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Implementation And Assessment Of Automated Quality Control: Optical Coordinate Measurement And Surface Defect Detection In Metal Casting Operations

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Abstract: This paper presents the development and assessment of an automated optical Quality Control (QC) system to optimize defect detection and dimension measurement in metal casting operations, merging high-resolution imaging, motorized positioning mechanisms, and machine learning algorithms to economize time and resources traditionally required in QC processes. Utilizing an optical method for coordinate measurement and a fine-tuned DETR model for defect detection, the system demonstrates a promising reproducibility error of 0.005mm in dimension measurement and a moderate mean average precision metric (mAP-50) score of 20 in surface defect detection, pinpointing a need for further model optimizations. The paper suggests enlarging the training dataset and exploring alternative computational models or pre-processing techniques to enhance system performance, thereby contributing a foundational framework for advancing automated QC systems in the metal casting industry towards a more accurate and resource-efficient paradigm.

***Index Terms* – Quality Control, Coordinate Measurement Machine, Defect Detection, Deep Learning.**

I. INTRODUCTION

In the pursuit of manufacturing excellence within the modern, highly competitive global market framework, the quest for near-zero-defect production lines has become a paramount objective. The contemporary consumer, informed and discerning, demands products of superior quality, propelling manufacturers to incessantly explore avenues to hone the precision and reliability of their production processes. The overarching goal is not merely to attain high conformance but to inch closer to the epitome of perfection, where the occurrence of defects is a rare anomaly rather than a regular occurrence. This aspiration transcends the realm of competitive advantage and ventures into fulfilling a burgeoning market expectation, with quality emerging as a seminal parameter defining market success and sustainability [1].

The narrative of quality control in manufacturing is undergoing a transformative shift with the integration of automation and computational intelligence. Particularly in the domain of metal casting operations, where the intricacies of product geometries and the exigencies of precision are profound, the traditional paradigms of quality control are being revisited. The advent of Optical Coordinate Measurement (OCM) systems, which meld the prowess of advanced optics and digital imaging, promises a pathway to heightened accuracy in dimensional metrology, and thereby, a more refined quality control mechanism. The potency of these systems is further enriched with the infusion of machine learning algorithms, capable of discerning subtle defects and anomalies that might elude conventional inspection mechanisms [2-3].

This manuscript is poised at the confluence of these technological advancements and explores the formulation, implementation, and evaluation of an automated quality control framework within a metal casting operational milieu. The framework delineated herein is predicated on a synergistic interplay between Optical Coordinate Measurement (OCM) and Surface Defect Detection mechanisms, each leveraging the strengths of machine vision and machine learning paradigms. By delving into the architectural and operational intricacies of this framework, and evaluating its efficacy in a real-world manufacturing scenario, this work seeks to contribute a meaningful narrative to the ongoing discourse on automated quality control systems in high-conformance manufacturing environments. The ensuing discourse elucidates the methodologies employed, the challenges encountered, and the performance metrics achieved, painting a comprehensive picture of the potential and the road ahead for automated quality control in metal casting and beyond.

II. Literature Review

The confluence of technological advancements in optics, digital imaging, and computational capacities has paved the way for Optical Coordinate Measurement (OCM) systems to burgeon as robust tools in manufacturing and quality control arenas. In [2], the authors underscored the potential of 3-D optical measurement in delineating the intricate internal surface profiles of machined parts, highlighting the rapid, non-contact, and highly accurate nature of this technology, which is especially potent for inline manufacturing settings.

Machine learning techniques, particularly convolutional neural networks (CNNs), have emerged as potent tools in tackling the challenges inherent in automated visual surface inspection. In [3], the researchers designed a unified CNN-based framework to effectuate precise segmentation and detection of surface anomalies, showcasing the high classification accuracy achievable with a compact CNN architecture.

The domain of metal casting is replete with opportunities for employing machine learning for quality control. The authors of [1] delineated a knowledge-based intelligent supervisory system to detect rare quality events, deploying l1-regularized logistic regression as the learning algorithm for the binary classification problem posed by defect detection. The demonstrated ability to detect 100% of defects underscores the potential of machine learning techniques in elevating quality control standards in metal casting operations.

