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Technical Paper

An improved fault diagnosis approach for FDM process with acoustic emission

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ABSTRACT

The reliability and performance of additive manufacturing (AM) machines affect the product quality and manufacturing cost. Developing effective health monitoring and prognostics methods is critical to AM productivity. Yet limited work is done on machine health monitoring. Recently, the application of acoustic emission sensor (AE) to the fault diagnosis of material extrusion or fused deposition modeling process was demonstrated. One challenge in real-time process monitoring is processing the large amount of data collected by high-fidelity sensors for diagnostics and prognostics. In this paper, the efficiency of machine state identification from AE data is significantly improved with reduced feature space dimension. In the proposed method, features extracted in both time and frequency domains are combined and then reduced with the linear discriminant analysis. An unsupervised density based clustering method is applied to classify and recognize different machine states of the extruder. Experimental results show that the proposed approach can effectively identify machine states of the extruder even within a much smaller feature space.

1. Introduction

As a popular and low-cost additive manufacturing technique, material extrusion or fused deposition modeling (FDM) is able to fabricate prototypes and print parts with complex geometries. Thermoplastic materials, including nylon, acrylonitrile butadiene styrene, polylactic acid, and others can be used [1]. Several quality related issues exist in FDM, such as surface roughness [2], geometry deviation [3], shape shrinkage [4], and weak mechanical strength [5]. These quality issues limit the potential applications of the FDM products. As the core component in the FDM machine, the extruder is important to ensure the build quality. For example, feeding speed, extruding speed, and nozzle temperature of the extruder affect the bead width, which in turn determines the quality of extrusion. So far, the majority of commercial FDM machines are not equipped with extruder condition monitoring systems [6]. Fault diagnosis on these machines relies on human operators' visual inspection as well as individual experiences of operators. Thus product quality and consistency cannot be guaranteed. Material waste because of the delayed interruption and correction is significant. Serious process failures may also cause costly machine breakdown.

It is critical to develop automated condition monitoring and fault diagnosis systems such that the closed-loop control of FDM process can be realized for product quality assurance. Sensor-based fault diagnostics and prognostics have been widely applied in other manufacturing equipment, where machine conditions are monitored by analyzing signals acquired by sensors and extracting features to identify machine states. The future states can also be predicted from statistical machine learning models.

Limited research is done on monitoring the FDM process and machine health. Recently acoustic emission (AE) was used to monitor the condition [7–10]. In other related efforts, optical camera [11,12] and infrared camera [13] were applied to monitor the extrusion process non-intrusively, whereas fiber Bragg grating sensor [14] was applied intrusively.

AE sensor has several advantages and has been applied in traditional manufacturing processes [15–19]. First, AE sensor is sensitive to mechanical system dynamics caused by changes of friction, force, vibration, or structural defect. It contains rich information of machine states and their changes. Second, its implementation is simple. The source of signals can be directly from machines themselves, and no external stimulation is needed. Third, AE monitoring system can be made non-intrusive. Thus modification of the original equipment is not required.

To identify machine states from AE signals, the signals in waveform

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are first processed by some signal decomposition methods, such as wavelet analysis [20], empirical mode decomposition [21], and variational mode decomposition [22]. Features are then extracted from the processed signals. Mappings between the extracted features and patterns to be recognized are established. The mappings are then used to identify machine states when new signals arrive. The major challenges of this pattern recognition process for real-time applications include the large volume of data because of high sampling rate used by sensors and high dimensionality of feature space formed by various information extracted from the original signals, which both lead to high computational load. The sensitivity and robustness of identification depend on what features to be selected if the dimension of feature space is to be reduced.

In our previous work of AE-based FDM machine monitoring, the original AE waveform signals were simplified as AE hits. This significantly reduces the amount of data to be processed. It was shown that state classification with support vector machine based on single feature in time domain is effective [7]. The further consideration of multiple features in time domain increases detection sensitivity. Hidden Markov model based on the further reduced signals by principal component analysis (PCA) can improve efficiency [9].

In this paper, both time- and frequency-domain features from the AE hits are used for state identification. The inclusion of frequency-domain information in the feature vector prevents the information loss and provides a more comprehensive and accurate approach for state recognition. With the further increased dimension of feature space, more accurate classification approaches can be helpful. Here, the linear discriminant analysis (LDA) [23] is applied to customize the operator for dimensionality reduction. The customization is according to the nature of AE hits so that the sensitivity of feature detection is maximized. After the dimension of features is reduced, the clustering by fast search and find of density peaks (CFSFDP) approach [24] is taken for classification.

