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In-process measurement of the surface quality for a novel finishing process for polymer additive manufacturing

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Abstract

In the last decade, there has been considerable growth in the production of end-use polymer parts and components using additive manufacturing methods. A wide range of polymers, from Nylon-12 to thermoplastic polyurethane polymers, can be processed with complex geometry tailored to specific function. However, due to the nature of the layer-by-layer process used in additive manufacturing, high roughness surfaces remain on the parts. To reduce the roughness of the surfaces, a proprietary post-processing method, developed by Additive Manufacturing Technologies, is applied to the surfaces. To monitor and control the finishing of the surfaces, an in-process surface detection instrument has been developed based on machine vision and machine learning. This paper presents the machine learning approach and the effectiveness of the instrument for in-process measurement of the finished surfaces.

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1. Introduction

Additive manufacturing (AM) has been extensively used for the production of end-use polymer parts during the last decade. With AM, a wide range of polymers, including Nylon-12 and thermoplastic polyurethane polymers, can be shaped into complex geometries designed for specific functions.

However, due to the layer-by-layer nature of AM, the so-called “stair-case effect” on the surface of a produced part occurs [1], causing the part to have a rough surface. Various surface inclinations due to the orientation of a part during processing and the excess of support structures increase the effect [2].

To reduce the texture of AM polymer parts, post-processing procedures can be applied. Manual and laborious post-processing procedures are commonly used. These procedures are very time consuming and reduce the productivity of AM processes.

A new automated solution for the post-processing of polymer AM parts has been developed by Additive

Manufacturing Technologies (AMT). AMT offers a proprietary post-processing machine for polymer AM parts that can automate the process to improve the quality of the surface texture. The automated process results in a significant increase in productivity due to a substantial reduction of the post-processing time and an improvement of the surface texture quality.

An integrated measurement system for use with the proprietary machine is required to detect surface conditions and to send feedback to the machine for closed-loop control [3]. With integrated measurement, a closed-loop feedback control and a significant quality improvement of processed parts can be obtained [4]. In this paper, an in-process instrument has been developed to monitor and control surfaces processed by the post-processing machine. The paper describes a new in-process surface detection solution for polymer AM parts.

This paper is structured as follows. Section 2 describes the proprietary post-processing machine including an example of a

surface condition of a polymer AM part before and after post-processing. Section 3 describes the in-process surface detection requirements, hardware and software developments, instrument testing and sensitivity analysis of the detection process. Finally, section 4 concludes the paper and describes future work.

2. PostPro3D: a novel finishing process for polymer additive manufacturing

Surface smoothing technology Postpro3D (see Fig. 1) is a physical-chemical process partly based on the chemical PUSH™ method, developed at the University of Sheffield [5,6]. The technology can smooth a wide variety of polymers used in AM, including Nylon-12, Nylon-11, Nylon-6, thermoplastic polyurethane (TPU), thermoplastic elastomers, ULTEM 9085, PMMA or the like. Postpro3D is a non-line-of-sight process meaning it can smooth complex-to-reach internal cavities of polymer components.

The PostPro3D smoothing process is highly controllable. This capability allows for reproducible results and a desired level of surface finish to be achieved, which effectively becomes comparable to that of polymer components manufactured using injection moulding (see Fig. 2). During the process, the surface pores of the component are closed, which in turn provides water tightness properties to the AM polymer material.



Fig. 1. PostPro3D automatic smoothing machine.

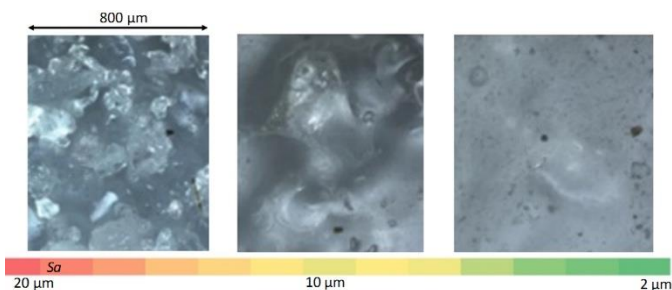


Fig. 2. Surface of a TPU material smoothed to different controllable levels.

3. Development of in-process measurement for the finishing process

We define “in-process measurement” as the use of an instrument that measures an aspect of product quality, for example, surface texture and/or geometrical characteristics,

during, before or after a manufacturing process. The instrument is placed within the process cycle, either inside or outside the process chamber. The results of the measurement can be used to inspect the product or control the process.