In [4], the authors introduced non-contact electro-optical techniques for internal thread inspection of machined parts, a critical quality control aspect in automotive manufacturing. Their innovative methodologies encompassed high-precision laser sensing and image processing to ensure precise geometrical measurements and defect detection, thereby addressing vital quality control requisites. Metrological considerations are at the core of quality control mechanisms. Finally, in [5] the researchers provided an insightful overview of the optical methods available for dimensional metrology in production engineering, emphasizing the critical attributes of speed, accuracy, robustness, and automation that these optical methods bring to the fore.

The proliferation of optoelectronic components and increased computational power has enriched the domain of dimensional metrology with numerous novel technical approaches, facilitating enhanced accuracy and efficiency in quality control procedures. The corpus of literature accentuates the imperative for integrating sophisticated optical measurement and machine learning techniques in devising robust automated quality control frameworks. This work seeks to contribute to this burgeoning field by presenting a comprehensive assessment of an automated quality control system tailored for metal casting operations, shedding light on the implementation intricacies and performance metrics of Optical Coordinate Measurement and Surface Defect Detection mechanisms.

III. METHODOLOGY

3.1 Design of the Optical CMM

The foundation of our module is constructed using 2040 aluminum V-slot extrusions, providing stability and rigidity. A single extrusion piece is utilized for each side of the base, resulting in a resilient and durable structure capable of withstanding the rigors of the measurement process. At the module's top section, we employ two 2040 V-slot extrusions on each side, positioned 10cm apart. This specific configuration significantly enhances overall strength and stability, a critical factor in preserving measurement accuracy during movement.

Two Nema 17 open-loop stepper motors are securely affixed to V-slot plates positioned at the top of the unit. These motors are equipped with gear mechanisms that operate on belts attached to the ends of the extrusions, enabling precise movement along the X-axis. The dual-motor setup enhances system stability, ensuring flawless linear movement. The V-slot plates housing the X-axis stepper motors are linked by an additional 2040 V-slot extrusion, serving as the driving element for the Y-axis. The mobile unit's movement is controlled by the xPRO V3 CNC controller, purpose-built for CNC applications. This integration ensures precise control and accurate measurements by the optical CMM. An Allied Vision Mako G-503 PoE camera, chosen for its 2,592 x 1,944-pixel resolution, sensitivity, and wide dynamic range, plays a central role. It captures intricate metal surface details and corrects exposure discrepancies, crucial for identifying imperfections. The final module is depicted in Figure 1.

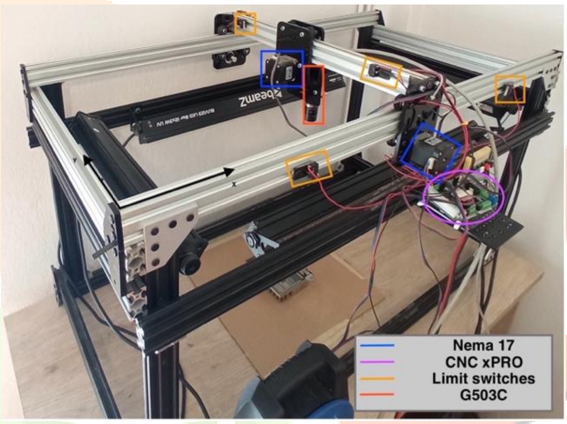

Figure 1 The experimental setup

UV lights are the core of our setup, including the BUV123 UV BAR LED and BUV83. These high-intensity UV sources enhance defect visibility through fluorescence. Their strategic placement at 30 and 45-degree angles ensures uniform and directional illumination, minimizing shading effects and optimizing measurements.

A calibration of the camera is of paramount importance to ensure accurate measurements. To rectify radial distortion and adjust projection parameters, a series of images featuring a calibration pattern with known geometry (i.e., a chessboard pattern) are captured from varying orientations and distances. The DiscorPy library [6] processes these images to compute distortion coefficients and the camera matrix, which are then utilized to calibrate images captured during the inspection process.

3.2 Image Acquisition and ROI Detection

We identify the regions of interest (ROIs) utilizing the cv2 library in Python [7]. First, we increase the image's contrast to make mounting holes' bounds more profound. Following, we utilize a blob detector to find their centers coordinates with sub-pixel accuracy.

The system computes the centroid of the set of points determined by the ROIs and actuates the stepper motors to re-position the camera such that its optical center aligns with the computed centroid. This mechanism ensures that each image acquisition occurs from a consistent angle, thereby minimizing variability and enabling precise geometric comparison. At this point, we acquire a final image of the part from a known angle (the centroid, Figure 2).

