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Comparison of Advanced Camera Vision Systems for Defect Inspection of 3D Print Parts

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Abstract: The quality inspection of 3D-printed parts is of paramount importance in ensuring their structural integrity and functional reliability. The present study compares four advanced camera vision systems for defect detection in additive manufacturing. Each system was evaluated on 3D-printed samples that exhibited common defects, including surface irregularities, cracks, voids, and material inconsistencies. The evaluation criteria encompassed aspects such as detection accuracy, processing speed, repeatability, and suitability for automated inspection. The experimental results obtained highlighted the superior performance of multispectral imaging in detecting material inconsistencies, while structured white light was found to be effective for precise surface topography analysis. The Keyence AI system demonstrated adaptability in identifying complex defects through machine learning, offering fast and reliable detection. The macro-optical SLR, despite its high level of detail, was found to be less efficient for real-time automated inspection. The findings suggest that hybrid approaches, which combine multiple imaging techniques, can optimize defect detection performance for various types of flaws. This research provides valuable insights for industrial engineers and manufacturers seeking to enhance quality control in additive manufacturing. By comprehending the strengths and limitations of each vision system, industries can select or integrate the most suitable technology for their specific inspection needs, ultimately enhancing production efficiency and reducing defective output.

Key words: Camera vision system, Defect detection, Additive Manufacturing Quality Control.

1. INTRODUCTION

With the increasing use of additive manufacturing in industrial applications, the need for an effective quality control system for manufactured parts is also increasing. The 3D printing process is sensitive to several parameters that can affect the quality of the output and lead to the formation of various defects such as surface irregularities, micro-cracks, internal voids or material inhomogeneities. [1] These defects can negatively affect the mechanical strength, dimensional accuracy and overall functionality of the resulting components. Therefore, in additive manufacturing environments, there is an increasing emphasis on the integration of advanced machine vision systems that enable automated and reliable real-time quality monitoring. [2]

Currently, several types of visual systems are applied in the quality control of 3D printed parts. Among the most used is multispectral sensing, which uses multiple spectral ranges to detect material variations that are not visible to the naked eye. [3] Further, structured white light illumination is applied to accurately reconstruct surface topography and detect geometric errors. [4] A prominent representative of modern solutions is an artificial intelligence-enabled machine vision system that uses machine learning algorithms to identify complex defects in different conditions and configurations. [5] Another category is a macroscopic optical system based on a digital SLR, which provides high image resolution and is suitable for detailed documentation but is more technically challenging to integrate into automated processes. [6]

This study focuses on a systematic comparison of selected types of camera systems

in terms of their suitability for inspection of parts produced by additive manufacturing. [7] The aim is to provide an objective view of their technical capabilities, advantages and limitations, and thus contribute to a more effective selection of vision technologies in industrial additive manufacturing environments.

2. LITERATURE REVIEW

The quality of parts produced by additive manufacturing (AM) depends largely on the ability to reliably detect defects arising during the manufacturing process. To this end, machine vision technologies that enable automated quality control at the level of geometry, structure and material composition have been developed significantly in the last decade. The literature in this field presents a wide range of approaches, from traditional optical imaging to the integration of artificial intelligence and real-time sensor fusion.

A fundamental research direction is the use of structured light for accurate surface analysis. The work of Jeon et al. can be considered as a representative example, as the authors proposed a 3D scanning technique based on structured light for in-line inspection of the powder bed surface in powder additive manufacturing [8]. Similarly, the study by Gomez et al. analyses coherent scanning interferometry to reduce noise in topography measurements, thereby increasing the accuracy of detection of fine surface irregularities [9]. The second dominant trend is the use of multispectral and hyperspectral imaging, which allows analysis not only of shape but also of chemical composition and material anomalies. Wang et al. integrated multispectral imaging with the YOLOv3 algorithm, achieving high detection speed and accuracy. [10] Similarly, Chen et al. used sensor fusion in a digital twin environment, enabling real-time quality monitoring and suggesting corrective actions directly during printing. [11]