3.1. In-process measurement requirement

An in-process measurement for the surface condition detection has several requirements:

- The size of the instrument should be $< (200 \times 200 \times 200)$ mm to fit the end-effector of a collaborative robot.
- The mass of the instrument should be < 2 kg to meet the payload of a small collaborative articulated robot arm.
- Stand-alone robust and fast software.
- Detection of surface condition within < 15 s.
- The cost of the system should be $< 5\%$ of the cost of the post-processing machine.
- The instrument should be flexible and portable.
- The instrument should be simple to be integrated into the post-processing machine.

Two possible solutions for the development of the in-process surface detection instrument are 3D surface measurement and 2D machine vision methods. 3D surface measurement is deemed to be not currently suitable for several reasons:

- 3D surface measurements still require longer measurement times (typically in the order of one minute) compared to the required detection time (< 15 s).
- The cost of the system will be high due to the need for a precision optical system and many systems require a linear motion stage to scan through a focus position so that a sequence of images can be captured.

For the above reasons, a solution based on 2D machine vision was selected. Reasons of the selection are as follow:

- Quantitative surface analysis is not required. The measurement involves image comparison of a measured and a reference surface. The reference surface is a surface considered as a pre-defined surface with smooth surface finish.
- A low-cost instrument can be obtained with a 2D machine vision method since the cost of imaging sensors has been significantly reduced.
- The 2D machine vision measurement capability can be optimised by utilising a machine learning method to improve the detection capability of various surface textures.

3.2. Instrument development

The instrument design is shown in Fig. 3. The design complies with the requirements for low-mass, flexibility and portability. With the instrument, a small area of a surface can be captured and magnified for further analysis. In Fig. 1 (top) the dimensions of the instrument are $(203 \times 121 \times 84)$ mm.

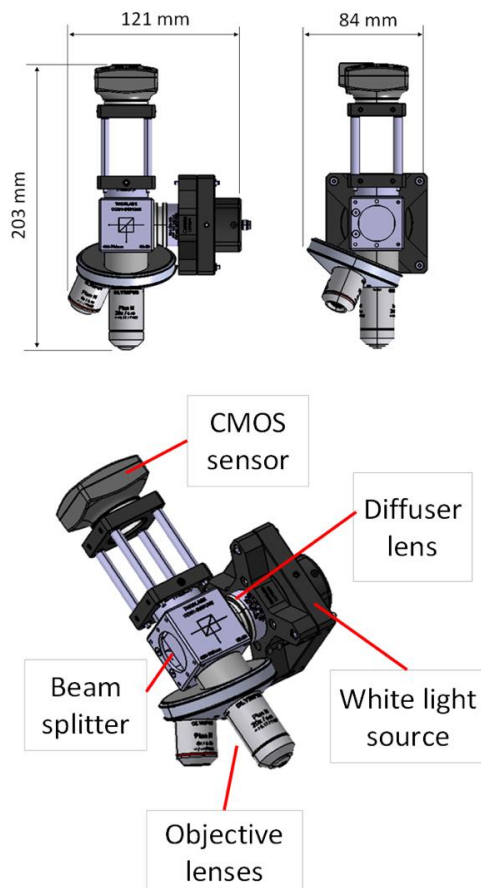


Fig. 3. The 3D solid model of the in-process surface detection instrument.

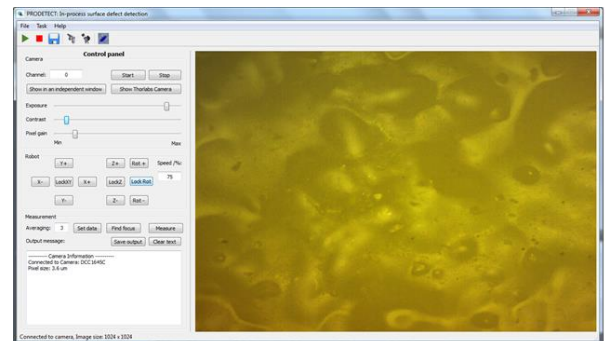
The instrument is made from illumination and microscope modules. The illumination module consists of (see Fig. 3 bottom) a white light light emitting diode (LED) and a diffuser lens. The LED has a total power output of 250 mW with an intensity of 3 mW/cm^2 . The LED's emission has a spectrum of 400 nm to 700 nm. To improve the cross-sectional intensity distribution of the light from the LED, the diffuser lens, with a transmission spectrum of 380 nm to 1100 nm, is used. With the diffuser lens, the LED will have a uniform intensity across the field of view of the microscope's objective lens [7].