The standard linear dimension reduction techniques such as PCA reduce the dimension of feature space with a generic criterion of sample variance. Their use is not optimal when the ultimate goal is classification, where the differentiation power between classes after the data size reduction is important. In contrast, in the LDA method, the linear transformation operator for dimension reduction is customized to maximize the differentiation power between classes based on a particular set of data. This approach can provide the optimum projection directions in the application of classification. With the optimum transformation operator, the data processing and feature identification based on LDA can be more accurate than the ones based on traditional PCA.

In fault diagnosis for the FDM process, conventional supervised classification methods, such as hidden semi-Markov model [9] and support vector machines [7], have been applied to identify the machine states. However, the system models need to be trained based on the previously determined features and states. Therefore, supervised classification methods have the limitation in real-time system identification when the knowledge about the system states is incomplete or limited. The premise of applying classification methods is that all machine states are known a priori. In addition, the decisions of how to choose the training data sets and training methods will affect the final identification results. As an alternative, unsupervised clustering methods have been used to recognize and classify machine states in manufacturing [25–27].

In unsupervised clustering analysis, typically cluster centers need to be determined first. Then feature point regrouping and cluster update are performed iteratively. Different machine states thus can be identified by analyzing clusters without supervised training process. In this paper, a density-based clustering method, CFSFDP method, is used. Different from distance-based clustering methods such as hierarchical and partitioning algorithms (e.g. k-means), density-based clustering methods do not group data and update the clusters iteratively. This can significantly save computational cost in real-time applications. More importantly, density-based clustering algorithms, such as the recently developed CFSFDP method, do not necessarily group clustering into spherical domains. Clusters with more generic topology can be generated. Therefore, some inherent nonlinear relationships among data within a cluster can be preserved.

In summary, the efficiency of feature extraction as well as effectiveness of dimensionality reduction for state classification in existing research approaches need to be improved. In this work, the CFSFDP method is applied to fault diagnosis of FDM process for the first time, where the centers of clusters are efficiently identified. With the LDA-based dimension reduction and classification methods, the overall capability for real-time fault diagnosis is improved.

The rest of the paper is organized as follows. In Section 2, the architecture of the proposed fault diagnosis approach is introduced, including feature extraction, hybrid feature space construction and reduction, and unsupervised clustering. Experimental results in the FDM process are analyzed to demonstrate the performance of the proposed approach in Section 3, with comparison with other approaches. Section 4 concludes the paper.

2. Methodology

The basic flow chart of the improved AE sensor-based fault diagnosis system is shown in Fig. 1. The AE sensor is used to collect vibration signal of the extruder. The acquired AE signals contain the information of different machine states. The time and frequency domain features in AE signal are then extracted to form the hybrid feature vector. The high-dimensional hybrid feature space is constructed to avoid information loss. The LDA method is applied to reduce the dimension of the hybrid feature space and thus the computational cost in the following classification step. Then the unsupervised density-based clustering technique is used to identify the reduced hybrid features. Finally, machine states of the extruder in FDM process is recognized and classified for fault diagnosis.

2.1. Signal acquisition and feature extraction

The AE signals from the AE sensor are first processed and AE hits are counted. An AE hit $u(t)$ is illustrated in Fig. 2, where time-domain features including amplitude, count, and duration are shown. Other typical features such as root mean square (RMS), peak frequency (P-Freq), absolute energy (ABS-Energy), and signal strength are also used [7–9].

Specifically, the amplitude is the peak voltage of the wave within an AE hit, which is defined as

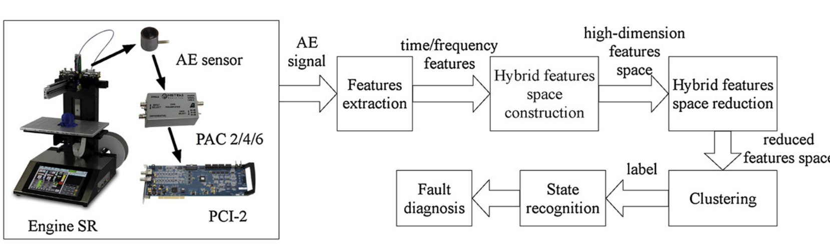

Fig. 1. Basic flow of proposed healthy condition monitoring method.