Low-cost and Small-sample Fault Diagnosis for 3D Printers Based on Echo State Networks

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Abstract—**With the 3D printing rapidly expanding into various fields, 3D printers, as the equipment, should adopt a low-cost and small-sample fault diagnosis methods. A fault diagnosis method based on echo state networks (ESN) for 3D printers is proposed in this paper. A low-cost attitude sensor installed on the 3D printer is employed to collect raw fault data. Subsequently, feature extraction is carried out on the raw fault data. Using these features, ESN, as a shallow learning network, is modeled to diagnose faults of 3D printers. Experimental results show that the fault diagnosis method based on ESN still effective for 3D printers in low-cost and small-sample, which can make the fault recognition accuracy of 3D printer reach to 97.26%. Furthermore, contrast results indicated that the fault diagnosis accuracy of ESN is higher and most stable when compare with support vector machine (SVM), locality preserving projection support vector machine (LPPSVM) and principal component analysis support vector machine (PCASVM).**

Keywords-echo state networks; fault diagnosis; 3D printer; machine learning; feature extraction

I. INTRODUCTION

Recently, the application of 3D printing is rapidly expanding into various fields due to many advantages [1]. On the one hand, the production cycle can greatly shorten for that 3D printing is based on the idea of rapid prototyping. On the other hand, it has the advantages of saving materials, environmental protection and generating almost any geometric products since 3D printing is an additive manufacturing technology [2].

3D printers as the important equipment in the field of 3D printing are the focus research topic [3]. With the gradual development of the design and manufacture of 3D printers, the structure of 3D printer trend to be more complex and sophisticated. For this reason, the quality of the printed product will be seriously affected when the 3D printer fails during the working life [4]. Hence it is necessary to develop fault diagnosis technology for 3D printers. Currently, work exploiting machine learning to diagnose 3D printer includes [5] where support vector machine (SVM) with an expensive attitude sensor is employed to diagnose 3D printer and [6] where an error fusion of multiple sparse auto-encoders, a deep learning method, is proposed to reduce the cost of fault diagnosis. It should be noted that it is mentioned in [6], the collecting data from the low-cost attitude sensor often contains a large amount of interference information (i.e. noises). All of these researches have played an important role in the fault diagnosis of 3D printers. However, an effective fault diagnosis method for 3D printers is attempted to propose under the circumstance of low-cost and small-sample in this paper. Hence, a shallow learning method that is still effective in high noise should be proposed to diagnose the faults of 3D printers.

Following the analysis above, a low-cost sensor and a shallow learning networks are required to diagnose the faults of 3D printers under the conditions of low-cost and small-sample. One approach that has been used to address this issue resorts to Echo State Networks (ESN) [7]. Compared to deep learning networks, ESN, as a shallow learning network, is preferred for fault diagnosis with relatively small dataset [8]. As a simple and effective model, ESN is gradually applied in fault diagnosis. For examples, ESN is employed to predicter potential railway door system failures [9] and adopted to diagnose helical gearbox [10]. Notice that ESN is a powerful fault diagnosis method under when using under the condition of high noises and small samples [9-11] . Consequently, ESN is suggested for fault diagnosis of 3D printers.

The rest of this paper is organized as follows. The fault diagnosis methodologies based on ESN is introduced in Section II. Section III presents the details of the experiment of

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using the proposed method for fault diagnosis of 3D printer. Results discussions and conclusions were reported in Section IV and Section V, respectively.

II. Fault Diagnosis Methodologies Based on ESN

As depicted in Fig. 1, Echo state network (ESN) is a type of recurrent neural network, which includes an input layer, an output layer and a reservoir that is a large, sparse, and randomly connected a set of neurons [8].

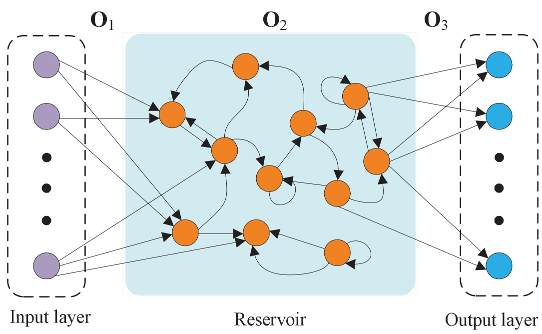

Figure 1. Schematic of the ESN.

