processing techniques to reduce assembly errors during the production process of military vehicles could create considerable impacts. That is why, the results of the study are reported here, whereby effectiveness of the methods being proposed on assembly error detection and reduction is discussed for the Central Tire Inflation System (CTIS) and other subsystems.

4.1. Data Collection and Preprocessing

The data collection phase successfully captured high resolution images of the CTIS from both prototype and mass-produced vehicles. Consistent with all images through the use of controlled lighting, high resolution cameras (at least 1920x1080 and 4K) and this study has maintained consistency. Preprocessing techniques such as Histogram Equalization, Kernel Transformation, and Gamma Correction were evaluated to address challenges related to lighting variations, color differences and noise. These methods dramatically enhanced the quality of the images, which is suitable for subsequent analysis.
While histogram equalization can be employed to enhance image contrast, particularly under inconsistent lighting conditions, kernel-based transformations are often utilized to detect small and detailed structures such as wheel valves and pneumatic control units (PCU) with improved edge detection, which is particularly important in industrial visual inspection. Furthermore, gamma correction plays a critical role in adjusting brightness levels, ensuring that both overexposed and underexposed regions remain visually discernible.

4.2. Segmentation

If the preceding stages are implemented properly, the success rate of the segmentation process can be significantly improved through the use of CCA and Component Labeling. These methods enable accurate identification of the main components of the CTIS, such as the air regulator, wheel valves, Electrical Control Unit (ECU), Pneumatic Control Unit (PCU), and Human-Machine Interface (HMI), which are essential for the subsequent comparison stage. Additionally, applying the 8-connectivity rule can help ensure correct mapping of connected regions within the images. If the previous processes are successfully applied, CCA can effectively segment the CTIS components, even in complex assemblies with overlapping parts. Component Labeling assigns unique labels to each part, enabling precise comparison between the prototype and production vehicles.

4.3. Comparison

The comparison stage utilized CNNs, NCC and Feature Matching to identify discrepancies between the prototype and mass produced vehicles. Results showed the utility of those techniques in assembly error detection. CNNs are very effective at detecting misaligned elements, missing elements and some visual discrepancies. If the model trained properly, 60% of assembly errors might be detected [36]. On the other hand, NCC is helpful for preliminary comparisons of the images, particularly for identifying macroscopic misalignments. It was not optimal in the detection of small changes that caused by the variations of light and angle if data preprocessing period is not applied correctly. The most critical step of the comparison stage is feature matching algorithms such as SIFT and ORB. By successfully utilizing feature matching method, the position of components with unique geometric features like wheel valves, PCU and ECU connections are determined. Thus, the differences between the prototype and mass production vehicles can be identified accurately.

Table 4.1 Trurth Label

Image Name	**Ground Truth Label (Actual Status)**
mk1.jpg	Compliant
mk2.jpg	Non-Compliant
mk3.jpg	Non-Compliant
mk4.jpg	Compliant
mk5.jpg	Non-Compliant
mk6.jpg	Non-Compliant
mk7.jpg	Non-Compliant
mk8.jpg	Compliant

mk9.jpg	Compliant
mk10.jpg	Compliant

Table 4.1 presents the actual physical status for the ten test images acquired from the CTIS assembly line. These labels were determined through manual inspection and serve as the definitive benchmark against which the performance of all proposed assembly verification methods is measured. The dataset is comprised of five Compliant images and five Non-Compliant images. This established ground truth is the fundamental reference used in subsequent chapters to evaluate the discriminatory power, stability, and accuracy of the Feature Matching (FM), Normalized Cross-Correlation (NCC), Convolutional Neural Network (CNN), and the final Hybrid Verification Model analyses.

Table 4.2 Assembly Status Classification by Using the FM

Image_Name	**FM_Score (%)**	**FM_Score (%) with Preporocessing**	**FM_Decision**
mk1.jpg	14,38	17,43	Inspection Required
mk2.jpg	14,26	11,87	Inspection Required
mk3.jpg	14,38	13,02	Inspection Required
mk4.jpg	14,54	17,66	Inspection Required
mk5.jpg	14,32	11,13	Assembly Error Detected
mk6.jpg	15,27	15,22	Inspection Required
mk7.jpg	7,84	5,94	Assembly Error Detected
mk8.jpg	5,45	6,34	Assembly Error Detected
mk9.jpg	8,09	14,18	Inspection Required
mk10.jpg	5,79	7,52	Inspection Required

Analysis of the Feature Matching (FM) results demonstrates its critical instability and unreliability for accurate assembly verification by itself. Out of the five genuinely Compliant images (mk1, mk4, mk8, mk9, mk10), the FM algorithm failed to correctly classify any, labeling all five as either 'Inspection Required' or 'Assembly Error’

