SURFACE QUALITY ASSESSMENT USING A MULTISPECTRAL CAMERA FOCUSING ON ACCURACY AND COLOR VARIATIONS OF PRINTED PARTS MADE WITH FDM TECHNOLOGY

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DOI: 10.17973/MMSJ.2025_06_2025054

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This study investigates the dimensional accuracy and detectability of parts manufactured by Fused Deposition Modeling (FDM) technology through multispectral imaging analysis. Experimental samples fabricated from PLA (Polylactic Acid) and translucent PLA/PHA (Polylactic Acid/ Polyhydroxyalkanoates) were examined to assess surface quality, with a focus on the geometric precision of fundamental shapes. Specifically, the distance between opposite edges of squares was measured, and the diameter of circles was evaluated. A Keyence VS-L-160MX multispectral camera was employed using various lighting conditions, including UV, blue, infrared, and combined configurations, to optimize material transmittance analysis, contrast enhancement, and surface feature detection. High-contrast backgrounds were systematically chosen depending on the sample color to improve image sharpness and edge definition. Dimensional measurements were compared against nominal values, revealing that the greatest deviations approximately 10% occurred in the smallest geometrical features. These findings are attributed to the inherent limitations of optical resolution, calibration precision, and depth of field when analyzing fine structures. The study advances the methodology of surface quality assessment and underscores the necessity for optimized scanning parameters in the dimensional verification of additively manufactured components.

KEYWORDS

Additive manufacturing, Multispectral sensing, Dimensional accuracy, Geometric analysis, Optical detection.

1 INTRODUCTION

Additive manufacturing (AM), also referred to as rapid prototyping (RP), is a contemporary technique for producing three-dimensional objects by adding material in layers in a stepwise fashion [Lian et.al. 2018]. This process facilitates the direct conversion of computer-aided design (CAD) models into physical prototypes with a high degree of accuracy and flexibility [Bose et.al. 2018]. The technologies encompassed within the AM category include Stereolithography (SLA), Selective Laser Sintering (SLS), Fused Deposition Modeling (FDM) [Husar et.al. 2022], and 3D printing (3DP) [Singh et.al. 2017]; [Mitaľová et.al. 2023].

Color variations have been shown to have a significant impact on the surface quality assessment of parts produced using FDM technology. These variations affect not only the visual properties of the parts but also their mechanical characteristics [Cojocaru et.al. 2024]. The utilization of diverse color filaments has the potential to introduce variability in evaluation metrics, thereby augmenting the intricacy of the surface quality assessment process [Nancharaiah et.al. 2010]. This complexity arises from the interplay between the color properties of the material and the parameters of the printing process. Together, these factors influence dimensional accuracy and surface roughness [Garg et.al. 2015].

The assessment of the surface quality of components fabricated by FDM technology constitutes a pivotal step in the identification of manufacturing deficiencies and the optimization of printing processes. A plethora of methodologies have been advanced in the extant literature, including image entropy analysis for color-independent quality assessment [Okarma et.al. 2017] and optical measurements utilizing confocal laser scanning microscopy [Medina Sánchez et.al. 2023]. The primary factors that influence surface quality are print orientation, layer height, and plane tilt angle [Medina Sánchez et.al. 2023]. Furthermore, the resolution of surface details has been examined through the use of reference samples exhibiting varying detail sizes and print orientations [Armillotta et.al. 2006]. This approach facilitates a more precise investigation of the influence of production parameters on the final surface quality. The divergent approaches to the technical implementation of defect detection in FDM components are indicative of the intricacy of the aforementioned issue and the dynamic developments in this field [Kalman et.al. 2024]. The prevailing solutions accentuate the incorporation of artificial intelligence, multispectral analysis, real-time monitoring, image data processing, adaptive systems, and transfer learning. The implementation of machine learning and artificial intelligence algorithms is paramount in the automated detection of defects [Duhančík et.al. 2024]. Kadam [Kadam et.al. 2021] proposed models based on AlexNet and Support Vector Machines (SVM) algorithms for layer-by-layer anomaly detection. Siegel [Siegel et.al. 2020] employed deep neural networks to analyze thermographic signals. Wang [Wang et.al. 2020] implemented convolutional neural networks (CNNs) in an adaptive monitoring system. Moreover, Yang [Yang et.al. 2023] applied transfer learning in combination with ensemble learning. Yeh [Yeh et.al 2023], on the other hand, developed an approach based on YOLOv5 to analyze in-depth image data.