Given $\mathbf{H}_t$={H_1, H_2, H_b}, $\mathbf{K}_t$={K_1, K_2, K_x} and $\mathbf{L}_t$={L_1, L_2, L_g} denote the input signals, reservoir states and output at the t-th time, respectively. The state update of the network is governed by Equation (1) and Equation (2).

$$\mathbf{K}_t = V\left(\mathbf{O}_1\mathbf{H}_t + \mathbf{O}_2\mathbf{K}_{t-1}\right), \tag{1}$$

$$\mathbf{L}_t = \mathbf{O}_3[\mathbf{H}_t;\mathbf{K}_t], \tag{2}$$

where $\mathbf{O}_1 \in R^{b\times x}$, $\mathbf{O}_2 \in R^{b\times b}$ and $\mathbf{O}_3 \in R^{(b+x)\times g}$ represent the input weights matrix, reservoir weights matrix and output weights matrix respectively, [$\mathbf{H}$; $\mathbf{K}$] denotes the extended state vector. $V(\cdot)$ is the activation function as chosen in Equation (3), which is a sigmoid function.

$$V(n) = \frac{1}{1-e^{-n}}, \tag{3}$$

where n represents the dataset of the activation function.

When build the ESN model, it is the key step to determine and optimize $\mathbf{O}_1$, $\mathbf{O}_2$ and $\mathbf{O}_3$. As for $\mathbf{O}_1$ and $\mathbf{O}_2$, it must be randomly initialized for a standard normal distribution to ensure that ESN has property of echo state. In addition, the spectral radius of $\mathbf{O}_2$, which can be calculated in Equation (4), must be smaller than 1 to ensure the separability of ESN.

$$E = \max\left\{\sqrt{\lambda(\mathbf{O}_2)}\right\}, \tag{4}$$

where E is the spectral radius and $\lambda(\mathbf{O}_2)$ is eigenvalues of $\mathbf{O}_2$. As after initialization, $\mathbf{O}_1$ and $\mathbf{O}_2$ remain fixed, the optimization effort is only necessary for $\mathbf{O}_3$. The optimization objective function of $\mathbf{O}_3$ is written in Equation (5).

$$\begin{cases} \mathbf{O}_3 = \arg\min MSE\left(\mathbf{L}^{ept},\mathbf{L}\right) \\ MSE\left(\mathbf{L}^{ept},\mathbf{L}\right) = \dfrac{1}{S}\sum_{i=1}^{S}\left(L_i^{ept}-L_i\right)^2 \end{cases}, \tag{5}$$

where $\mathbf{L}^{ept}$ and $\mathbf{L}$ represent the expect label sequence and the predicted label of the training datasets and S is the total number of samples. The ESN model can be built according to the aforementioned methods.

The fault data of 3D printer are required as the input when ESN is applied to diagnose the fault of 3D printer. In this work, a low-cost attitude sensor is employed to collect the fault data. Since the data collected from low-cost attitude sensor has the characteristic of high dimensionality, it is necessary to extract some features before modeling ESN. Both ten time-domain and eight time-frequency features are selected to diagnose 3D printer in this work. Choosing both time-domain and time-frequency features can reflect fault information more comprehensively, reduce noise interference and increase model robust [12]. Given a set of data y_i (i=1, 2, ..., n), where y_i represents the data at the i-th time. The selected time-domain and time-frequency features are listed in Table I and Table II respectively [13].

TABLE I. Selected Ten Time-Domain Features and Its Calculating Formula

Feature	Feature definition	Feature	Feature definition
Mean square	$Y_{MS} = \frac{\sum_{i=1}^{n} y_i^2}{n}$	Crest factor	$T_{cf} = \frac{Y_{peak}}{Y_{RMS}}$
Root mean square	$Y_{RMS} = \sqrt{\frac{\sum_{i=1}^{n} y_i^2}{n}}$	Skewness	$T_{sk} = \frac{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^3}{(n-1)Q_{sd}^3}$
Kurtosis	$T_{ku} = \frac{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^4}{(n-1)Q_{sd}^4}$	Impulse factor	$T_{if} = \frac{Y_{peak}}{\bar{Y}}$
Waveform factor	$T_{wf} = \frac{Y_{RMS}}{\lvert\bar{Y}\rvert}$	Peak value	$Y_{peak} = \max\{y_i\}$
Mean	$\bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n}$	Clearance factor	$T_{clf} = \frac{Y_{peak}}{Y_R}$
P.S.: Q_{sd} represents standard deviation of data.			