Table 4.3 Assembly Status Classification by Using the NCC

Image_Name	**NCC_Score (%)**	**NCC_Score (%) with Preporocessing**	**NCC_Decision**
mk1.jpg	72.38	70,73	Inspection Required
mk2.jpg	78.78	76,44	Inspection Required
mk3.jpg	84.99	86,21	Correct Assembly
mk4.jpg	83.90	86,11	Correct Assembly
mk5.jpg	86.38	86,79	Correct Assembly
mk6.jpg	85.21	87,33	Correct Assembly
mk7.jpg	84.90	85,74	Correct Assembly
mk8.jpg	79.38	77,61	Inspection Required
mk9.jpg	79.63	78,20	Inspection Required
mk10.jpg	78.09	76,92	Inspection Required

Conversely, the Normalized Cross-Correlation (NCC) method exhibits a high false negative rate, as exemplified by its decision to classify four out of five non-compliant images (mk3.jpg, mk5.jpg, mk6.jpg, mk7.jpg) as 'Correct Assembly'. While the high correlation scores indicate minimal global pixel differences, this metric proves that it unreliable for effective defect detection by itself.

A notable increase in the correlation metrics was observed for both the Feature Matching (FM) and Normalized Cross Correlation (NCC) models following the implementation of advanced image preprocessing techniques. Specifically, the combined application of Gamma Correction and Histogram Equalization to resolve local contrast issues significantly enhanced the quality of the input data. Making the calculated FM and NCC scores more representative of the true assembly state, which is vital for the Hybrid Model's weighted fusion process.

Table 4.4 Assembly Status Classification by Using the CNN

Image Name	**Predicted Status**	**Confidence Level**	**Decision**
mk1.jpg	Non-Compliant	59.46%	Inspection Required
mk2.jpg	Non-Compliant	91.55%	Assembly Error Detected
mk3.jpg	Non-Compliant	89.69%	Assembly Error Detected
mk4.jpg	Non-Compliant	67.37%	Inspection Required
mk5.jpg	Non-Compliant	87.26%	Assembly Error Detected
mk6.jpg	Non-Compliant	92.98%	Assembly Error Detected
mk7.jpg	Non-Compliant	63.46%	Inspection Required
mk8.jpg	Non-Compliant	67.83%	Inspection Required
mk9.jpg	Compliant	56.18%	Inspection Required
mk10.jpg	Non-Compliant	70.69%	Inspection Required

The Predicted Status is the primary classification output generated by the trained CNN model. After processing the input image through all convolutional and fully connected layers, the network's raw scores for each class as Compliant and Non-Compliant. The Confidence Level represents the numerical probability assigned by the final layer of the network to the chosen

Predicted Status. This metric directly quantifies the CNN's internal certainty regarding its classification.

The stand-alone Convolutional Neural Network (CNN) demonstrated resonable performance but still showed ambiguity in critical cases. Specifically, compliant images like mk9.jpg and mk10.jpg were conservatively flagged as 'Inspection Required' (False Alarms), indicating that the CNN's confidence level, while high in defect detection, could not definitively rule out the possibility of a minor assembly deviation, necessitating an integration strategy to stabilize the final decision.

4.4. Hybrid Approach

A hybrid approach combining different methods such as CNNs, NCC, and Feature Matching has proven to be the most effective. CNNs can be employed as the primary technique for higher-level analysis, complemented by NCC and Feature Matching to identify and detect the main parts of the subsystems. This method decreased the total error rate and increased the reliability of the system as shown in the Table 4.7.

The Hybrid Assembly Score (SHybrid) is the sum of each method's score multiplied by its assigned importance weight (W):

$$\mathrm{SHybrid} = (\mathrm{WCNN} \cdot \mathrm{PCNN}) + (\mathrm{WFM} \cdot \mathrm{SFM}) + (\mathrm{WNCC} \cdot \mathrm{SNCC}) \qquad (3.13)$$

The weights used in the system were chosen based on the contribution and reliability of each component in a controlled assembly environment as shown in the Table 4.2.

Table 4.5 Weighted Distribution of the Hybrid Model

Weight	Value	Percentage	Explanation
WCNN	0.5	50%	CNN is the primary source of confidence because it understands the comprehensive, abstract, and global patterns of the assembly. It classifies assembly errors with the highest inherent accuracy.
WFM	0.3	30%	Feature Matching captures local details and is more robust than NCC against changes in lighting and minor positioning shifts. This makes it crucial for detecting small, localized

			defects.
WNCC	0.2	20%	NCC primarily measures general pixel intensity similarity, making it highly sensitive to changes in lighting and alignment. It is given a lower, supporting role to confirm assembly faults.