In terms of machine learning and artificial intelligence, several studies can be identified that document the significant contribution of AI tools in detecting complex defects. Niu et al. used Semi-Siamese networks for robust change detection in data, which is particularly relevant

in cases with high defect variability. In [12], Gobert et al. applied supervised learning to defect detection during metal powder bed melting, showing the advantage of high-resolution imaging combined with classification models. In [13], Wang et al. developed a deep learning-based strategy and implemented real-time AI models in an industrial environment. [14]

There is also growing interest in multimodal systems and sensor fusion, where data from multiple types of sensors are combined to increase detection reliability. In a separate study, Chen et al. demonstrated the effectiveness of a multimodal approach in a laser-directed energy deposition process where the defect location significantly affects the output. In [15], Ahsan et al. used transfer learning to classify defects in cylindrical objects, confirming the applicability of pre-trained models even with smaller datasets. [16]

Research attention has also been focused on in-situ tracking and correction during manufacturing. Grasso proposed a method to monitor powder bed homogeneity in EBM using in-situ sensing, thus minimizing the need for follow-up inspection. [17] Guerra et al. used high-resolution optical tomography for in-process layer-by-layer monitoring, which allows defects between layers to be identified and acted upon immediately [18].

Based on the above, it can be concluded that research in the field of visual inspection in additive manufacturing is moving towards the integration of multiple imaging techniques with elements of artificial intelligence. The most effective systems are those that combine high resolution, fast response, material selectivity, and the ability to autonomously adapt to the environment. [19] Not only detection accuracy, but also integrating the system into the production line and its ability to operate in real time is crucial for practice. Therefore, the literature recommends hybrid approaches and sensor fusion as a route towards an optimal solution for defect detection in 3D printing.

3. RESEARCH METHODOLOGY

This study aims to compare four different camera systems in terms of their ability to

identify macroscopic defects on 3D printed parts. Testing was conducted on two samples fabricated using Fused Deposition Modeling (FDM) technology from PLA material. The samples were deliberately created with specific defects to simulate common defects in 3D printing - surface irregularities, horizontal gaps due to disconnected layers, and geometric edge deformations. [20] All parts were placed on a neutral substrate with calibration marks and illuminated with a homogeneous LED light to ensure consistency in scanning conditions.

The following camera systems were selected for comparison: the Keyence CA-H044CX industrial camera with the addition of a structured white light module, the Keyence CA-H048MX camera for high-quality color imaging, the Keyence VS-L160MX smart camera with AI algorithm, and the Canon EOS 250D consumer DSLR with 18-55 IS STM lens. Each system was used to image both samples in the same position, orientation and distance (ranging from 180-220 mm), taking images of the entire part as well as close-ups of areas with defects.

The Keyence CA-H044CX camera used structured illumination to reconstruct the surface topography through light pattern deformation. Calibration and processing were performed using an XG-X Series system with illumination in the 400-700 nm band. The CA-H048MX camera provided high-resolution color images using diffuse LED light and an exposure time of 5 ms. The VS-L160MX camera was configured with a machine learning algorithm that was trained on manually annotated defect examples from each part. The system allowed for real-time adaptive classification of anomalies. A Canon EOS 250D consumer SLR camera was placed on a tripod in macro mode (see Fig. 4).

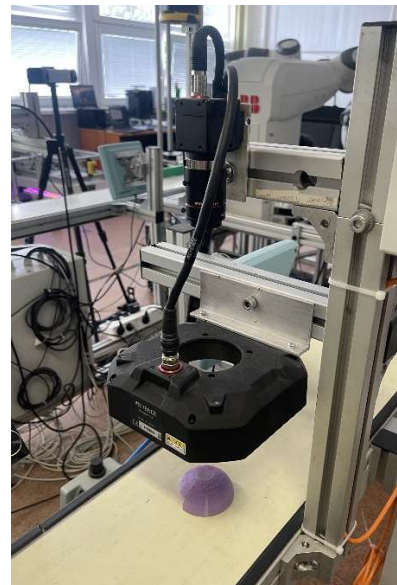


Fig. 1. Keyence CA-H044CX with white structured light.