TABLE II. Selected Eight Time-Frequency Features and Its Calculating Formula

Feature	Feature definition
Wavelet packet energy (w1, w2, … , w8)	$w_i = \frac{W_{3i}}{\sum W_{3i}} = \sum y(3,i)$, where the W_{3i} means the i-th frequency range of three level wavelet packet.

III. Experiments

Experimental configuration includes a laptop (Inspiron N4110, DELL, Round Rock, DX, USA), a delta 3D printer

(SLD-BL600-6, SHILEIDI, Dongguan, China) and an attitude sensor (BWT901, WIT, Shenzhen, China) as shown in Fig. 2. The cost of the attitude sensor is about 20$. The attitude sensor that connects to the laptop is mounted on the extrusion nozzle of the 3D printer. The fault data can be read and collected from the laptop employing this experimental configuration. The data collected from the attitude sensor contain nine channels including three-axial angular velocity signals, three-axial acceleration signals, and three-axial magnetic field intensity signals.

The main faults of the 3D printer are considered in this work. As listed in Table III, faults of the 3D printer are divided into 16 classes include normal, faulty a to l (i.e. twelve classes), and faulty synchronous belt a to c (i.e. three classes). The joint bearing is loosened by 0.35mm and the synchronous belt is loosened by 1.5 mm in simulating each class of fault.

TABLE III. FAULT PATTERN 3D PRINTER IN THE EXPERIMENT

Pattern number	Fault description	Degree of fault
I	Normal	/
II	Fault occurred on joint bearing A	0.35 mm
III	Fault occurred on joint bearing B	0.35 mm
IV	Fault occurred on joint bearing C	0.35 mm
V	Fault occurred on joint bearing D	0.35 mm
VI	Fault occurred on joint bearing E	0.35 mm
VII	Fault occurred on joint bearing F	0.35 mm
VIII	Fault occurred on joint bearing G	0.35 mm
IX	Fault occurred on joint bearing H	0.35 mm
X	Fault occurred on joint bearing I	0.35 mm
XI	Fault occurred on joint bearing J	0.35 mm
XII	Fault occurred on joint bearing K	0.35 mm
XIII	Fault occurred on joint bearing L	0.35 mm
XIV	Fault occurred on synchronous belt A	1.5 mm
XV	Fault occurred on synchronous belt B	1.5 mm
XVI	Fault occurred on synchronous belt C	1.5 mm

The experiment can be performed after the above preparation. The frequency of data acquisition by attitude sensor is set to 100 Hz. As illustrated in Fig. 3, the main steps of the experiment are as follows.

- Prepare printing program for 3D printer;
- Install the attitude sensor into the extruder nozzle of the 3D printer and connect it to the laptop;
- Simulate faults and run the prepared 3D printer program;
- Collect raw data from the attitude sensor on the 3D printer via the laptop;
- Extract features from raw data;
- Train the ESN model by using the extracted features;
- Test the accuracy of the fault diagnosis of the 3D printer; and
- Output the accuracy of fault diagnosis; end.

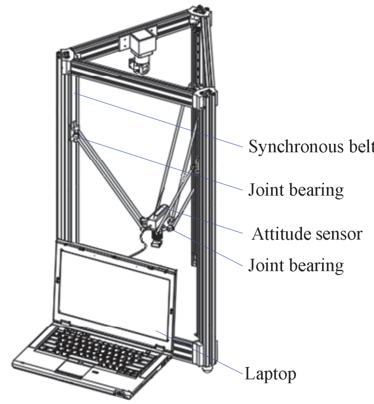

Figure 2. Experimental configurations.

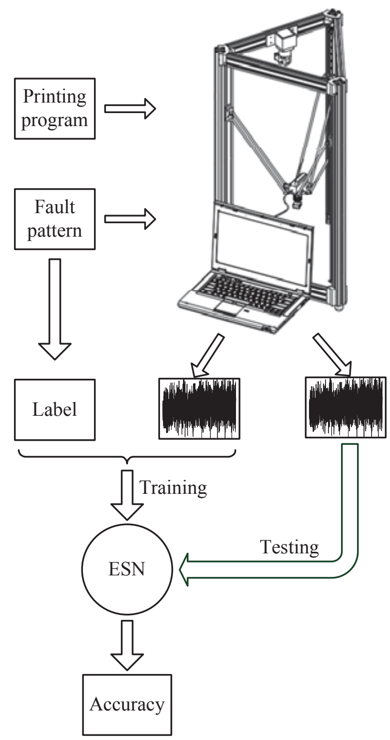

Figure 3. Experimental procedure.