Post image acquisition, we once again detect the mounting holes' center coordinates. Following, a graph is created where each node denotes a mounting hole and the edges between them denote the distances between them. The generated graph is then compared to an ideal graph with nominal edge weights. If there are inconsistencies beyond the pre-defined tolerance levels, the part is flagged for further inspection.

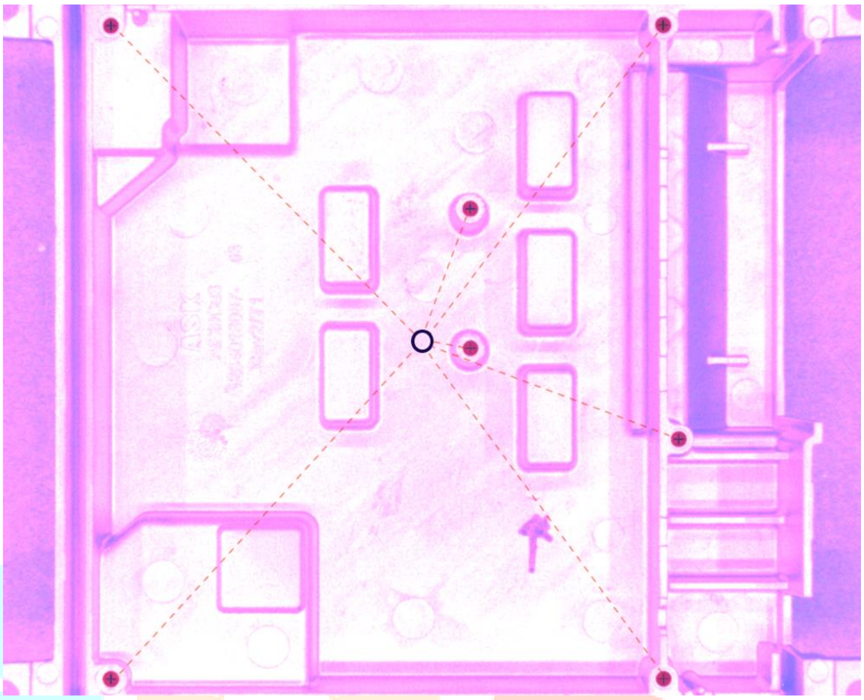

Figure 2 Centroid calculation from ROIs

3.3 Fine-tuning DETR for Defect Detection

Fine-tuning is a valuable technique in machine learning that offers several advantages. It allows the utilization of pre-trained models trained on large-scale datasets, without the need to re-train them extensively. Building on these pre-trained models, we can benefit from the knowledge and internal representations that the model learns. Fine-tuning allows the transfer of this knowledge to a similar problem, even when the dataset is relatively small. In addition, it speeds up the process compared to models trained from scratch. Since pre-trained models have already learned general characteristics, the setup focuses on adapting these characteristics to the specific task, while requiring less computational resources. In addition, pre-trained models have often learned good internal representations from different datasets, leading to improved generalization capabilities. Setting up these models allows them to integrate domain-specific knowledge, allowing them to better generalize to new, invisible data in the target domain. This helps address overfitting and improves performance on demanding datasets. It's especially beneficial when the target dataset is small, which is often the case in specialized areas, or when tagged data collection is expensive and time-consuming, as is in our application.

To detect surface defects in the cast metal parts, we employ a pre-trained DETR model [8] and fine-tune it on our custom dataset. The goal was to gather a diverse and comprehensive dataset that could be used to develop and train machine learning models to detect defects. While the main focus was on a specific component type (heat sinks for automotive audio systems), two additional types of components were included in the dataset to enhance it (a heatsink of a different type and a cover). The data collection process included taking images of components, identifying defects using the VGG Image Annotator, and exporting annotations in CSV format according to the COCO (Common Objects in Context) specification [9]. The components were selected to include common defects found in cast metal parts, such as defective spots, stains, and wrinkles.

High-resolution photographs of the selected parts were taken using the imaging equipment. The images were taken under standard lighting conditions to ensure homogeneity between the data. The VGG Image Annotator was used to manually annotate the surface defects present in the captured images. Experts in cast metal parts participated in this process as commentators. Each defect area was carefully described using bounding boxes and corresponding labels were given to indicate the type of defect. To maintain accuracy and consistency, a comprehensive review process was implemented. Annotators cross-checked and validated each other's annotations to ensure reliable and accurate flaw labeling. Ambiguous cases or areas requiring further clarification were discussed and resolved by consensus.