The microscope module consists of (see Fig.3 bottom) a camera with a complementary metal-oxide semiconductor (CMOS) sensor, a beam splitter, a tube lens, and objective lenses with $4\times$ and $10\times$ magnifications. The tube lens is used to transform a parallel ray reflected from the measured surface through the objective lens into an image on the CMOS sensor. Both the beam splitter and the tube lens have transmission spectra of 400 nm to 700 nm. The CMOS sensor has a pixel density of (1280×1024) pixels with a frame rate of 30 fps.

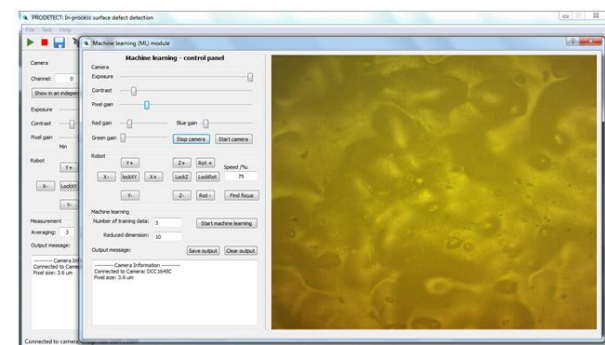
3.3. Software development

There have been many studies about surface texture analysis using 2D machine vision methods. Examples are the use of machine vision methods to estimate surface texture parameters from turning [8], milling [9] and grinding [10] processes. The studies commonly capture and process an image, calculate some image parameters specific to the features of interest from

a process and statistically correlate the calculated image parameters to certain texture parameters.



(a)



(b)

Fig. 4. The developed software. (a) The measurement module and (b) the machine learning module.

Most of the existing studies only focus on a specific type of surface and are based on regression analysis. With regression analysis, the correlation of a specific image condition to specific texture parameters is only limited to a specific surface from a specific process.

In this paper, a general classifier of various different surface types from different AM processes and different polymer materials is developed. The classifier is based on an unsupervised machine learning approach using principal component analysis (PCA) [11]. The goal of PCA is that high dimension data, in this case the (1280×1024) dimensions of the image size obtained from the CMOS sensor, can be reduced to a lower number of dimensions that still contains the important surface texture information.

To improve the computation efficiency of the PCA, a total of 54 image parameters are calculated from the captured image of a surface, obtained from the developed instrument. By calculating these parameters, a first step in data reduction is applied to speed up the classification process using PCA. The 54 image parameters are divided into two categories: colour-related and texture-related parameters. The parameters are:

- A total of 17 colour-related parameters.
- A total of 37 texture-related parameters.

The colour-related parameters are obtained from the calculation of statistical parameters of the colour (RGB and HSV) of a 3-channel image, and the histogram entropy of the 3-channel image [11]. Meanwhile, the texture-related parameters are obtained from the calculation of statistical

parameters of blobs of an image, local edge descriptors and binary local patterns [13].

Local edge descriptors [12] and image colour parameters are part of the multimedia content description interface (MPEG-7) [13]. Binary local pattern parameters are image parameters that are calculated from analysis of many small sub-regions in an image [14,15].

The PCA classification of the images of different surface conditions are calculated from the 54 image parameters. With this strategy, the calculation of the PCA classification is more efficient compared to the calculation of the PCA from all the images' pixels.

The software is implemented in the C/C++ programming language as stand-alone software that controls the instrument and process images to detect surface conditions. The image processing uses the OpenCV robust image processing library [16] and the graphical user interface (GUI) uses the Qt4 library [17]. Fig. 4 shows the developed software with the two main modules: measurement and machine learning. The software is able to control a collaborative robot in order to move the microscope and find the focus position with respect to a surface.

The measurement module provides functionality to control the collaborative robot and to detect a surface condition and compare to a reference surface. The detection process is carried out based on machine learning approach that learns distinctive image properties data from a reference surface. Based on the learning process, a surface can be detected and classified as similar or dissimilar to the reference surface.