A multitude of scholarly papers have been published that explore various aspects of multispectral camera systems and their applications in color evaluation and imaging. Shimano [Shimano at.al. 2005] proposes a methodology for evaluating the quality of multispectral image capture systems, incorporating considerations of spectral sensitivity and noise variance. Direl [Dierl et.al. 2018] present a novel approach to evaluating the accuracy of multispectral imaging systems. This method involves the use of ΔE measurements, a statistical technique known as "Bayesian statistics," particularly in the context of inline print inspection applications. Zainuddin [Zainuddin et.al. 2018] concentrate on the calibration of lightweight multispectral cameras for photogrammetric applications and investigate the variation of calibrated parameters at different wavelengths. In a related study, Shimano [Shimano at.al. 2005] applied a colorimetric evaluation model to multispectral color image capture systems, proposed a method for estimating noise variance, and demonstrated its effectiveness in real multispectral cameras. A collective analysis of these studies indicates a contribution to the advancement of multispectral imaging technology. The studies address issues of accuracy, calibration, and color evaluation in a variety of applications.

Multispectral imaging is frequently integrated with infrared thermography to enhance detection capabilities. AbouelNour and Gupta [AbouelNour et.al. 2023] utilized a combination of optical imaging with infrared thermography to identify internal defects. In a related study, Siegel [Siegel et.al. 2020] employed infrared thermography to analyze interlaminar delamination. Shen [Shen et.al. 2019] proposed a multi-view visual detection method to enhance the capabilities of single-view techniques by overcoming their respective limitations.

Image processing methodologies underpin the identification of defects through the analysis of image data. Behseresht [Behseresht et. al. 2024] implemented texture analysis using the gray-level co-occurrence matrix (GLCM). Concurrently, Okarma [Okarma et.al 2018] directed their efforts toward the analysis of image entropy. In a related study, Yi [Yi et.al. 2017] integrated machine vision analysis with statistical process control.

Defect detection is frequently influenced by variations in fiber color, thereby compromising the reliability of color-sensitive algorithms [Okarma et.al 2020].

Notwithstanding the substantial progress in automated defect detection in FDM printing, several substantial limitations persist. The absence of standardized methodologies for assessing accuracy and reliability gives rise to a multitude of metrics, impeding the capacity to draw meaningful comparisons between diverse approaches. Moreover, the paucity of research focusing on a wide array of defects, such as delamination drop [Siegel et.al. 2020] or intrinsic defects [AbouelNour et.al. 2023], hinders the generalizability of the methods employed.

The extant research demonstrates that multispectral imaging techniques provide quantitative indicators of surface quality, with porosity emerging as the most consistent parameter measured. The findings indicate that the interplay among material composition, printing parameters, and the resultant surface quality is of considerable importance in the FDM process. The most significant effects of printing parameters on surface quality have been thoroughly investigated in the works of Vidakis [Vidakis et.al. 2022] and Özen [Özen et.al. 2022]. Vidakis [Vidakis et.al. 2022] conducted an analysis of six key process parameters, including raster deposition angle, fill density, nozzle temperature, substrate temperature, printing speed, and layer thickness. Despite the absence of explicit correlations between these parameters and surface quality, the authors developed predictive quadratic regression models. These models facilitate the quantification of the interrelationships between the parameters.

Despite the contributions of numerous studies to the development of surface quality assessment, a standardized methodology to verify the accuracy of these approaches remains elusive. Bowoto [Bowoto et.al. 2020], Okarma [Okarma et.al. 2020], Shen [Shen et.al. 2019], Straub [Straub et.al. 2016] presented their methods for defect detection. However, these studies did not provide specific accuracy and reliability metrics.