To increase the sample size, data augmentation was also employed. We utilized the following common data augmentation techniques. Horizontal flipping: with a 50% probability, each image is flipped horizontally. This means that the image is reflected along the vertical axis. When applying this transformation, the relevant bounding boxes are also modified accordingly. Vertical flipping: similar to horizontal flipping, each image has a 50% chance of being flipped vertically. This causes the image to be reflected along the horizontal axis (bounding boxes are again adjusted). 90-degree rotation: again, this transformation has a 50% chance of being applied to each image. When the image is rotated 90 degrees clockwise, the associated bounding boxes must also be modified. The transformation involves toggling the coordinates of the bounding box to account for rotation.

To fine-tune the model, the pre-trained weights of the base DETR are loaded as an initialization point. These pre-trained weights record general object detection knowledge gained from a large-scale dataset and provide a solid starting point for the fine-tuning process. The model itself uses a CNN-like ResNet-50 architecture and has been trained on the COCO dataset for 300 epochs. The AdamW optimizer [10] was selected for optimization to update the model parameters during training. It addresses the limitation of the initial Adam optimizer, where L2 regularization can affect the adaptive mechanism of learning rate. In addition, by effectively manipulating L2 regularization, AdamW produces better results in terms of generalization. Finally, we train the network for 4000 epochs. Data points are fed into the network in batches of 4. An overview of the whole methodology is depicted in Figure 3.

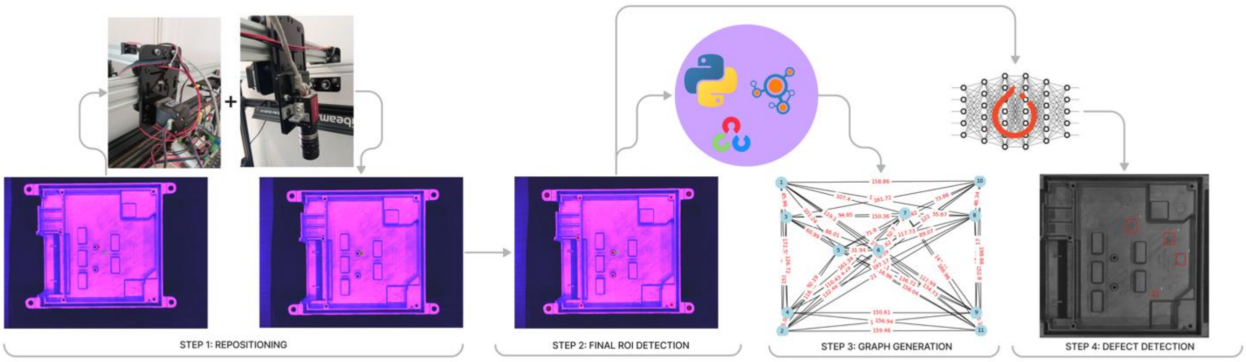

Figure 3 The complete methodology

IV. RESULTS

4.1 Dimension Measurement

In the initial phase of our process, the precision and reliability of the camera's repositioning mechanism were evaluated. The camera exhibited the capability to realign itself to the centroid of the target area within 0.1 pixels, a feature indispensable for ensuing measurement tasks. Post repositioning, the focus shifted towards assessing the system's accuracy in measuring the dimensions of the subjected parts. The measurement tasks were conducted meticulously and yielded an accuracy of 0.01mm, thereby indicating a high level of precision essential for quality control in metal casting operations. Subsequently, to gauge the reproducibility error, the same parts were measured repeatedly in a set of 50 iterations.

In the subsequent analysis, a bootstrap estimation was employed, encompassing 1000 samples each with a sample size of 50, to procure a more comprehensive understanding of the reproducibility error (Figure 4). The computed reproducibility error was satisfactory at 0.00527mm, signifying a good level of precision retention over multiple measurement iterations. However, a slightly elevated reproducibility error of 0.00825mm was observed in the Region Of Interest (ROI) coordinates. This heightened error can be traced back to the inherent error in camera re-positioning to within 0.1 pixels of the centroid, which though minuscule, manifested in the ROI coordinate measurements.

