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The use of smart in-process optical measuring instrument for the automation of Additive Manufacturing processes

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Abstract

During the past decade many new applications for components made using additive manufacturing techniques have emerged [1]. The appeal of additive manufacturing is broad and includes the potential for digital integration into the manufacturing process chain, creating opportunities for an Industry 4.0 revolution [2]. However, manual post-processing of parts creates many issues with the control and monitoring of surface quality, due to the resulting high variability in surface topography [3]. This variability should be controlled for critical parts and parts that are mass produced and have undergone several post-processing stages. To overcome this issue, fast and effective in-line optical measurements are required. This paper presents a novel measuring instrument for part surfaces with millimetre- to micrometre-sized features[1].

Introduction

The current standard for surface evaluation is mechanical-probe based surface profile roughness measurement according to EN ISO 4287 and EN ISO 16610-21. The method is useful for the indicative assessment of the surface roughness of the small sample area of intersection between workpiece and the probe-tip. The method has found use in Additive Manufacturing applications, mostly for research purposes of surface quality assessment for both as-printed and post-processed parts [4]. Unfortunately, tactile-based surface measurement methods are proving to be too impractical in automated Additive Manufacturing processes: among the issues are measurements of intricate, difficult-to-reach surfaces; automation of the process; possibility for surface damage; and limited amount of surface data that can be obtained describing the final component.

Optical methods, including image analysis for surface measurements, avoid many of the drawbacks of mechanical-probe based techniques [3]. A number of image analysis methods for surface measurements have been developed to date, especially for use in cell analysis in the biomedical industry [5, 6] and also for detection of surface-specific defects in automotive/manufacturing industries [7, 6]. Some of the methods include basic learning algorithms, however, all of the current image analysis techniques require manual supervision and focus only on specific features. The nature of the Additive Manufacturing Industry means that the

[1] The presented technology is covered by multiple pending patents.

design of components, including their geometry, surface finishes and applications are always changing according to customer needs [2]. This makes current optical surface measurement systems unfit for this purpose and requires a new AM-specific optical surface measurement system, able to analyze a wide variety of surfaces, with machine learning capacity and the ability to send feedback on the surface condition back to the system at every single post-processing stage [3].

To develop such a metrology system, Additive Manufacturing Technologies (AMT), a UK-based technology manufacturer has partnered with the University of Nottingham [9, 10]. A novel in-line surface measurement system with machine learning capacity called PostProMet was designed and constructed. The system is able to mass-analyze and recognize a wide variety of surfaces, e.g. polymers, metals, ceramics, synthetic surfaces etc. This paper presents this system and discusses its application possibilities.

Methodology

The surface measuring system was developed according to the Information Rich Metrology (IRM) method [11]. This method involves the use of any additionally-available data about the manufacturing process and the components to be measured to improve the developed system. Based on the undertaken IRM process, the design features of the system, type of measurement and the required data analysis process were designed [9, 10].

Hardware

An optical in-process measurement was found to be the most promising for the purpose of quality control of additively manufactured components. The reasons for this was that optical measurements can analyze high-density data fast, are free of surface damage and can scan difficult-to-reach surfaces, which is especially pertinent for complex additively manufactured components. The available machine vision solutions include 3D and 2D measurements. The latter was selected for this purpose due to faster measurement time and lower hardware costs [9, 10].

In-process measurement means the use of the instrument for the measurement of the surface condition before, during and/or after the machining/manufacturing process. The measurement apparatus may be integrated into a robotic arm, an industrial desk or any other electrically guided railing system able to take multiple images of the component surface. The analyzed surface results are used as the digital feedback for the machining/manufacturing process.