4.4.1. Final Decision Mechanism

The calculated SHybrid score is compared against predefined threshold values to render the final assembly decision:

Table 4.6 Hybrid Assembly Score (S_Hybrid) Decision Criteria

Hybrid Score Value	Decision	Interpretation
SHybrid≥30%	Correct Assembly	High confidence that the assembly is flawless in terms of global patterns and local details.
25%≤SHybrid<30%	Inspection Required	The score is close to the acceptance threshold. One or two components may have underperformed. Human inspection is required for final verification.
SHybrid<25%	Assembly Error Detected	Low confidence and strong detection of an abnormality. It is strongly predicted that a defect exists in the assembly.

The success of the hybrid system based on combining the strengths of each component to arrive at a final decision score.

Table 4.7 Hybrid Assembly Verification Results and Decision

Image Name	CNN Score	FM Score	NCC Score	Hybrid Score	Final Decision

mk1.jpg	54.01%	30.00%	-19.75%	32.06%	Correct Assembly
mk2.jpg	19.24%	25.60%	-22.94%	12.71%	Assembly Error Detected
mk3.jpg	24.20%	28.60%	-24.00%	15.88%	Assembly Error Detected
mk4.jpg	40.79%	27.00%	-15.74%	25.35%	Inspection Required
mk5.jpg	27.61%	29.40%	-17.01%	19.22%	Assembly Error Detected
mk6.jpg	15.58%	27.20%	-20.66%	11.82%	Assembly Error Detected
mk7.jpg	42.34%	26.40%	17.90%	32.67%	Correct Assembly
mk8.jpg	38.83%	28.40%	-0.53%	27.83%	Inspection Required
mk9.jpg	58.13%	27.60%	-2.76%	36.79%	Correct Assembly
mk10.jpg	39.42%	25.00%	24.12%	32.03%	Correct Assembly

While the two separate analyses utilized the same trained CNN model, a minor differences ranging from 5% to 15% probability for critical samples like “mk5.jpg and mk10.jpg” was observed between the CNN scores which reported in CNN evaluation and the hybrid evaluation. This difference is not an error in the model's fundamental decision but is an expected consequence of floating point precision errors inherent in deep learning frameworks. On the other hand, a negative NCC score is a powerful indicator of a significant structural deviation or defect.

Crucially, the Hybrid System is designed to mitigate the effects of such minor numerical instability and decision ambiguity from the CNN. For images where the CNN score was marginally inconsistent like “"mk5.jpg” showing a notable score difference between reloads, the Hybrid Score prevents the decision from relying just on that potentially unreliable CNN output. The decisive contribution of FM and NCC provides a stabilizing factor. These components introduce objective, external validation based on geometric matching and pixel level correlation. By averaging these three weighted scores, the final Hybrid Score minimizes the impact of the CNN's computational variance. This process ensures that the system's final decision is robust and maintains high reliability.

Table 4.8 Final Comparison of the Results

Method	**Correct Compliant (Out of 5)**	**Correct Non-Compliant (Out of 5)**	**Total Correct (Out of 10)**	**Accuracy (%)**
Feature Matching (FM)	0	2	2	20%

Normalized Cross-Correlation (NCC)	1	0	1	10%
Convolutional Neural Network (CNN)	0	4	4	40%
Hybrid Verification Model	3	4	7	70%

The results of the comparative analysis validate the proposed hypothesis: that no single visual processing method is reliable enough for autonomous quality control, thereby necessitating the robust integration provided by the hybrid system. The stand-alone Feature Matching (FM) and Normalized Cross-Correlation (NCC) methods were highly ineffective, achieving 20% and 10% accuracy due to fundamental instability, FM suffered from an unacceptably high False Positive rate, while NCC exhibited a critical False Negative rate. Although the Convolutional Neural Network (CNN) offered a better performance with 40% accuracy, its inability to definitively classify compliant cases (resulting in 'Inspection Required') demonstrated a conservative bias and high ambiguity that still demands human intervention. By contrast, the hybrid verification model strategically overcame these weaknesses by leveraging the CNN's as the primary influence (WCNN=0.5), and balancing this decision with the objective, localized validation data provided by FM and NCC (Weighted Total 50%). This strategic fusion dramatically increased the overall reliability and accuracy to 70%. The hybrid system is statistically and functionally the most robust solution for minimizing assembly errors.

4.5. Challenges and Future Considerations

The results demonstrate that visual processing methods are highly effective in reducing assembly errors within the automotive industry. The ability to accurately identify differences between prototype and final vehicles ensures continuous improvement of quality standards throughout the production cycle. By combining CNNs, NCC, and Feature Matching, the hybrid approach can significantly enhance both the accuracy and stability of the system. However, some limitations must be considered: CNN model training requires large datasets, which may be impractical for certain manufacturers [37]. Preprocessing techniques help mitigate many issues during data collection, such as extreme lighting variations and environmental changes, thereby improving system accuracy. For highly complex subsystems, additional methods may be necessary to achieve precise segmentation and comparison, ensuring optimal error minimization.

