Review on Low-Cost Image Processing Solution for Rivet Quality Inspection

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Abstract— Rivets are critical fastening elements used in aerospace, automotive, and construction industries where structural integrity is essential. Traditional inspection methods rely on manual techniques, which are slow, inconsistent, and prone to human error. This paper presents a low-cost automated rivet inspection system using image processing and computer vision techniques. The proposed system integrates Python-based image processing, Programmable Logic Controllers (PLC), and Internet of Things (IoT) technologies to enable real-time inspection and monitoring. The system improves inspection accuracy, reduces processing time, and provides an affordable solution for small and medium-scale industries.

Keywords— Image Processing; Rivet Inspection; Computer Vision; PLC; IoT; Quality Control

I. INTRODUCTION

Riveted joints are widely used in aerospace, automotive, and construction industries where safety and durability are critical. The quality of rivets directly influences structural integrity and long-term performance of assembled structures. Even minor defects such as improper head formation, cracks, or misalignment can lead to severe failures.

Traditional inspection methods rely heavily on manual visual inspection and mechanical measurement tools. Such methods not only require time but are also prone to inconsistencies due to human fatigue and subjective judgment. Typically, manual inspection systems process only 20–30 rivets per minute, which significantly limits production efficiency in high-speed manufacturing environments.

With the emergence of Industry 4.0, there is a growing demand for intelligent, automated inspection systems capable of delivering accurate and real-time results. Computer vision-based systems offer a promising solution by enabling automated defect detection and dimensional analysis.

This paper focuses on developing a low-cost rivet inspection system by integrating image processing, PLC-based control, and IoT-enabled monitoring. The proposed solution aims to balance cost, performance, and scalability, making it suitable for small and medium enterprises.

II. LITERATURE REVIEW

A. Machine Vision-Based Inspection Systems

Machine vision systems have significantly improved industrial inspection processes by enabling automated, high-speed, and accurate defect detection. Smith et al. [1] developed a machine vision system capable of achieving inspection speeds of 300–500 rivets per minute using high-resolution cameras and edge detection techniques. Similarly, Kim et al. [2] demonstrated the effectiveness of morphological operations and contour analysis for precise measurement and defect detection. These approaches provide improved efficiency compared to manual inspection; however, their performance is often sensitive to environmental conditions such as lighting variations and surface reflections.

B. Deep Learning and Advanced Inspection Techniques

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly enhanced defect detection capabilities. CNN-based systems can achieve accuracy levels of up to 98% and are capable of detecting micro-defects that are difficult to identify using traditional methods. Despite their high accuracy, these systems require large datasets and computationally expensive hardware, which limits their adoption in cost-sensitive industrial environments.

In addition to deep learning, 3D sensor-based systems have been explored for high-precision inspection. Techniques such as 3D scanning, point cloud processing, and structured light imaging provide highly accurate geometric analysis. However, these approaches involve complex setups and high implementation costs, making them less practical for small and medium-scale industries.

C. Rivet Inspection and Dataset Challenges

Rivet joint inspection plays a critical role in aircraft manufacturing, where structural integrity depends on the quality of thousands of rivets. Traditional inspection methods rely on manual visual examination, which is time-consuming, labor-intensive, and prone to human error, especially for detecting subtle defects in complex structures.

Early research in defect detection focused on general surface defects such as cracks, scratches, and corrosion using datasets like NEU-DET and GC10-DET. While these datasets have facilitated advancements in defect detection, they are not specifically designed for rivet inspection. Rivet defects have unique structural characteristics, making it difficult to directly apply models trained on general-purpose datasets.

Classical machine learning techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) have shown reasonable performance under controlled conditions. However, these methods are highly sensitive to variations in lighting and background, which reduces their effectiveness in real industrial environments.

A major challenge identified in the literature is the lack of publicly available datasets specifically designed for rivet defect detection. To address this issue, Amosov et al. developed a dedicated dataset using a physical model of riveted plates, providing images of both normal and defective rivets [24].

D. Two-Stage Deep Learning Frameworks

Modern defect detection systems increasingly adopt two-stage frameworks that separate localization and classification tasks. Object detection models such as YOLO (You Only Look Once) are widely used for real-time detection due to their balance between speed and accuracy [25]. Among these, YOLOv5 has demonstrated strong performance in industrial inspection applications. For classification, lightweight CNN architectures such as MobileNetV3 provide an efficient solution with reduced computational requirements. The combination of YOLOv5 for rivet detection and MobileNetV3 for classification forms a robust and scalable inspection framework capable of real-time operation.