The optical device consists of illumination and microscopes modules. The developed surface analysis algorithm can work with any magnification and any pixel density images. The system used for the results presented in this report includes 250mW light emitting diode (LED) with an intensity of 3 mW/cm^2, emission spectrum of 400 nm to 700 nm and a diffuser lens with a transmission spectrum of 380 nm to 1100 nm. The microscope module consists of a camera with a complementary metal-oxide semiconductor (CMOS) sensor with 1280 x 1024 pixel density, frame rate of 30 fps and objective lens with 10x magnification [9, 10].

Surface analysis

The developed algorithm scans the surface and searches for a set of pre-calculated parameters. These parameters include texture and color based image descriptors and were defined during the IRM development stage [9, 10]. Instead of analyzing all the parameters, the algorithm applies Principle Component Analysis (PCA) to reduce the number of image-describing parameters to the minimum number that can still define each image. The remaining parameters contain a unique combination of values that can be assigned a quantitative image-describing value set by the user.

Results and Discussion

Five Polyamide 12 surfaces of different smoothness levels were scanned with the developed instrument (see Figure 1a). The results of the surface analysis are presented in Figure 1b. The samples were additively manufactured using 3D Systems sPro-Sinterstation and post-processed with AMT's PostPro3D machine.

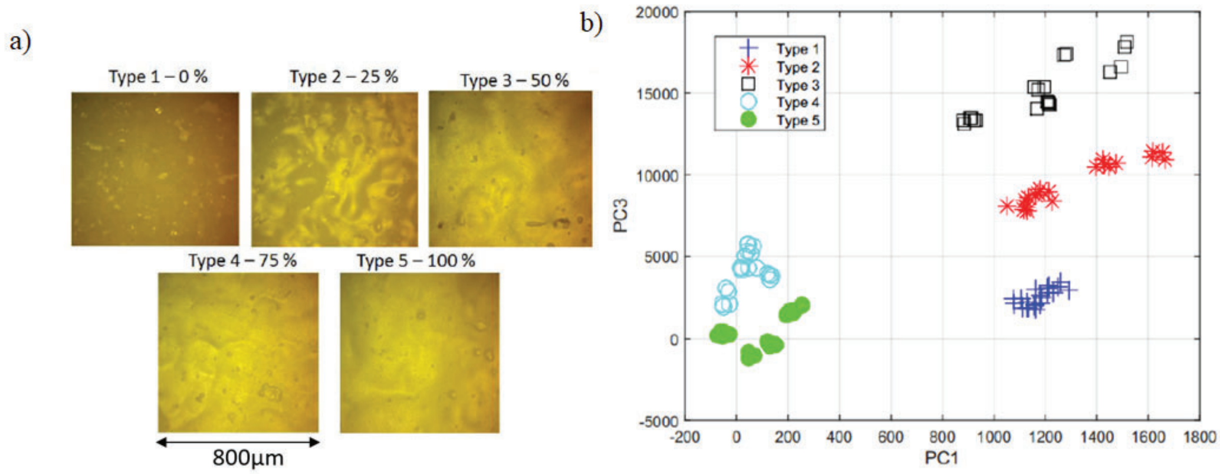

Figure 1. A) Surfaces of Polyamide 12 material scanned at different levels of smoothness. The surfaces were smoothed using PostPro3D smoothing system. B) Images of scanned Polyamide 12 surfaces categorized by the algorithm in the PC matrix.

The algorithm differentiated between the five surfaces as shown in Figure 1b and assigned a quantitative value to each surface, which in this case was the relative processing (smoothness) level of the material. Furthermore, the algorithm can be trained to assign different values to the surface, such as gloss/matte level, color saturation, roughness level, surface quality, defects etc. The algorithm is trained by the user on the values of each image category and the similarity value each time a new surface is scanned. The similarity value helps to distinguish between the groups of similar surfaces. Once the training is completed and the values of each group are assigned, the algorithm is able to mass-analyze and categorize given surfaces.