During data acquisition, 150 samples were collected in each failure mode. In this experiment, 150 samples were collected for each fault pattern. There are 16 fault patterns in total as shown in Table III. Thus, there are a total of 2,400 samples collected in this experiment.

As mentioned above, data collected from attitude sensors include 9 channels and data acquisition frequency is set at 100Hz. Each sample was collected for 2.16 seconds while collecting data. Thus, there are 216 data acquisition points for 9 channels in each sample i.e. 216×9. Subsequently extract 18 features listed in Table I and Table II for each channel in each sample. Accordingly, each sample consists of 18×9 data points i.e. 162 data points. The sequence of all the samples is randomly sorted when the samples is used to model an ESN.

IV. RESULTS AND DISCUSSION

When the percentage of training samples is 50%, the fault diagnosis of the ESN for the 3D printer is tested five times, and the results were listed in the Table IV. As shown in Table IV, the mean accuracy of fault diagnosis is 96.47% and the highest accuracy of fault diagnosis reach to 97.26% under this circumstances. What indicated in Table IV is that the ESN is an effective method in low-cost fault diagnosis of 3D printers.

TABLE IV. THE FAULT DIAGNOSIS ACCURACY OF ESN UNDER 50% OF TRAINING SAMPLES

Accuracy of the repeated times					Mean (%)	Variance
1(%)	*2(%)*	*3(%)*	*4(%)*	*5(%)*		
95.78	96.75	96.20	96.38	97.26	96.47	0.31

For analysis, the modelling and testing of ESN under different percentage of training samples is performed in this work. As depicted in Fig. 4, the accuracy and stability of fault diagnosis will increase with the increase of training percentage. Even if only 20% of the training proportion is used, the fault diagnosis accuracy can reach to approximately 82%, which indicates that the fault diagnosis method of 3D printer based on ESN is still effective under small-sample.

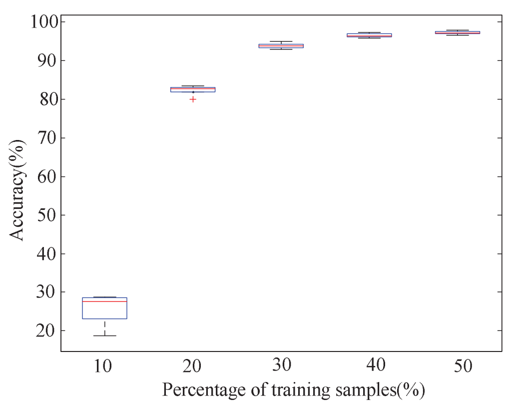

Figure 4. The comparison of accuracy of ESN under different percentage of training samples.

In this work SVM, principal component analysis support vector machine (PCASVM) and locality preserving projection support vector machine (LPPSVM) are adopted for comparison with ESN. As depicted in Fig. 3, The highest mean accuracy of fault diagnosis reached to 97.17%, which is obtained when using ESN model. As can be seen from Fig. 5, the fault diagnosis accuracy of SVM, LPPSVM and PCASVM is gradually rising. However, the highest accuracy of these 3 methods is only 51.87%. Furthermore, compared to ESN, the fault diagnosis accuracy of the three methods is not stable.

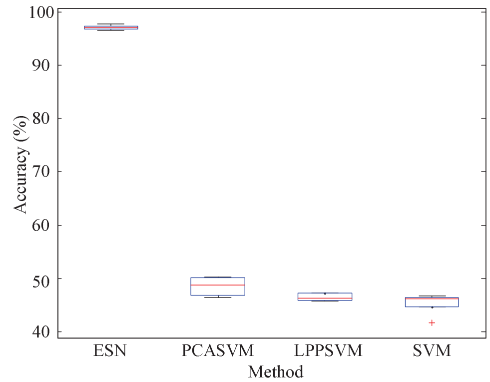

Figure 5. The comparison of accuracy of different methods.

V. CONCLUSIONS

In this work, a low-cost and small-sample methods based ESN is proposed to diagnose the fault of 3D printers. Feature extraction is performed after using a low-cost attitude sensor to collect raw fault data. The ESN model was built by using these features. The experimental results show the effectiveness of the proposed method for fault diagnosis of 3D printers. The highest fault diagnosis accuracy of this method is 97.26%. Compared with PCASVM, LPPSVM and SVM, The fault diagnosis accuracy of ESN is the highest and most stable.

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