E. Industry 4.0 and System Integration

The emergence of Industry 4.0 has transformed manufacturing through the integration of automation, data exchange, and intelligent systems. Technologies such as IoT, artificial intelligence, and cloud computing enable real-time monitoring and decision-making in industrial environments [3].

Machine vision systems play a central role in automated quality control by converting visual data into digital information for defect detection and analysis. When integrated with Programmable Logic Controllers (PLCs), these systems enable closed-loop control, ensuring synchronization between inspection and production processes. PLCs have evolved significantly, offering high-speed processing, deterministic control, and support for industrial communication protocols such as Ethernet/IP, Profinet, and Modbus TCP/IP [1].

F. Vision-PLC Integration and Industrial Applications

The integration of machine vision systems with PLCs introduces challenges related to communication latency, synchronization, and reliability. Industrial communication protocols play a crucial role in ensuring efficient data exchange between components. Recent studies have demonstrated the effectiveness of cyclic communication models, which enable continuous data exchange with minimal latency [14]. Integration with Manufacturing Execution Systems (MES) further enhances production efficiency through data-driven decision-making.

Industrial case studies in welding inspection, automotive manufacturing, and electronics assembly have shown that vision-PLC systems can achieve detection accuracy above 95% while reducing false positives [6]. These systems provide improved consistency, adaptability, and operational robustness.

G. Machine Vision System for Rivet Inspection

The study titled "A Machine Vision System for Online Metal Can-End Rivet Inspection" presents a significant contribution to the domain of automated industrial inspection by addressing the problem of rivet defect detection in metal can-end manufacturing. The paper highlights the importance of rivet integrity in ensuring the functionality and safety of easy-open can systems, particularly in the food packaging industry.

The authors review existing approaches for defect detection in manufacturing systems, noting that simple sensing techniques such as proximity sensors and strain gauges are limited in scope. These methods can detect only specific types of defects related to mechanical parameters, such as thickness variations or missing components. In contrast, machine vision systems have emerged as a powerful alternative for industrial inspection tasks.

A key contribution of the reviewed work lies in proposing a dedicated machine vision-based approach tailored for rivet defect detection. The system employs classical image processing techniques, including segmentation using Otsu's method, morphological filtering, and connected component analysis. These techniques are used to isolate the rivet region and extract relevant features such as area and circularity.

Experimental evaluation of the system demonstrates high performance, with an accuracy of 98.13%, precision of 97.67%, and recall of 95.83%. The system achieves an average processing time of approximately 38 milliseconds per image, making it suitable for high-speed industrial environments.

H. Research Gaps and Future Directions

Despite significant advancements, several research gaps remain. Many studies focus on improving model accuracy while overlooking system-level challenges such as real-time communication, latency, and industrial safety requirements. Additionally, most solutions are validated in controlled environments, with limited deployment in real-world industrial settings.

Future research should focus on hybrid AI–PLC architectures that combine intelligent defect detection with deterministic control. The integration of edge computing and predictive maintenance can further enhance system performance. Additionally, the development of domain-specific datasets and robust communication protocols will be critical for advancing automated rivet inspection systems.

I. Summary

The literature indicates a clear transition from manual inspection and traditional image processing techniques to advanced deep learning-based systems integrated with industrial automation technologies. While machine vision and AI provide high accuracy in defect detection, PLCs ensure reliable and synchronized operation. The convergence of these technologies represents a key enabler for smart manufacturing systems under the Industry 4.0 paradigm.

III. SYSTEM ARCHITECTURE

The proposed system architecture is designed to enable automated rivet inspection by integrating machine vision, edge computing, industrial control systems, and cloud-based analytics into a unified framework. The architecture follows a modular and layered approach to ensure scalability, real-time performance, and seamless communication between components.

At the input stage, cameras and sensors capture real-time image data of rivet joints from the production line. The captured images are transmitted to the edge processing unit for further analysis. The core processing is performed within the edge microservices layer, which handles real-time data processing close to the source.

This layer consists of multiple functional modules. The image acquisition module receives and preprocesses incoming images to ensure consistency in format and quality. The major analysis module performs defect detection using computer vision and deep learning algorithms, identifying rivets and analyzing their structural condition. Following this, the measurement module extracts quantitative parameters such as dimensions, alignment, and surface characteristics to support precise inspection.

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The edge layer is supported by an edge technology stack, which includes tools and platforms such as Python, OpenCV, and NumPy for image processing and model execution. Containerization technologies like Docker enable modular deployment and scalability, while compatibility with operating systems such as Windows and Linux ensures flexibility in industrial environments.