Application

The developed algorithm can be integrated into different hardware to be used in the Additive Manufacturing process chain, e.g. industrial bench with electrically guided railing or a robotic arm. At AMT, the system is used for the generation of digital feedback and data collection from the post-processing of AM components (see Figure 2). The process is as follows: the metrology system receives the post-processed parts and the surface is scanned. The feedback on the surface condition is then sent to each of AMT's automated post-processing systems: de-powdering PostProDP, smoothing PostPro3D and coloring PostProCol. If a deficiency is detected due to the fault of a specific post-processing stage, the system can self-correct; for example, if insufficient color saturation is identified, the machine learning iteration circle is started and a new set of parameters is sent to the appropriate post-processing unit (e.g. coloring) to fix the surface condition. Therefore, the developed smart in-process surface measurement system makes use of the other automated post-processing equipment to close the digital manufacturing loop. The resulting Digital Manufacturing System, developed by AMT, removes the need for manual labor in post-processing, increases part quality and enables automation for the Additive Manufacturing process chain.

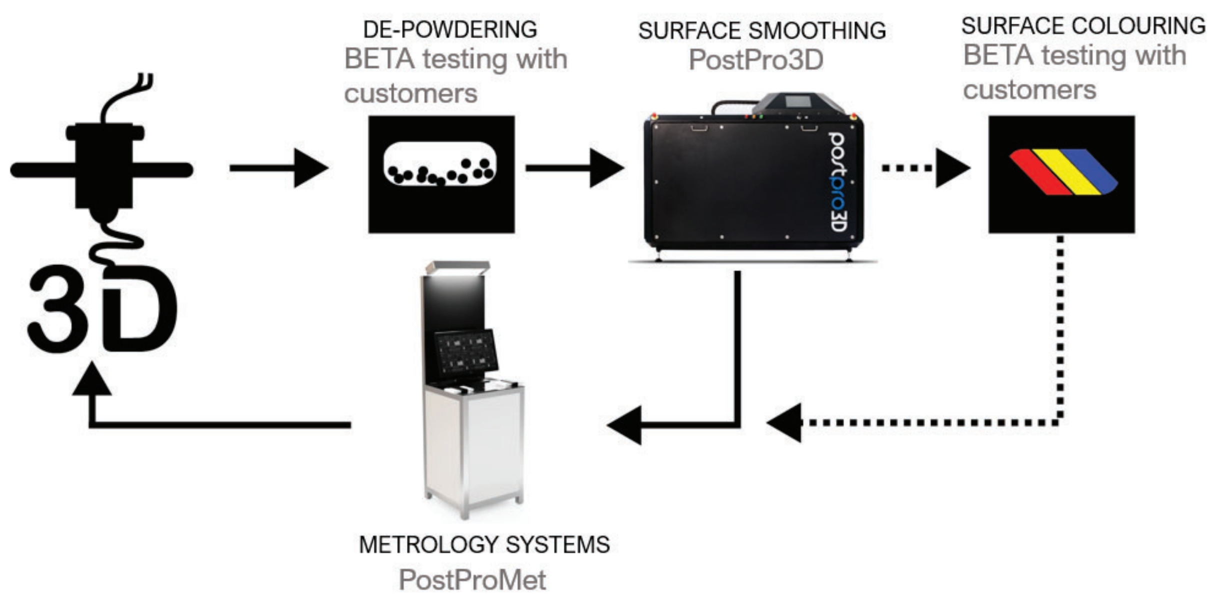

Figure 2. Digital Manufacturing System with full digital feedback, developed by Additive Manufacturing Technologies.

Conclusion

Growing application and usage of additively manufactured components uncovered the demand for automated surface measurement system, especially for components that have undergone several post-processing stages. Unfortunately, currently used surface measurement methods are impractical to use, and slow down the quality control stage of the Additive Manufacturing process. To solve this issue, a smart in-line measurement system enabling automation of the Additive Manufacturing process was developed using an optical device and Principal Component Analysis based machine learning algorithm. The developed system opens new opportunities in the digitization process and helps to enable Industry 4.0 update in the AM process chain.

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