In light of the aforementioned findings, it is evident that multispectral imaging serves as an effective tool for analyzing the surface quality of components fabricated by FDM. To ensure accurate comparisons, a systematized evaluation methodology is needed. Standardized metrics are crucial for evaluating the accuracy of detection methods and performance comparisons of different additive manufacturing materials.

2 MATERIAL AND METHODS

FDM technology has spread widely in AM, and the quality of the resulting print is influenced by the choice of material. Polylactic acid (PLA) is one of the most used FDM materials. This is due to its ease of processing, biodegradability and availability. PLA is a thermoplastic polyester made from cornstarch, sugar cane or beet molasses [Tauberová 2024]. Its environmental advantage and good appearance and properties make PLA a preferred material for hobbyist and industrial prototyping.

PLA's main features include a low melting point (180-220 °C) and a smooth, glossy surface, which makes it easy to print with FDM printers. Its parts have low deformation upon cooling, ensuring high accuracy and reducing defects. PLA extrusions are also strong and shiny. However, its strength, flexibility, and heat resistance are lower than those of other materials, like ABS and PETG, and it starts to break at temperatures above 60°C.

PLA and PLA/PHA were used for the experimental part and for printing the samples, and the table below summarizes the basic mechanical properties of the materials:

Properties	PLA	PLA/PHA (transparent)
Density	1.24 g/cm³	1.21–1.24 g/cm³
Tensile Strength	60–70 MPa	50–65 MPa
Young's Modulus	3.5–3.8 GPa	3.0–3.5 GPa
Elongation at Break	4–10 %	10–20 %
Melting Temperature	180–220 °C	180–210 °C
Heat Deflection Temperature (HDT)	~60 °C	~55 °C
Optical Properties	Opaque	Semi-transparent (translucent)

Table 1. Basic mechanical properties of the materials used

PLA and PLA/PHA materials processed on a Bambu Lab X1 Carbon 3D printer. The printer is characterized by precision, process stability and the ability to print engineering and composite materials. The following table provides a comprehensive overview of the basic printing characteristics and parameters for the materials tested:

Name	Properties	
PLA	Fan speed	Auto (200)
	Extrusion temperature	220
	Build platform temperature	55
	Layer [mm]	0.20
	Infill	15%
PLA/PHA	Fan speed	Auto (200)
	Extrusion temperature	220
	Build platform temperature	55
	Layer [mm]	0.20
	Infill	15%

Table 2. Specimen print parameters description

The experiment tested different 3D-printable models with variations in geometric elements to evaluate quality. Figure 1 presents a technical drawing of a specimen utilized in the experimental phase of the research endeavor, which was undertaken with the objective of assessing the surface quality and dimensional accuracy of components fabricated through the FDM technique. The drawing contains various basic geometric elements, including squares and circles, which formed the primary subject of the experimental analysis. The dimensional accuracy of the structures was evaluated through the use of multispectral imaging, with square and circular structures employed for this purpose. A meticulous analysis was conducted on the dimensions, shapes, and edges of these structures, with the results compared to the nominal values. Specifically, the distance between opposite edges of the squares was measured, and the diameter of the circles was evaluated. Other geometric elements, including octagons, letters, and varied radii, were incorporated to provide a more comprehensive validation of the technological capabilities of the print. However, the primary focus of the analysis was on the accuracy of simple shapes, with the objective of minimizing the influence of complex factors on the measurement outcomes.

