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A new collaborative fault identification strategy using multivariate hierarchical dispersion entropy

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A new collaborative fault identification strategy using multivariate hierarchical dispersion entropy

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Abstract. This article presents a fault recognition strategy using multivariate hierarchical dispersion entropy to monitor the conditions of rolling bearing. First, the vibration data would be measured from multi-channel sensors synchronously. Then, the proposed mvHDE is employed to capture fault information from the collected data. Finally, the fault features are input into the ELM classifier to automatically identify fault types of bearing. The feasibility and effectiveness of the presented intelligent fault diagnosis schemes are verified through experimental studies.

1. Introduction

Bearing fault identification is of considerable consequence to ensure the normal operation of the mechanical system and saving maintenance expenses. Many scholars have recently researched bearing fault diagnosis and developed many well-established studies[1], especially vibration-based fault diagnosis approaches. In the vibration-based fault diagnosis framework, fault feature representation is pivotal to accurately recognizing fault types. Many feature representation schemes, such as signal processing-based fault feature detection[2] and statistical index-based fault feature identification[3], have proven effective for bearing fault identification. Whereas, for modern signal processing schemes, the vibration signal includes the complex frequency characteristics in mechanical systems, causing general users may not timely make the correct decisions. For the statistical index, the extracted indicators might have different orders of magnitude, resulting in some critical indicators that are difficult to play in bearing fault recognition.

Entropy is a valuable theory for detecting dynamic characteristics of the nonlinear signal. Several common entropy methods have been used for bearing fault identification, such as sample entropy (SE), approximate entropy (ApEn), and fuzzy entropy (FE). Nevertheless, those entropy-based feature extraction strategies have their shortcomings. In particular, when the data length is large, the above-mentioned entropy methods are time-consuming. Permutation entropy (PE)[4] can quantify the dynamical complexity through the permutation of orbits, which has high computational efficiency. However, PE overlooks the difference between amplitudes for a given data. The recently proposed DE overcomes the problem of losing some vital information regarding PE amplitudes. Whereas DE only thinks about the fault details from one scale, inevitably overlooking more important fault details hidden in other scales. To solve this drawback of DE, several improved dispersion entropy methods, such as hierarchical dispersion entropy (HDE) and multi-scale dispersion entropy (MDE), are proposed.

As multisensory technology develops, collaborative fault diagnosis as a hot point has widely attracted widespread attention, especially for large mechanical equipment. In general, the measured multi-channel data provides richer fault information compared with single-channel data. However, the above-mentioned entropy methods cannot synchronously extract fault information from multi-channel vibration data. Hence, A collaborative feature extraction algorithm, namely multivariate hierarchical dispersion entropy (mvHDE), is developed to provide a robust relative complexity measure for multi-channel vibration data. After fault feature extraction through mvHDE, the extracted features are input into the extreme learning machine (ELM) classifier for pattern recognition. Eventually, a new bearing fault identification algorithm based on multivariate hierarchical dispersion entropy and ELM is presented in this article, and the effectiveness of the presented strategy is confirmed using the benchmark dataset.

The remaining part of this article is organized as follows. In section II, the theory of mvHDE is introduced. Section Ⅲ illustrates the detailed procedures of the developed fault recognition strategy. Experimental verification and investigation are conducted to confirm the effectiveness of the developed algorithm in section IV. Eventually, the conclusion of this article is summarized in section V.

2. Multivariate hierarchical dispersion entropy

The purpose of this section is to extend the hierarchical analysis into the multichannel signal, and the mvHDE is estimated through the following procedures.

1) For the multichannel data $Y=\left\{y_{c,1},y_{c,2},\ldots,y_{c,N}\right\}_{c=1}^{P}$, two operators Q_0 and Q_1 are respectively written as below

$$Q_0\left(Y\right)=\frac{y_{c,n}+y_{c,n+1}}{2} \tag{1}$$

$$Q_1\left(Y\right)=\frac{y_{c,n}-y_{c,n+1}}{2} \tag{2}$$

where $n=1,2,\cdots,N-1$; Q_0 denotes the low-frequency component operator; Q_1 denotes the high-frequency component operator.

