A Study on Monitoring and Fault Diagnosis of Fused Deposition Modeling Process Based on Data-driven Approach

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ABSTRACT

Additive manufacturing (AM) is a layer by layer manufacturing process that can fabricate a three-dimensional part directly from a computer aided design (CAD) model. In particular, a fused deposition modeling (FDM) process is the most widely used AM technique for fabrication of thermoplastic parts. They can be used for making functional prototypes with advantages of low cost, minimal wastage and ease of material change. Despite its recent popularity, FDM still faces many technical challenges for insufficiency of process reliability and controllability and product quality. Therefore, to overcome such disadvantages, the monitoring and fault diagnosis on FDM process is of much significance. In this study, the monitoring on quality of parts and components fabricated by the FDM process is conducted by analyzing mass data which are obtained from various sensors such as accelerometers, acoustic emission sensors and temperature sensors. After extracting critical features from the measured process signals, they are related with quality evaluation indices in the model by using data-driven modeling techniques. Finally, the developed model is validated via a series of experiments.

1. INTRODUCTION

AM is a technique to fabricate a three-dimensional part by depositing material layer by layer based on a CAD model [1]. This technology has recently received much attention from both industry and academia for the challenging possibility to fabricate parts with complex shapes and minimal use of harmful chemicals at a reasonable speed [2~4]. Among many AM techniques, a FDM process has been widely used for fabrication of thermoplastic parts. In this process, a thermoplastic filament is extruded through a nozzle at above melting temperature and deposited layer by layer on a platform to fabricate a three-dimensional part. It can be used for making functional prototypes with advantages of low cost, minimal wastage and ease of material change [5]. However, the FDM process still faces many technical challenges for insufficiency of process reliability and controllability and product quality [6]. Therefore, a monitoring and fault diagnosis for the FDM process is necessary to overcome such challenges.

Rao et al. identified normal and abnormal conditions of the FDM process by using signals collected from temperature and acceleration sensors in a 3D printer. They attached a temperature sensor to the nozzle, and studied relationship between the test part quality and temperature change. In addition, three states – normal, abnormal and fault – of the quality were diagnosed [7]. Yoon et al. carried out the quality monitoring study on bolts and nuts produced from the 3D printer by attaching an acoustic emission sensor. They identified the difference of measured acoustic emission signals in the cases between normal and abnormal parts, and then, they developed the defect detection technology for the 3D (FDM) printed bolts and nuts [8].

Although there were some studies on the identification of dominant process parameters influencing on FDM part quality, studies on health monitoring and diagnosis of FDM process based on a data-driven approach are very little. Therefore, in this paper, the health monitoring and diagnosis of FDM process are studied based on the data-driven approach using mass data collected from an acceleration sensor. The collected acceleration data are then processed to extract the key feature – root mean square (RMS), and the RMS values are used to build the model predicting the part quality. A support vector machine (SVM) methodology is introduced to establish the model, and it is experimentally validated.

2. EXPERIMENTAL SETUP AND CONDITIONS

The photo of the experimental system is given in Figure 1, and three accelerometers (353B03, PCB Piezotronics Inc.) were installed in the FDM 3D printer (Ultimaker 2+, Ultimaker Inc.) to capture acceleration signals along x, y and z axes. The filament material for FDM process was acrylonitrile butadiene styrene (ABS). The specification of the FDM 3D printer and experimental conditions are summarized in Table 1.

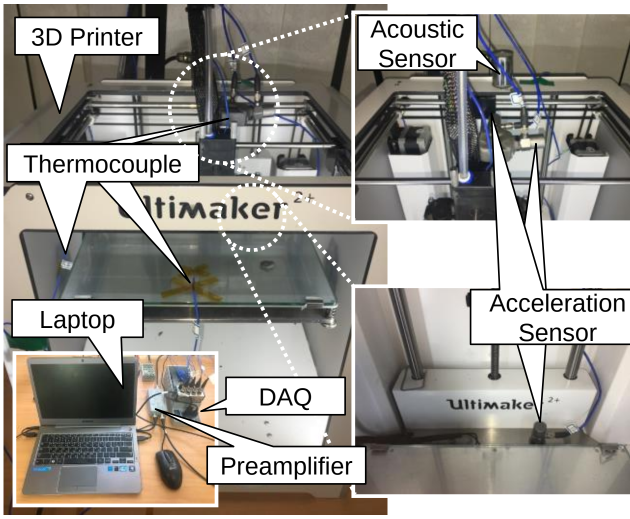

Figure 1. Experimental setup of the FDM process.

Table 1. Experimental specifications and conditions.