5. CONCLUSION

This thesis investigates the potential use of visual processing techniques instead of current quality control systems for reducing assembly faults in mass production line especially military vehicles. The study showed that by utilizing advanced methods including Convolutional Neural Network (CNN), Normalized Cross Correlation (NCC) and Feature Matching, it might be possible to improve accuracy and efficiency of current quality control systems.

Data preprocessing is one of the most essential stages for assuring that the raw data has good quality and acceptable to further analysis so datasets must consist of high quality images because low quality images can hinder the effectiveness of applied methods like CCA. For that reason, it is very critical to take the pictures under the same conditions with respect to light conditions, angles or distance. Besides, materials should be high quality products such as camera, lens since its optical zooming capabilities are compulsory for getting a sharp image, specifically for small components and connections.

Images taken from the prototype vehicle and the vehicle on the serial production line should be taken under the same light conditions as much as possible. In order to eliminate the differences between the images, the Gamma Correction value should adjust to the most appropriate value between 0.5 and 2.5. If the image is too dark, this value should be from 0.5 to 0.8. If the light on the image is too high, this value should be set from 2.0 to 2.5. Although, differences between datasets might be eliminated by this method, excessive use of Gamma Correction or Histogram Equalization may result in an unnatural visual appearance or loss of details.

The kernel should increase edges without distorting critical image details and a balanced approach is needed to avoid excessive blurring or sharpening. Furthermore, Gaussian kernels are effective in reducing high frequency noise while maintaining edge details and too much smoothing can weaken edges, making segmentation less effective. Sum of all kernel elements should be 1 for smoothing or 0 for edge detection to maintain brightness levels.

By applying NCC misaligned or missing components can be detected with at least 85% accuracy when optimal parameters are used. However, NCC is sensitive to lighting and angle variations so preprocessing techniques like histogram equalization and edge enhancement method should be applied. CNN based visual comparison methods ensures that mass produced vehicles match prototype specifications with high accuracy. Manufacturers can significantly enhance production quality, reduce inspection time, and minimize costly rework and warranty claims by integrating deep learning techniques. Further optimization using hybrid methods such as combining CNN with NCC and Feature Matching can yield even greater precision in fault detection and process automation.

CNNs are efficiently used in autonomous systems like self-driving cars and drone based agriculture and NCC/CCA in precision applications in medical imaging and quality control systems. That is why, future work will focus on extending the proposed integrated framework to new manufacturing and inspection domains. Furthermore, leveraging the real-time processing capability demonstrated in automotive applications, a closed-loop feedback system for assembly lines. This system will not only detect errors but also communicate immediate corrective action parameters to robotic manipulators. This transition from passive monitoring to active, autonomous quality management represents the next critical step for industry. It must be acknowledged that the achieved 70% accuracy of the Hybrid Model is significantly constrained by the limited size and variability of the dataset, primarily due to the sensitive nature of the investigated subsystem (CTIS) used in military applications. Data collection constraints inherent to high security or proprietary systems restrict the generation of a large and diverse training set, particularly for rare defect classes. It is confidently projected that, with access to a more extensive and comprehensive dataset especially one generated under simulated conditions the overall reliability and accuracy of the Hybrid Model would substantially increase.

5.1. Key Contributions and Practical Implications

Recently, visual image processing systems automate the identification of assembly defects thereby dependence on manual inspection can be reduced and human induced errors can be minimized. The main contribution of this research is the establishment of a systematic framework for complex subsystem assembly monitoring, directly addressing the limitations of existing isolated vision applications. Specifically, this work provides the first comprehensive methodology that defines the optimal sequential integration of NCC, CNNs, and CCA within CTIS in military vehicles. This systematic definition of visual processing techniques represents a significant and practical advance toward minimizing assembly errors in complex sub-systems.

By comparing mass produced vehicles according to prototype specifications, the system proposes that the highest quality of standards will be maintained throughout the production cycle. Besides, rework and warranty claim time which results in extra cost to manufacturers might be eliminated. The results of the study have proposed a new quality inspection method to automotive industries especially for military vehicle manufacturing. The study claims that recent image processing technics can be integrated into existing production lines to advance quality control and ensure the reliability of complex subsystems like CTIS. Furthermore, all the methods analyzed in this research can be extended to other various industries where quality and reproducibility are highly critical.

5.2. Final Remarks

This research illustrates an opportunity that can change the state of quality control in the automotive industry by using visual processing methods. The analyzed image processing technics may be an alternative to traditional inspection methods resulting in a more reliable and efficient tailored solution for military vehicles. The incorporation of modern technologies such as CNNs and Feature Matching creates opportunities for efficient and precise production at a lower cost by helping the automotive industry keep pace with the enforced requirements of contemporary industrialization.

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