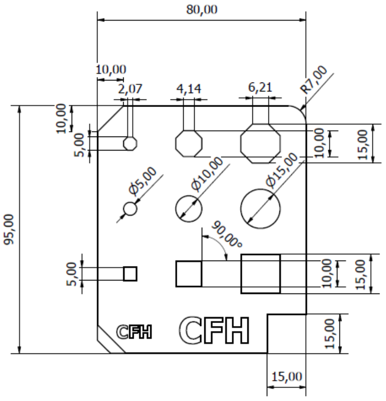

Figure 1. Technical drawing of the test sample for experimental analysis of dimensional accuracy and surface quality of samples

The manufacturing process used three batches of samples with varied materials and colors, following specifications and recommendations. The printing parameters were selected based on the Original Equipment Manufacturer (OEM) recommendations and prior experiments. The following Figure 2 shows a 3D view of a test sample generated in the cutting software. This view shows the distribution of the different line types according to their function in the layered structure of the model. The view also reflects the optimized printing parameters, which were adjusted to achieve a balance between dimensional accuracy and time efficiency of the manufacturing process.

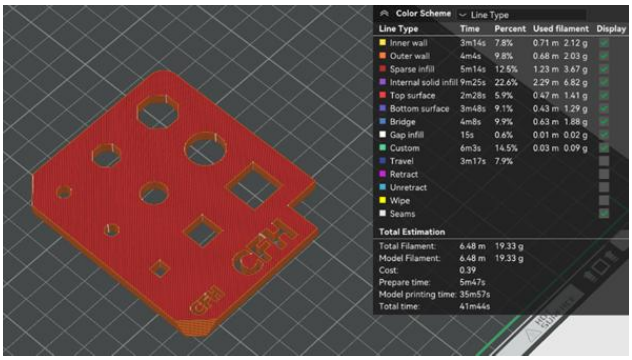

Figure 2. Preview of the printing process and print parameters

This displays the model's printing lines (inner and outer walls, fillers, top and bottom layers). It also shows the optimized printing parameters. Visualization data indicates that inner fillers (22.6% of the time, 5.29 g of filament) and the top and bottom surface layers consumed the most time and material. The total filament use was 6.48 meters (19.33 g). The preparation phase took 5 minutes and 47 seconds, and the printing took 35 minutes and 57 seconds. The total production time was 41 minutes and 44 seconds. This quantitative data provides an accurate view of material needs and production times, making it useful for further optimization.

In the next phase of the experiment, a comparative visual analysis of the surface of the printed samples was performed using a Keyence VS-L-160MX industrial multispectral camera in combination with a CA-DRM10X high-precision illumination module [Hrehová et.al. 2022]. The VS-L-160MX camera is part of Keyence's intelligent camera series and is designed for applications that require high accuracy, stability, and real-time imaging speed. The unit is equipped with ZoomTrax technology, which allows the field of view to be smoothly changed without reducing the native resolution and without any mechanical intervention in the optical system. Key specifications of the VS-L-160MX include (see Table 3):

Specifications of the Keyence VS-L-160MX	
Sensor resolution	up to 21 megapixels
Sensor type	CMOS, colour/multispectral
Magnification range (zoom)	motor-operated optical zoom (approx. 16×)
Spectral resolution	colour detection capability in both RGB and near infrared (NIR) spectrum
Compatibility with AI analysis	integration with machine learning algorithms for automatic classification of surface defects
Illumination	homogeneous, circular diffuse light provided by the CA-DRM10X module

Table 3. Key specifications of the Keyence VSL-160MX

In order to establish the most favorable imaging conditions for each specimen, a variety of backgrounds were meticulously chosen based on their optical properties. This approach was implemented to ensure maximum contrast, minimize glare, and optimize light distribution on the surface of the structure under investigation. In the case of the black sample, a white background was selected, which, due to its high reflectivity, provided sufficient contrast between the dark object and the light background. This eliminated the risk of shadows and optical artefacts caused by insufficient illumination or local overexposure.