Fig. 2. Keyence CA-H048MX.

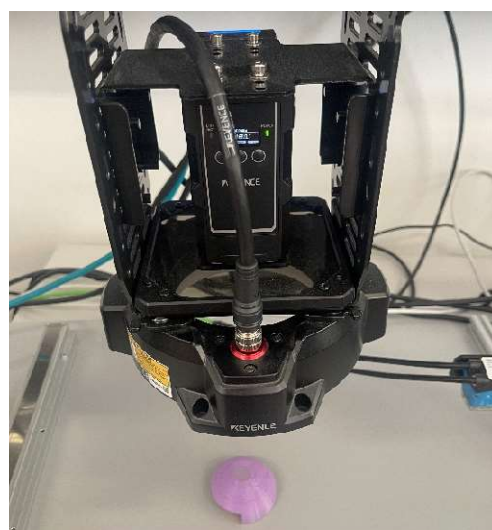


Fig. 3. Keyence VS-L160MX with artificial intelligence algorithm.



Fig. 4. Canon EOS 250D.

The outputs of the four tested camera systems were analysed based on a set of qualitative and quantitative parameters that reflect their ability to identify macroscopic defects on 3D printed parts. The evaluation focused on visual image quality, edge resolution accuracy, image noise level, data processing speed, automation capabilities, and measurement repeatability. These parameters were chosen to reflect the practical requirements of industrial quality control.

Visual quality was subjectively assessed by three independent experts who assigned scores to each image on a five-point scale, focusing on defect legibility, edge sharpness and overall image contrast. The assessment was carried out independently for each type of defect (surface waves, horizontal gaps, corner deformations), thus ensuring the objectivity and reliability of the results. In terms of imaging detail, systems with structured illumination (CA-H044CX) and high optical resolution (Canon EOS 250D) were considered the most effective, although their applicability in automation was limited.

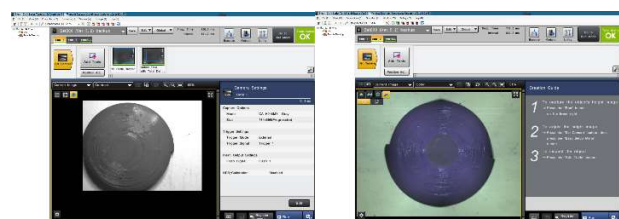
Resolution accuracy was analysed quantitatively by calculating the pixels per millimeter (px/mm) ratio using a calibration element scanned with the part. The defect boundary was then identified using the Canny edge detection algorithm, from which the defect geometry was calculated and compared with reference physical measurements. The highest edge accuracy was demonstrated by the

structured light system, where a deviation of less than 3% concerning the reference dimension was achieved. The Canon mirror, although providing detailed images, showed variability in the tilt of the optical axis without geometric correction.

Evaluation of the image noise level was performed by histogram analysis of homogeneous regions of the image. The obtained pixel intensity standard deviation values allowed for evaluation of the illumination uniformity and the occurrence of noise. The VS-L160MX system showed the lowest noise due to optimized illumination and internal digital image processing, while the Canon SLR, operating with natural illumination, showed higher variability in homogeneous areas.

Processing speed and automation capabilities were evaluated for the system's ability to independently detect and evaluate defects without the need for operator intervention. In this respect, the Keyence VS-L160MX system with integrated artificial intelligence dominated significantly, showing a detection time of under 2 seconds and high classification accuracy after training on a sample of defects. Other systems required manual image evaluation or post-processing in external software, reducing their effectiveness for real production deployments.

Measurement repeatability was verified by scanning each defect three times with each system. The measured values of the defect dimensions were analysed for the occurrence of outliers, and the standard deviation was calculated for each defect and system. The CA-H044CX system exhibited the highest repeatability, with minimal deviation values, which was attributed to the stability of its optical-mechanical configuration. In contrast, the Canon EOS 250D experienced the greatest variation between measurements due to manual manipulation of the device. A view of the individual images analysed can be seen in Figs. 5, 6.