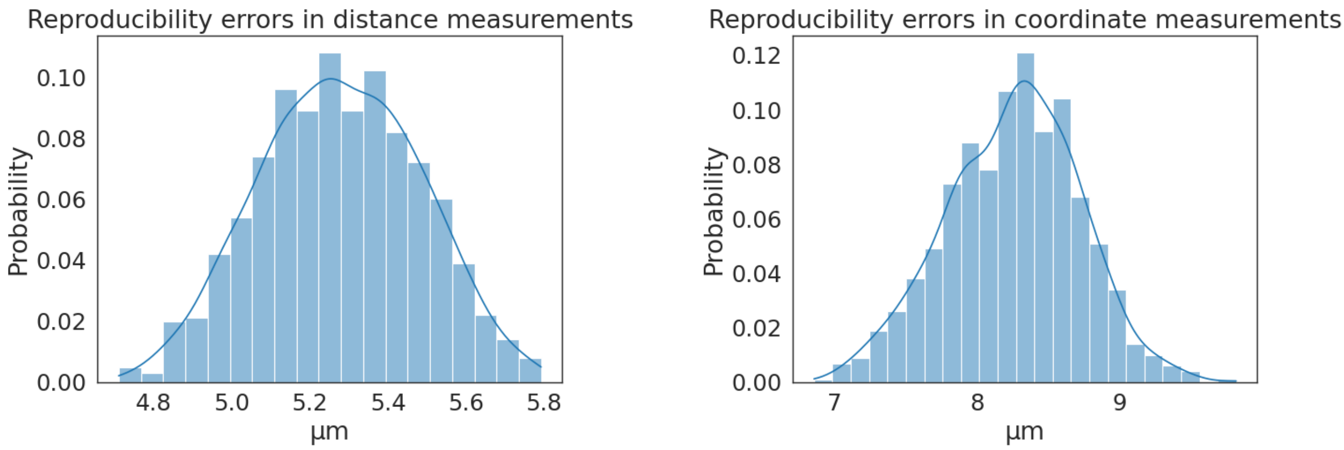

Figure 4 Distributions of bootstrap-estimated mean reproducibility errors.

4.2 Surface Defect Detection

The model's efficiency was evaluated using the 50% overlay mean average precision metric (mAP-50), which is suitable for quantifying accuracy in object detection tasks (Everingham et al., 2010). The results revealed that the fine-tuned DETR model, upon processing monochromatic image datasets, achieved a mAP-50 score of 20. This score is indicative of a satisfactory level of accuracy in identifying defects within metal cast parts, showcasing the model's potential as a substantial asset for automated defect detection in metal casting operations.

However, the mAP-50 score of 20, while promising, hints at room for further optimization. Augmenting the training dataset by including images captured from various angles could potentially lead to a refined model with enhanced accuracy. Future efforts will focus on data augmentation and exploring synergies with other advanced computational models or pre-processing techniques. This iterative refinement, bolstered by a rich, diversified dataset and innovative techniques, is envisioned to significantly elevate the model's defect detection prowess, propelling the automated quality control paradigm forward within the realm of metal casting enterprises.

V. Conclusions

This study presented the design, implementation, and assessment of an automated optical Quality Control (QC) system, aimed at enhancing defect detection and dimension measurement in metal casting operations. By integrating high-resolution imaging, precise motorized positioning mechanisms, and machine learning algorithms, the system attempts to curb the time and resources traditionally required for QC processes, whilst striving for accuracy in detecting surface defects and geometrical inconsistencies. The primary focus is on streamlining the QC processes to mitigate potential financial and safety risks associated with defect oversight in critical applications such as automotive, aerospace, and construction sectors.

The developed system utilized optical coordinate measurement and deployed a fine-tuned version of the DETR model for defect detection. In dimension measurement, the system achieved a satisfactory reproducibility error of 0.005mm, albeit with a higher reproducibility error in the Region of Interest (ROI) coordinates. The surface defect detection, gauged by a mean average precision metric (mAP-50), yielded a score of 20, indicating a moderate level of accuracy in identifying defects. However, this score suggests that further optimizations are warranted to improve the defect detection accuracy. The method of fine-tuning, although promising, showed that the adaptation to the specifics of metal casting defect detection might require a richer and more diversified dataset, alongside further model refinements.

Going forward, our aim is to augment the training dataset and explore synergies with other computational models or pre-processing techniques to enhance the system's performance. It is believed that iterative refinements, supported by a diversified dataset and innovative techniques, could potentially lead to a more robust automated QC system. This study thus provides a foundational framework upon which subsequent efforts can build to further hone automated quality control systems in the metal casting industry.

VI. Acknowledgment

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