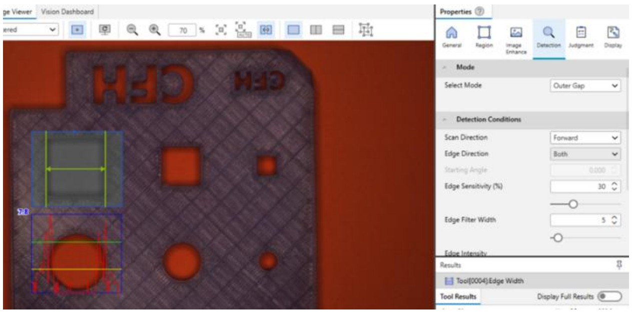

Figure 3. Stepping up the process of geometric hole identification

Conversely, a red substrate was selected for the white sample, as its background color facilitated the discernible delineation of edges and surface transitions. This contrast proved to be of particular importance when combined with blue and infrared illumination, which facilitated the enhancement of fine geometric details under the high reflectance conditions of the sample itself.

A transparent sample with purple coloration was also analyzed on a red pad (see Figure 3). The selection of the red background was driven by the objective of accentuating the contours of the transparent material, which otherwise absorbs and scatters light in an unpredictable manner. This contrast solution has been demonstrated to enhance the detection of edges and morphological transitions at the interface between the specimen and the pad, thereby augmenting the precision of dimensional analysis, even for materials that present significant optical challenges.

To ensure image analysis accuracy and detect geometric samples features reliably, lighting conditions were tested and optimized. Investigations included variability in illumination intensity, its spectral composition and color representation, with emphasis on light volumes and source temperature. Material properties such as light reflectance, absorption and diffusion significantly affect visual data quality. The experimental setup utilized advanced multispectral illumination technology, which facilitated meticulous regulation of the spectral composition of the light impinging on the objects under investigation. Multispectral light sources enabled the selective highlighting of specific geometric features of the samples, with the greatest precision in detecting edges and shape transitions exhibited by combinations of illumination in the blue and infrared regions of the spectrum.

The selection was not arbitrary. It was based on a previous analysis of the materials' optical behavior. Blue light was highly sensitive to fine surface textures. Infrared radiation allowed penetration through thinner layers or enhanced contrast where traditional methods failed. The combination of these spectral components was key to determining precise geometric contours. This is important to evaluating the dimensional accuracy of 3D-printed parts. The process of identifying optimal lighting parameters for samples is illustrated in Figure 4.

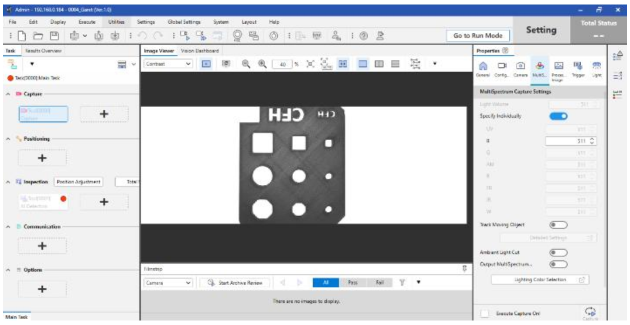

Figure 4. The process of identifying optimal light parameters for samples

Optimizing illumination was a step in designing a measurement methodology for different samples. This methodology reflected the specifics of each sample's color, surface finish, and material transparency.

3 RESULTS

Figure 5 shows the analyzed square which was fabricated through the use of the FDM process, and its dimensional precision was validated employing a Keyence VS-L-160MX multispectral imaging apparatus. The measurement was conducted within a dedicated visual quality control software environment, wherein a specific geometric element - a square with a nominal dimension of 15 millimeters—was targeted for analysis. The camera was configured to utilize a combination of blue and infrared (IR) illumination, enabling the effective highlighting of edges and their accurate detection, even in the presence of slight color or texture variations caused by the surface texture of the print. The specimen was white with a red background, chosen for optimal multispectral imaging. The red background, with its combination of blue and IR illumination, allowed for high edge contrast. This enhances edge resolution, even when slightly blurred by surface defects or FDM layered structure.