3D Printer (FDM)	Ultimaker 2+	
Specimen model	ASTM D 1708	
Filament	Material	ABS
	Diameter	2.85 mm
Nozzle diameter	0.6 mm	
Support type	None	
Extruder speed	0.4 m/s	
Extruder temperature	260 ℃	
Bed temperature	90 ℃	
Layer thickness	0.1 mm	
Infill	100 % (45°)	
Sampling frequency	6 kHz (Acceleration)	

3. MONITORING AND FAULT DIAGNOSIS MODELING AND VALIDATION FOR THE FDM PROCESS

In general, a 3D printer has a lot of feeding motions along lateral axes – x and y axes in this research while fabricating parts. Thus, as the number of times of use increases, the bolt in the feeding unit can be loosened and it can cause abnormal movement of the shaft. As a result, this abnormal movement can result in part quality degradation. Therefore, in this study, abnormal movements were generated by loosening the bolt, and it was found that the loosened bolt can cause faulty FDM parts. However, the loosened bolt cannot easily be found during the process, and therefore, the acceleration signals were used to indirectly identify the loosened bolt.

Among the acceleration signals along with x, y and z axes, the x-axis acceleration signals were more sensitive than others, and their RMS values were selected to be related with either good and faulty states of the FDM process. As can be seen in Figure 2, it was obviously observed that there existed a difference in the RMS values of the x-axis acceleration signals between normal and abnormal processes. In more detail, the x-axis acceleration RMS values in the case of the loosened bolt (abnormal state) were larger than those in the case of the tightened bolt (normal state). Besides, the photos of good and faulty FDM parts are shown in Figure 2.

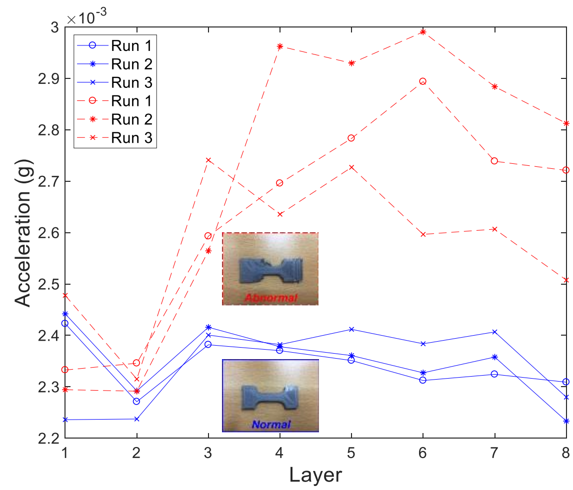

Figure 2. RMS values of the x-axis acceleration signals in the cases of normal and abnormal FDM processes.

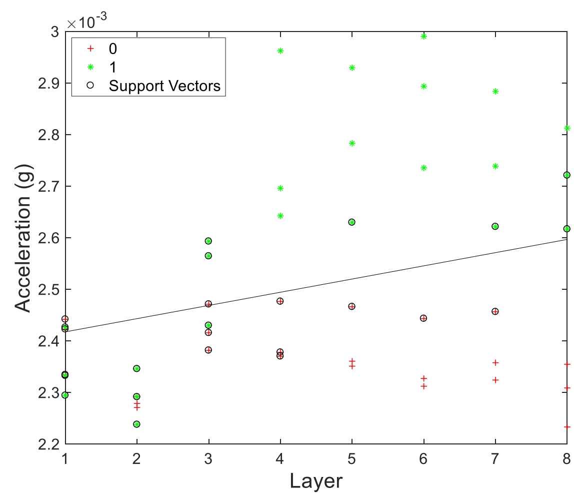

Figure 3. Diagnosis results based on SVM for the normal and abnormal FDM processes

For monitoring and fault diagnosis of the FDM process, the SVM-based model was developed. While training the model, the RMS values were input variables, and the output responses were numerical confidence values, which are 0 for the normal process and 1 for the abnormal process. Additional experiments were conducted to validate the model, and the diagnosis rate for the normal FDM process was 100 % and that for the abnormal FDM process was 75 %, as can be seen in Figure 3. Therefore, the model was validated.

4. CONCLUSION

This paper addressed the monitoring and diagnosis of normal and faulty FDM processes based on the data-driven approach. The accelerometers were installed in the FDM 3D printer to collect mass data of the acceleration during the FDM process in the normal (tightened bolt) and faulty (loosened bolt) states. The collected acceleration signals were processed to obtain their RMS values, and they were correlated with the numerical confidence values – 0 for the normal and 1 for the faulty processes based on the SVM methodology. The results showed high diagnosis rates, and the developed monitoring and diagnosis model was validated. Therefore, it is expected that the developed model could be used for monitoring and diagnosing the health state of the FDM process and improving the part quality with a timely preventive maintenance.

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