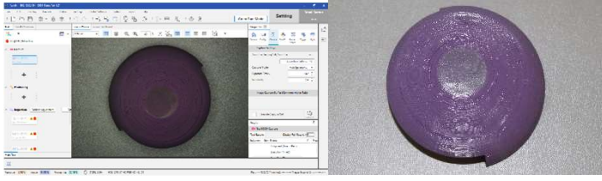


Fig. 5. Images of a circular print part created using Keyence CA-H044CX, Keyence CA-H048MX, VS-L160MX and Canon EOS 250D.

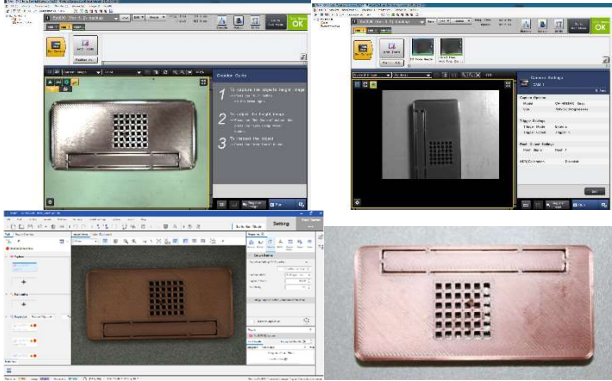


Fig. 6. Images of the lid created by Keyence CA-H044CX, Keyence CA-H048MX, VS-L160MX and Canon EOS 250D.

Based on all collected parameters, a summary efficiency profile was compiled for each camera system and quantified using a weighted index. The weights were assigned according to the importance of each parameter for the industrial application. The resulting values were visualized in the form of radar plots and comparison tables. The results thus obtained serve as a basis for recommendations on the selection of an appropriate vision system depending on the requirements of a particular production task.

3. RESULTS

The results of an experimental comparison of four camera systems for identifying macroscopic defects on 3D printed parts confirmed significant differences in their ability to visualize and quantify defects, as well as in their suitability for automated inspection. The comparison was performed on three types of defects (surface waves, open layers, corner deformations) on three samples of printed parts. For each system, several parameters were measured and evaluated according to a defined methodology. In terms of visual image quality, the Canon EOS 250D (4.7/5) achieved the highest average score, providing very detailed

and high-resolution images. This was followed by Keyence CA-H048MX (4.3/5) and CA-H044CX (4.2/5). The Keyence VS-L160MX camera, despite lower visual acuity (3.9/5), demonstrated a very good ability to highlight relevant areas of defects through AI analysis. Defect edge resolution, expressed in pixels per millimeter (px/mm), was highest for the Canon EOS 250D (124 px/mm), followed by the CA-H048MX (96 px/mm), CA-H044CX (85 px/mm), and VS-L160MX (72 px/mm). However, in the case of CA-H044CX, the use of structured light resulted in more accurate surface topography and higher dimensional fidelity (less than 3% deviation from the microscopic reference measurement).

When analyzing the noise level and illumination uniformity, the VS-L160MX proved to be the most stable system, with a pixel intensity standard deviation of only 2.1 in the homogeneous region. In contrast, the Canon EOS 250D showed the highest illumination variability ($\sigma = 5.4$), which was due to a less controlled lighting environment. In terms of processing speed and automation, the Keyence VS-L160MX system dominated significantly, enabling fully automated defect detection with an average identification time of under 2 seconds. The CA-H044CX and CA-H048MX systems required manual image processing, with evaluation times per sample ranging from 30 to 70 seconds. The Canon EOS 250D did not allow for any automation and the entire evaluation process was dependent on post-processing. The repeatability of the measurements was evaluated based on three repeat scans of each defect. The CA-H044CX system ($\sigma = 0.09$ mm) showed the lowest standard deviation for defect dimension measurements, followed by the CA-H048MX ($\sigma = 0.12$ mm), VS-L160MX ($\sigma = 0.15$ mm) and Canon EOS 250D ($\sigma = 0.21$ mm), where variability was mainly affected by manual intervention during setup.