The machine learning module provides functionality to control the collaborative robot, to adjust camera settings and to train the software with a specific reference surface. The camera settings can be adjusted to find an optimal surface colour. An auto-exposure algorithm [18] and a white-balancing algorithm [19] are implemented to optimise the colour adjustment. This module allows the setting of the number of training data and the number of reduced dimensions from 2 to 54.

The machine learning process is as follows. An image is taken from the CMOS sensor according to a number of training images n that are set by the user. The 54 image parameters are calculated. By extracting the parameters, the first data reduction is applied to increase training efficiency so that only hundred number of images are required to effectively conduct the machine learning process. A mean of the total 54 parameters is calculated and a difference matrix between the 54 parameters of each image and the mean parameters is derived. A $54 \times n$ training matrix is constructed. Finally, the PCA method is applied to the training matrix. The eigenvectors and eigenvalues of the trained data are stored in a file. The file can be recalled when a specific surface detection is to be carried out.

A similarity value is calculated between the reference surface and the measured surface to decide whether the two surfaces are similar or not. The value is calculated as the Euclidean distance between the reference surface and the measured surface in their principle component (PC) space. With the calculation of the similarity value, subjectivity for determining a specific surface texture condition can be eliminated.

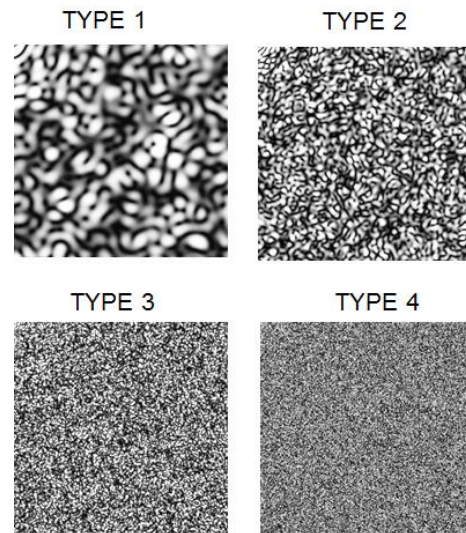


Fig. 5. One example for each type of simulated images with speckle patterns.

3.4. Instrument and software testing

Instrument and software testing was carried out to study their effectiveness for surface detection. Two stages of testing were implemented: testing with simulated images and testing with real TPU surface images.

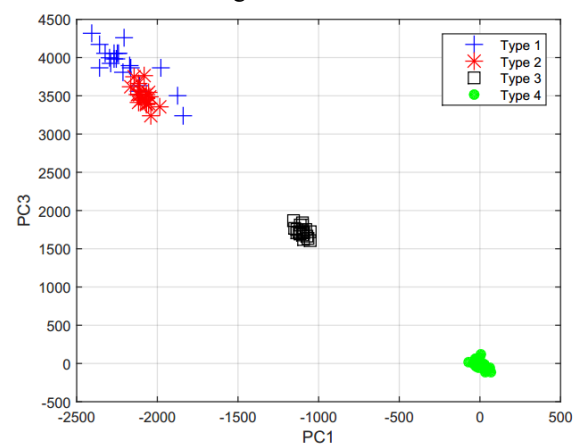


Fig. 6. Separation of each type of simulated images in PC space (2D view).

The testing with simulated images uses generated images with simulated features. The simulated features are speckles with different size and density to represent different features on a surface. Four types of simulated images with speckle features are generated, namely Type 1, Type 2, Type 3 and Type 4 (see Fig. 5). The method to generate the speckle images can be found elsewhere [20]. A total of 100 images are generated for each type. Type 1 images, representing an un-processed surface, have the largest size of speckle patterns with the lowest density. In contrast, Type 4 images, representing a processed surface, have the smallest size of speckle patterns with the highest density.

A Type 4 simulated image is selected as a reference surface. A total of 100 images are used for training. The trained data are used to detect a different type of simulated image with respect to the reference image. The PCA uses three dimensions of PC space for the surface detection.

Fig. 6 shows the separation plot, considering only two PCs, from each image type in PC space. From Fig. 6, it can be observed that the different types of surface can be classified into different groups. The Type 4 surfaces can be largely separated from the other types. Calculated similarity values will be significantly smaller for Type 4 compared to other values for other types. Table 1 shows the calculated similarity values for the four types of surfaces compared to the reference surface (Type 4). From table 1, by setting a threshold, Type 4 surfaces can be detected.

