Universitat Autònoma de Barcelona

Bachelor's Degree in Artificial Intelligence

Real-Time Quality Inspection for Laser Marking Systems

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1 Introduction

In today's rapidly evolving manufacturing landscape, technological advancements are reshaping production processes. Automation, data exchange, and the integration of advanced technologies have become central to improving efficiency, productivity, and overall quality control. Among these innovations, laser marking technology stands out as a critical tool for product identification and traceability. This technology allows manufacturers to engrave vital information, such as serial numbers, manufacturing dates, and identification codes, directly onto products. These permanent markings are essential for tracking product history, ensuring regulatory compliance, and maintaining supply chain integrity. They also enhance product safety and help prevent fraud.

Laser marking provides a reliable and durable solution for product labeling, making it invaluable for industries such as automotive, electronics, and pharmaceuticals. However, while laser marking offers clear advantages, it introduces challenges, particularly in high-speed, real-time production environments. The increasing speed and complexity of modern production lines demand effective quality control systems to ensure that each laser marking is accurate, legible, and correctly positioned. Any defects—such as incorrect placement, poor readability, or surface imperfections—can compromise product quality and traceability, leading to regulatory violations and customer dissatisfaction.

To address these challenges, there is a growing need for real-time quality inspection systems capable of detecting and correcting laser marking errors swiftly without disrupting production flow. This project aims to develop an efficient, lightweight pipeline for the real-time assessment of laser markings. The goal is to create a system that can quickly evaluate the quality of laser markings, identify errors, and minimize computational demands. This will enable manufacturers to maintain high production throughput while ensuring laser markings meet required standards without relying on heavy computational resources.

2 Problem Definition

The increasing demand for accurate product traceability and quality assurance in industrial manufacturing has driven the widespread adoption of laser marking technology. Laser marking is a reliable method for permanently encoding essential product information, such as serial numbers, production dates, and identification codes. These markings are crucial for compliance with regulatory standards, maintaining supply chain integrity, and ensuring product safety. As manufacturers strive to uphold high production quality, real-time inspection of these markings is essential to ensure both traceability and product integrity.

However, modern production lines operate at higher speeds, presenting significant challenges for real-time quality inspection of laser markings. The volume and speed of production make traditional quality control methods—such as manual inspection or slow, offline image processing—untenable. Manufacturers need a system that can continuously and accurately inspect laser markings as they are applied to products without causing delays or bottlenecks.

Although traditional image processing techniques have been effective in many applications, they often involve complex algorithms that are computationally expensive. These methods are unsuitable for real-time applications, particularly on resource-constrained edge devices. Many existing systems require significant hardware and software resources—such as high-end processors and large memory allocations—which are not feasible in environments where quick, efficient, and low-cost solutions are essential.

This project aims to address the challenge of designing an efficient, lightweight system for real-time quality inspection of laser markings on high-speed production lines. The system must identify common errors, such as incorrect placement, unreadable characters due to surface irregularities, or partial/missing text segments. Furthermore, it should operate with minimal computational overhead, making it feasible for deployment on edge devices with limited processing power and memory.

The project's goal is to develop a pipeline that can assess the quality of laser markings quickly and accurately while minimizing computational costs. By doing so, the system will ensure that manufacturers can maintain high production throughput, reduce errors, improve product traceability, and increase overall efficiency. This project will lay the groundwork for a scalable solution that can be deployed in real-time production environments, contributing to the future of automated, high-speed manufacturing.

3 Background and State of the Art

Traditional approaches to image processing for quality inspection often rely on complex algorithms that analyze various image features to identify defects. These methods can be computationally intensive and may not be suitable for real-time applications, especially on resource-constrained edge devices. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized image recognition and classification tasks. CNNs have demonstrated remarkable performance in various image-related tasks, including object detection, segmentation, and classification. However, the effectiveness of deep learning models depends heavily on the availability of large and balanced datasets. In the context of laser marking quality inspection, the available dataset may be limited and imbalanced, with a disproportionately low number of defective samples. This imbalance can lead to biased models that perform poorly on real-world data.

To address the challenges posed by limited and imbalanced datasets, researchers have explored various techniques, including data augmentation and generative AI. Data augmentation techniques artificially increase the size of the dataset by applying various transformations to existing images, such as rotation, scaling, and cropping. Generative AI techniques, such as Diffusion Models, can generate realistic synthetic images that resemble real-world defective samples. These techniques can significantly improve the performance of deep learning models by providing a more balanced and diverse dataset. Additionally, efficient text extraction and analysis methods are crucial for accurate error detection and classification in laser marking quality inspection. Optical Character Recognition (OCR) techniques and deep learning-based text recognition models have shown promise in extracting text from images. This project will leverage the latest advancements in these areas to develop a robust and efficient pipeline for laser marking quality assessment.

4 Objectives and Contributions

The main objective of this project is to develop an efficient pipeline for assessing the quality of laser-engraved codes in a production line, with a focus on minimizing computational overhead to enable future implementation on edge devices. To achieve this, the project will address the following specific objectives:

1. Data Augmentation and Balancing: Address the limitations of the available dataset by exploring and implementing data augmentation techniques and generative AI models to create realistic defective samples and ensure a balanced representation of all useful characters and error types.
2. Text Extraction and Analysis: Implement and evaluate methods for extracting text from laser-marked images, enabling analysis and comparison with intended content to identify errors.
3. Error Detection and Classification: Develop and train an algorithm to accurately classify common marking errors, such as incorrect placement, defective engraving, and partial or missing text segments.
4. Consideration for Future Real-Time Deployment: While not within the scope of this project, the methodology will prioritize efficiency and lightweight processing to enable future optimization and implementation on edge devices.

The project's contributions include the development of an efficient and lightweight pipeline for laser marking quality assessment, the exploration and implementation of data augmentation techniques and generative AI models for addressing dataset limitations, and the development of effective text extraction and error classification algorithms. The project will also provide insights into the challenges and considerations for deploying such systems in real-time on resource-constrained devices, paving the way for future research and development in this area.

5 Methodology and Work Plan

The project will follow a structured methodology consisting of the following key phases:

- Phase 1: Data Acquisition and Preprocessing (5 weeks). Gather and analyze the available dataset of laser-marked images. Develop and implement preprocessing techniques to enhance image quality and prepare the data for subsequent analysis. Address data imbalance issues by exploring and implementing data augmentation techniques and generative AI models.
- Phase 2: Text Extraction and Analysis (4 weeks). Investigate and implement suitable techniques or deep learning-based text recognition models to extract text from laser-marked images. Develop algorithms to analyze the extracted text, compare it with intended content, and identify potential errors.

- Phase 3: Error Detection and Classification (4 weeks). Develop and train a deep learning model to detect and classify common laser marking errors. Evaluate the performance of the model on a held-out test set and fine-tune its parameters to optimize accuracy.
- Phase 4: Evaluation and Optimization (4 weeks). Conduct a comprehensive evaluation of the entire pipeline, considering accuracy, efficiency, and computational constraints. Optimize the pipeline for potential deployment on edge devices by exploring techniques such as model compression and quantization. Finalize documentation and prepare project presentation.

6 Bibliography and References

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