The cumulative Efficiency Footprint Index (EFI), calculated as a weighted average of the parameters concerning industry requirements, was highest for the Keyence VS-L160MX (0.88), followed by the CA-H044CX (0.84), CA-H048MX (0.81), and Canon EOS 250D (0.76). Although the Canon provided the most

detailed images, its limited integration into automated processes and lower repeatability lowered its overall rating. These results confirm that a combination of several factors - accuracy, automated analysis, and reliability - play a key role in selecting the appropriate vision system for quality control of 3D printed parts. Therefore, solutions that combine intelligent algorithms with robust optical processing and stable illumination appear to be the most suitable in industrial practice.

4. CONCLUSION

The results of this study demonstrated that different types of camera systems provide different performance characteristics in detecting macroscopic defects on 3D printed parts. Industrial cameras with structured illumination (Keyence CA-H044CX) and AI support (VS-L160MX) demonstrated high levels of accuracy, repeatability and, most importantly, suitability for deployment in automated manufacturing processes. In contrast, the consumer DSLR Canon EOS 250D did provide detailed visual outputs, but its lack of stability and absence of automation features limit it for industrial deployments. The results obtained confirm that the selection of a camera system should be based on the requirements of the specific application, and it is important to consider not only optical quality, but also integration options, processing speed and level of automation. For the analysis of parts with different types of defects, the application of hybrid approaches that combine the advantages of multiple imaging techniques appears to be effective.

Future research should focus on extending the methodology to a wider range of defects, including sub-macroscopic and internal defects using CT and hyperspectral systems. Furthermore, the involvement of edge computing architectures for real-time image processing and the development of adaptive AI models capable of learning from unlabeled data seem promising. From a practical point of view, it will be crucial to validate the performance of vision systems under real production conditions including vibration, contamination and part variability.

The introduction of intelligent visual inspection into the additive manufacturing process thus represents a significant step towards fully automated and adaptive manufacturing, which will enable reduced defects, increased productivity and improved output quality in line with Industry 4.0 and 5.0 principles.

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Compararea sistemelor avansate de vedere cu cameră pentru inspectarea defectelor pieselor imprimate 3D

Inspecția calității pieselor imprimate 3D este de o importanță capitală în asigurarea integrității structurale și a fiabilității funcționale a acestora. Studiul de față compară patru sisteme avansate de vedere cu cameră pentru detectarea defectelor în fabricarea aditivă. Fiecare sistem a fost evaluat pe probe imprimate 3D care prezentau defecte comune, inclusiv neregularități de suprafață, fisuri, goluri și neconcordanțe de material. Criteriile de evaluare au cuprins aspecte precum acuratețea detectării, viteza de procesare, repetabilitatea și adecvarea pentru inspecția automată. Rezultatele experimentale obținute au evidențiat performanța superioară a imagisticii multispectrale în detectarea inconsistențelor materialelor, în timp ce lumina albă structurată s-a dovedit a fi eficientă pentru analiza precisă a topografiei suprafețelor. Sistemul Keyence AI a demonstrat adaptabilitate în identificarea defectelor complexe prin învățare automată, oferind o detecție rapidă și fiabilă. Sistemul macro-optic SLR, în ciuda nivelului său ridicat de detaliu, s-a dovedit a fi mai puțin eficient pentru inspecția automată în timp real. Rezultatele sugerează că abordările hibride, care combină mai multe tehnici de imagistică, pot optimiza performanța de detectare a defectelor pentru diferite tipuri de defecte. Această cercetare oferă informații valoroase pentru inginerii industriali și producătorii care doresc să îmbunătățească controlul calității în fabricarea aditivă. Prin înțelegerea punctelor forte și a limitelor fiecărui sistem de vedere, industriile pot selecta sau integra cea mai potrivită tehnologie pentru nevoile lor specifice de inspecție, îmbunătățind în cele din urmă eficiența producției și reducând producția defectă.

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