The Programmable Logic Controller (PLC) acts as the central control unit in the system. Communication between the edge system and the PLC is established using industrial protocols such as Modbus TCP, ensuring reliable and deterministic data exchange. The PLC receives inspection results and makes control decisions, such as triggering sorting mechanisms or flagging defective components.

A local user interface (UI) is integrated into the system to provide real-time feedback to operators. This interface displays inspection results, system status, and alerts, enabling human operators to monitor system performance and intervene when necessary.

In addition to edge-level processing, the system includes a cloud layer for advanced data management and analytics. Inspection data is transmitted to the cloud for IoT-based data aggregation, where it is stored and processed for long-term analysis. The cloud layer includes an analytics engine that performs trend analysis, defect pattern recognition, and performance evaluation.

Fig. 1. Proposed System Architecture for Rivet Inspection

IV. METHODOLOGY

The proposed rivet inspection system is based on a structured image processing pipeline designed to ensure accurate defect detection and dimensional analysis. The methodology follows a sequential approach consisting of image acquisition, preprocessing, segmentation, feature extraction, and classification. Each stage plays a crucial role in improving the overall performance of the system.

A. Image Acquisition

The first step involves capturing high-quality images of rivets using an industrial camera with a resolution of 2–5 megapixels. Controlled lighting conditions are maintained to minimize shadows and reflections caused by metallic surfaces. Uniform illumination ensures consistent image quality, which is essential for reliable analysis. According to Smith et al. [1], proper lighting significantly improves edge detection accuracy in machine vision systems.

B. Image Preprocessing

Preprocessing is performed to enhance image quality and reduce computational complexity. The captured RGB image is converted into grayscale to simplify processing. Histogram equalization is applied to improve contrast, making features more distinguishable. Noise reduction is achieved using median filtering, which effectively removes impulse noise while preserving edges.

Mathematically, the grayscale conversion is represented as:

$$I(x, y) = 0.299R + 0.587G + 0.114B$$

This step ensures that the image is suitable for further analysis while maintaining important structural details [2].

C. Segmentation

Segmentation isolates the rivet from the background using thresholding techniques. Adaptive thresholding is preferred over global thresholding as it handles varying lighting conditions effectively. The grayscale image is converted into a binary image, where the rivet region is separated from the background. The thresholding operation is defined as:

$$g(x, y) = \{ 1, \text{ if } f(x, y) > T; 0, \text{ otherwise } \}$$

where T is the threshold value. This step is critical for accurate feature extraction.

D. Feature Extraction

Feature extraction involves identifying key characteristics of the rivet using edge detection and contour analysis techniques. The Canny edge detection algorithm is widely used due to its robustness in detecting edges under noisy conditions. It involves gradient calculation, non-maximum suppression, and hysteresis thresholding. The extracted features include:

- Head diameter

- Circularity
- Surface irregularities
- Edge sharpness

Circularity is calculated as:

$C = 4\pi A / P^2$

where A is the area and P is the perimeter of the rivet contour. A perfect rivet has circularity close to 1.

E. Classification

The classification stage determines whether a rivet is acceptable or defective. This is achieved by comparing extracted features with predefined threshold values based on industrial standards. If the deviation exceeds permissible limits, the rivet is classified as defective.

Advanced systems may use machine learning models such as Support Vector Machines (SVM) or Convolutional Neural Networks (CNNs) for classification. According to Hussain [5], CNN-based systems can achieve accuracy above 96% in defect detection.

F. Integration with PLC and IoT

The final classification result is transmitted to a Programmable Logic Controller (PLC), which automates industrial processes such as rejecting defective rivets and controlling conveyor systems. IoT integration enables real-time data transmission to cloud platforms for monitoring and analysis. This integrated approach ensures efficient inspection, reduces human intervention, and enables data-driven decision-making in industrial environments [4].

Overall, the proposed methodology provides a robust and cost-effective solution for rivet quality inspection, balancing accuracy, speed, and implementation cost.

V. CONCLUSION

The proposed system provides a cost-effective and efficient solution for rivet inspection. It improves speed, accuracy, and reliability while reducing human intervention. The integration of image processing, PLC-based control, and IoT-enabled monitoring forms a robust framework suitable for small and medium enterprises in the Industry 4.0 era.

The system's structured pipeline—from image acquisition and preprocessing through segmentation, feature extraction, and classification—ensures consistent and reliable inspection performance. Future work may explore the deployment of this system on embedded platforms and the use of GPU-accelerated processing to further enhance throughput.

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