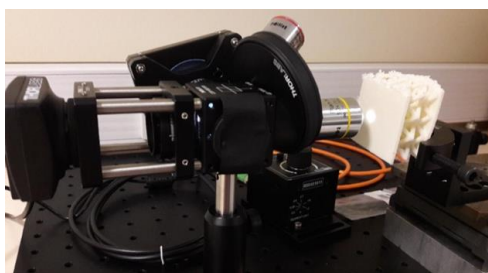


Fig. 7. The measurement of the TPU surfaces.

The testing with the TPU surface images uses five types of surfaces, namely: Type 1, Type 2, Type 3, Type 4 and Type 5 that represent 0 % (unprocessed), 25 %, 50 %, 75 % and 100 % (fully processed) post-processed surfaces, respectively. A total of 100 images for each type of surface are captured. The 100 images are captured from different areas that cover the entire TPU surfaces so that the images cover various types of features on each surface type. Fig. 7 shows a measurement process for one of the TPU surfaces.

Fig. 8 shows one of the images of the measured surface for each type of surface. From Fig. 8, the Type 1 (unprocessed) surface has high roughness and Type 5 (fully processed) has low roughness. The reference surface is a surface from Type 5.

Table 1. Similarity values, with respect to a reference surface, for the tested simulated and TPU surfaces. σ is a standard error.

Image type	Similarity value (mean $\pm$ σ) $\times 10^3$					Ref.
	Type 1	Type 2	Type 3	Type 4	Type 5	
Simulated	23797.6 $\pm$ 327	20117.5 $\pm$ 234	5219.6 $\pm$ 65	8.7 $\pm$ 0.09	-	Type 4
Image type	Similarity value (mean $\pm$ σ) $\times 10^6$					Ref.
	Type 1	Type 2	Type 3	Type 4	Type 5	
TPU	40.1 $\pm$ 0.3	176.2 $\pm$ 1.9	348.9 $\pm$ 3.4	48.2 $\pm$ 0.8	9.8 $\pm$ 0.3	Type 5

A total of 100 Type 5 TPU images are used for training with PCA. Three PCs from the training data are used to calculate the similarity of the measured surfaces with the reference surface. Fig. 9 shows the separation plot, considering only two PCs, of each TPU image type in PC space. From Fig. 9, the Type 5 TPU surfaces can be separated from the other types of TPU surface. The type 4 surfaces are grouped close to the Type 5 as can be qualitatively observed from the image (Fig. 6) that the Type 4 surface is similar to the Type 5 surface.

Table 1 shows the calculated similarity values for the five types of TPU surfaces compared to the Type 5 surface as the reference. From table 1, by setting a threshold, Type 5 surface can be detected. The detection time was around 2 s.

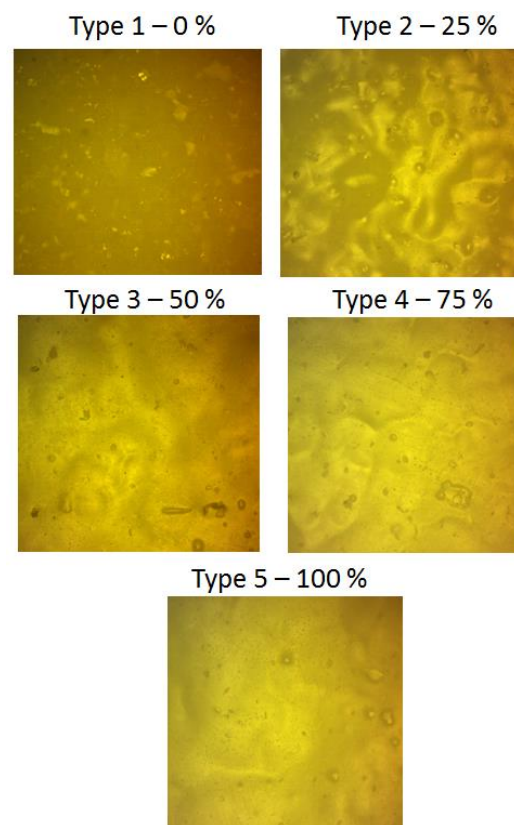


Fig. 8. The images of the five types of TPU surfaces.