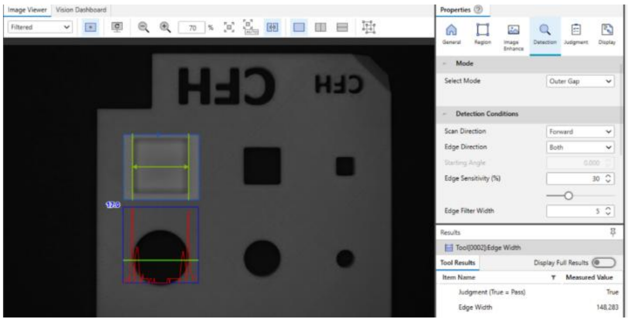

Figure 5. Identification process of the square hole for the white colour sample

The square under consideration was measured using the "Outer Gap" detection mode, a method optimized for the measurement of an object's outer dimensions. In this instance, the horizontal width of the square was monitored, with the camera recording a value of 14.823 millimeters. The nominal dimension of the square was 15 mm, representing a deviation of - 0.177 mm. This discrepancy signifies that the printed piece is marginally undersized, a frequent occurrence in FDM printing due to potential shrinkage of the plastic during cooling or inadequate material flow tuning during extrusion. The relative error, calculated to be approximately 1.18%, falls within the acceptable tolerance range for this printing method. Image analysis reveals the intensity waveform of the detected edges (red curve), showing sharp, contrasty capture, confirmed by the chosen illumination. The blue/IR combination enhanced the edge transition between the sample and background, enabling reliable detection and dimension calculation. Optimized detection parameters (30% edge sensitivity, bidirectional edge detection, 5-pixel edge filter) suppress noise while preserving detail, critical for print accuracy. The measurement result is "true," indicating that the part passed with dimensions within preset limits. The subsequent Table 4 offers a thorough dimensional analysis of the supplementary geometric apertures within the initial white paint sample examined. The results of this analysis constitute a quantitative evaluation of the dimensional accuracy in various regions of the test object. The measured values indicate that the deviations between the actual and detected dimensions are relatively small, suggesting a high degree of agreement between the design and real dimensions, respectively, and validating the performance of the machine vision system.

White color sample (Material PLA, red base)			
Item	**Measured value**	**Nominal dimension**	**Deviation**
Square 1	14.823 mm	15 mm	0.177 mm(1.18 %)
Square 2	9.926 mm	10mm	0.074 mm (0,74 %)
Square 3	4.653 mm	5mm	0.347 mm (6.94 %)
Circle 1	14.837 mm	15 mm	0.163 mm (1.09 %)
Circle 2	9.823 mm	10mm	0.177 mm (1.77 %)
Circle 3	4.632 mm	5mm	0.368 mm (7.36 %)

Table 4. Calculated percentage deviations regarding the nominal dimension of the geometric apertures for the white colour sample

The minimum deviation may be due to several factors. White material's reflectivity affects sharpness, accuracy of edge detection. Minor systematic inaccuracies may result from slight variations in calibration, slight geometric distortions during manufacturing. Inaccurate illumination or optical aberration compensation may also cause inaccuracy. These factors can affect edge-detection, especially when small geometric dimensions and high surface brightness are combined. When interpreting these results, consider the measured values and experimental conditions, including illumination properties, material type, and camera resolution.

A black sample was measured using a white pad and a combination of UV and IR light. This approach highlights the edges of the holes even in the less contrasting parts of the object, reducing distracting shadows and improving edge detection by increasing contrast. To optimize the contrast in edge detection, the black sample was placed on a white background (see Figure 6).

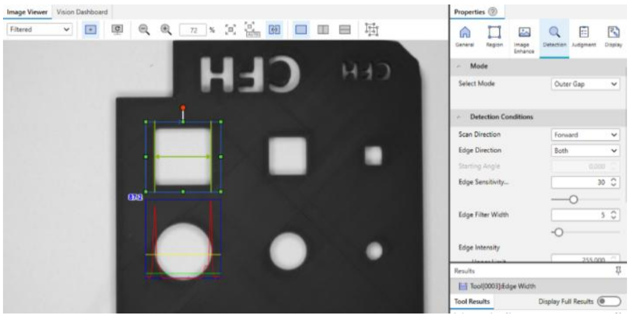

Figure 6. Identification process of the square hole for the black colour sample

Specifically, the upper left square, delineated by the green dots in the image, was targeted, with its horizontal dimension measured at 87.2 pixels. The actual dimension of the square is known to be 15 millimeters. The subsequent calculation of the scale for converting pixels to millimeters was performed as follows:

$$\frac{15mm}{87.2px} = 0.172mm/px \qquad (1)$$

Using this scale, the measured value in pixels can be converted back to real physical units:

$$87.2px \times \frac{0.172mm}{px} = 14.9984mm \qquad (2)$$

The measurement result thus shows that the deviation from the actual dimension is extremely low:

$$\Delta = 15mm - 14.9984mm = 0.0016mm \qquad (3)$$

The following Table 5 provides a comprehensive dimensional analysis of the additional geometric apertures within the second black colour sample analysed:

Black color sample (Material PLA, white base)			
Item	**Measured value**	**Nominal dimension**	**Deviation**
Square 1	14.9984 mm	15 mm	0.0016 mm(0.01 %)
Square 2	9.873 mm	10mm	0.127 mm (1.27 %)
Square 3	4.561 mm	5mm	0.439 mm (8.78 %)
Circle 1	14.898 mm	15 mm	0.102 mm (0.68 %)
Circle 2	9.769 mm	10mm	0.231 mm (2.31 %)
Circle 3	4.541 mm	5mm	0.459 mm (9.18 %)

Table 5. Calculated percentage deviations regarding the nominal dimension of the geometric apertures for the white colour sample

The next Figure 7 presents the result of the dimensional analysis of a square geometric hole. The sample analyzed is made of purple transparent material. A red-colored background was chosen because of its optical properties, which include partial light transmission and low reflection in the visible spectrum, to increase contrast and ensure good edge detection. This approach increased the contrast and ensured good edge detection, making the square's edges stand out more clearly against the background. Illumination was provided by a combination of UV and blue light, which penetrated the surface structure of the transparent material, highlighting the sample-background interface.

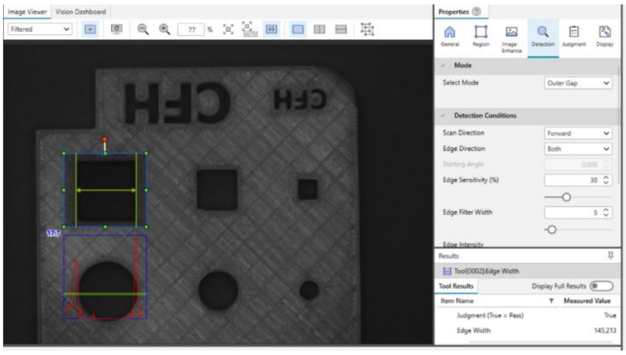

Figure 7. Identification process of the square hole for the purple transparent colour sample

The measurement indicates the largest square hole located in the upper left quadrant of the sample. The horizontal dimension of the square was recorded at a value of 145.213 pixels. The known dimensions of this aperture are 15 millimeters. Utilizing this data, the conversion value between pixel count and millimeters was determined as follows:

$$\frac{15mm}{145.213px} = 0.1033mm/px \tag{4}$$

By back-calculating, it is then possible to derive the actual dimension of the hole according to the data obtained:

$$145.213px \times \frac{0.1033mm}{px} = 14.999mm \tag{5}$$

From the above it follows that a deviation from the nominal dimension of 15 mm represents:

$$\Delta = 15mm - 14.999mm = 0.001mm \tag{6}$$

This value is within the negligible minimum systematic error range, as determined by the methodology used. The result indicates the multispectral camera is reliably able to measure the geometric properties of challenging, transparent materials. The following Table 6 provides a comprehensive dimensional analysis of the additional geometric apertures within the second analyzed sample from the purple transparent material:

Sample Purple transparent colour (Material PLA/PHA, red base)			
Item	**Measured value**	**Nominal dimension**	**Deviation**
Square 1	14.999 mm	15 mm	0.001 mm (0.1 %)
Square 2	9.899 mm	10mm	0.101 mm (1.01 %)
Square 3	4.517 mm	5mm	0.483 mm (9.66 %)
Circle 1	14.887 mm	15 mm	0.113 mm (0.75 %)
Circle 2	9.788 mm	10mm	0.212 mm (2.12 %)
Circle 3	4.465 mm	5mm	0.535 mm (10.70 %)

Table 6. Calculated percentage deviations regarding the nominal geometric aperture dimension for the purple transparent colour sample

4 DISCUSSION

The experiment showed that the Keyence VS-L-160MX multispectral camera is accurate in measuring the surface quality and dimensional parameters of parts produced by FDM technology. The size of a geometric feature correlates with the accuracy of its measurement. The largest deviations occur for the smallest measured details, e.g., squares and circles with dimensions of 5 mm. These deviations reach statistically significant values, indicating the method's limits when capturing fine and detailed geometric features. In contrast, larger objects, such as squares with a nominal dimension of 15 mm, showed minimal dimensional deviation, confirming the method's reliability in larger measurements.

Accurate measurement of small features is affected by optical resolution, focus quality, and uniform illumination. At very small sizes, poor edge sharpness or obstruction by shadows, reflections, or surface interference can reduce feature detection accuracy. This error is especially pronounced for transparent or glossy surfaces.

Insufficient calibration of the sensing system for spectral conditions can also lead to errors. Different light combinations (e.g., UV + blue, blue + IR, UV + IR) were used to optimize surface visualization and geometric feature contrast. Not all combinations worked equally well for each material. To ensure accuracy, it's essential to adjust the spectral conditions based on the sample's optical properties, especially for transparent or glossy materials where light absorption or scattering may occur. The contrast background chosen, such as red for white or transparent samples and white for black objects, contributed significantly to improving the quality of edge visualization, which is crucial for extracting accurate geometric parameters from the image. This methodological choice exerted a beneficial influence on measurement accuracy, particularly with regard to larger features. Nonetheless, for more minute details, even the optimal contrast was incapable of entirely eliminating system deviations. Multispectral imaging measurements require careful calibration, lighting optimization, and selection of the right spectral band and background. Higher image resolution and advanced processing algorithms can improve small-detail detection. Using reference calibration standards directly on measured images for correction is an option.

Multispectral sensing has potential in non-contact 3D printed part metrology, but results vary due to sample properties and geometry. This necessitates an individualized approach to measurement system settings.

5 CONCLUSIONS

The research that was conducted confirmed the effectiveness of using multispectral imaging technology in assessing the quality and dimensional accuracy of components manufactured using

FDM technology. Utilizing the Keyence VS-L-160MX camera system, experimental measurements were conducted, enabling the identification of pivotal factors influencing the precision of non-contact optical metrology. The analysis placed particular emphasis on the examination of geometric deviations exhibited by measured elements of varying dimensions and geometries. The findings showed high accuracy for large geometric features, with minimal deviations between nominal and measured values. However, systematic deviations were found for smaller details, especially apertures up to 5 mm, indicating system detection limits. While not extreme, these deviations affect interpretation in industrial inspection. The importance of correct illumination and contrast selection for optimal boundary detection was also stressed. In this regard, spectral combinations like UV+IR or UV+Blue increased contrast and highlighted fine geometrical details in transparent or dark materials.

Future research should focus on improving measurement accuracy with higher optical resolution, more advanced image segmentation and analysis algorithms, and artificial intelligence to automatically detect boundaries and eliminate optical artifacts. The measurement system should be dynamically calibrated when the spectral conditions and properties of surfaces change. The method should be extended to 3D reconstruction of surfaces in multispectral space to more accurately characterize the dimensional, morphological, and material properties of additively manufactured parts.

ACKNOWLEDGMENTS

This work was supported by the Slovak Research and Development Agency under the contract No. APVV-23-0591, and by the projects VEGA 1/0700/24 and KEGA 028TUKE-4/2025 granted by the Ministry of Education, Science, Research, and Sport of the Slovak Republic.

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