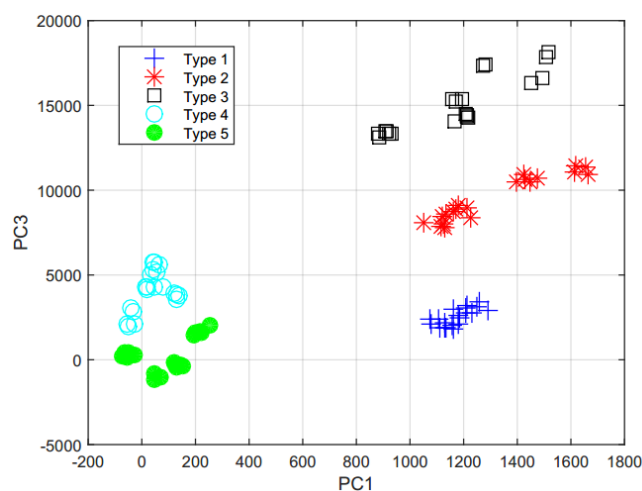


Fig. 9. Separation of each type of TPU images in PC space (2D view).

3.5. Sensitivity analysis

The pixel detector on the CMOS sensor has noise so that the intensity value of a pixel for each detector will vary over time. Sensitivity analyses were carried out to investigate the degree of the variation of the pixel intensity on the detector over time and to quantitatively analyse the effect of the pixel intensity variation to the similarity value.

The analysis of the intensity variation over time is carried out by analysing a single intensity value of a pixel on the detector. A Nylon-12 surface was used for the analysis. The sampling frequency of the detector was set to 15 fps. A total of 100 pixels were sampled over a period of 6.6 s. The sampling period is considered sufficient, since it is larger than 2 s for a

surface detection time. Fig. 10 shows the pixel intensity variation over 6.6 s. The results of the variation analysis shows that the standard deviation of the pixel intensity is 2 pixel unit.

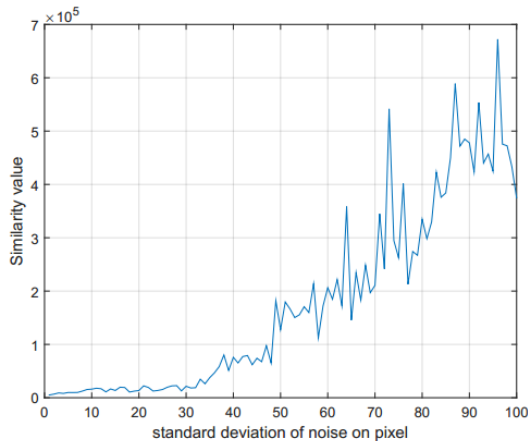


Fig. 10. The pixel variation over a period of 6.6 s (100 values).

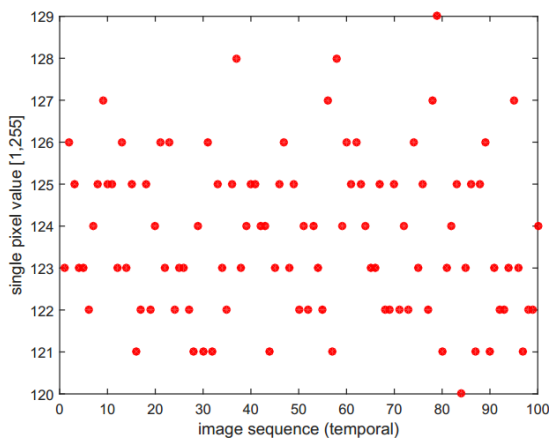


Fig. 11. The sensitivity of similarity value over the level of pixel variation.

The analysis of the similarity value is carried out by analysing the similarity value of a Nylon-12 surface with respect to increasing value of the pixel variation of the image of the Nylon-12 surface. The intensity value of the pixels of the image are perturbed by a Gaussian noise with a standard deviation ranging from 0 to 100 pixel unit.

Fig. 11 shows the results of the sensitivity analysis of similarity value. From Fig. 11, it can be observed that the similarity value is still stable until the pixel noise is more than 30 pixel values. From this result, a surface detection is considered robust, since the pixel intensity variation is only within 2 pixel unit value.

4. Conclusion

In this paper, the development of an in-process surface detection instrument for an automated post-processing machine for polymer AM parts has been presented. The instrument can significantly benefit the machine by providing closed-loop process control and removing subjectivity of surface quality verification. The instrument is equipped with software to control the instrument and classify a measured surface based

on machine vision and machine learning. Future work will fully integrate the instrument into the post-processing machine.

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