2) The operators $Q_j \in \mathbb{R}^{(N-2^k+1)\times(N-2^{k-1}+1)}$ (r =0 or 1) are illustrated through the following matrix:

$$O_j^k=\begin{bmatrix} \frac{1}{2} & \underbrace{0\cdots0}_{2^{k-1}-1} & \frac{(-1)^j}{2} & 0 & \cdots & 0 & 0 & 0 \\ 0 & \frac{1}{2} & \underbrace{0\cdots0}_{2^{k-1}-1} & \frac{(-1)^j}{2} & & 0 & 0 & 0 \\ \cdots & & & & & & & \\ 0 & 0 & 0 & 0 & \cdots & \frac{1}{2} & \underbrace{0\cdots0}_{2^{k-1}-1} & \frac{(-1)^j}{2} \end{bmatrix} \tag{3}$$

3) The subcomponents $y^{c,k,e}$ at the c -th channel are estimated as follows through the operators Q_j

$$y^{c,k,e}=O_{j_k}^{k}\cdot O_{j_{k-1}}^{k-1}\cdot\cdots\cdot O_{j_1}^{1}\cdot y^{c} \tag{4}$$

where e is the number of the hierarchical node. For $k\in N$, e is calculated through equation (5).

$$e=\sum_{\ell=1}^{k}2^{k-\ell}j_\ell \tag{5}$$

4) the hierarchical components can be calculated by repeating steps 1-3 for all channels. The mvHDE is estimated using

$$mvHDE\left(Y,k,e,m,r,d\right)=mvDE\left(Y_{k,e},m,r,d\right) \tag{6}$$

where d denotes the time delay and m denotes the embedding dimension. For the multichannel data $Y_{k,e}$, the mvDE is estimated by the following steps:

For a given data $Y_{k,e} = \left\{ y_n^{c,k,e} \right\}_{n=1}^{N'}$ ($N' = N - 2^k + 1$), mvDE mainly contains the following four steps:

- The data $Y_{k,e}$ is first divided into r classes. Firstly, the normal cumulative distribution function (NCDF) is used for mapping $\left\{ y_n^{c,k,e} \right\}_{n=1}^{N'}$ to $\left\{ s_n^{c,k,e} \right\}_{n=1}^{N'}$ from zero to one. Then, a linear method is employed to transform each $s_n^{c,k,e}$ to a positive integer from 1 to r . Each member of the mapped data is written as

$$z_n^{c,k,e,r} = round\left(r \cdot s_n^{c,k,e} + 0.5 \right) \tag{7}$$

where $round(\cdot)$ denotes the rounding operation.

- The embedding vector $z_n^{c,k,e,r,m}$ is established according to $z_n^{c,k,e,r,m} = \left\{ z_{n+(j-1)d}^{c,k,e,r} \right\}_{j=1}^{m}$, $n = 1, \ldots, N' - (m-1)d$. Each data $z_n^{c,k,e,r,m}$ is mapped to the dispersion pattern $\pi_{v_0 v_1 \cdots v_{m-1}}^{c}$, where $z_n^{c,k,e,r,m} = v_0$, $z_{n+d}^{c,k,e,r,m} = v_1, \cdots, z_{n+(m-1)d}^{c,k,e,r,m} = v_{m-1}$. Hence, the number of feasible dispersion patterns is equal to r^m .
- For the possible dispersion pattern, its relative frequency can be estimated by

$$p\left(\pi_{v_0 v_1 \cdots v_{m-1}}^{c} \right) = \frac{\left\| n \le N' - (m-1)d, \Gamma\left(z_n^{c,k,e,r,m} \right) = \pi_{v_0 v_1 \cdots v_{m-1}} \right\|}{N' - (m-1)d} \tag{8}$$

where $\Gamma(\cdot)$ denotes the map from each embedding vector to dispersion patterns, $\|\cdot\|$ denotes the cardinality of a set, $N' - (m-1)d$ is the total number of embedding vectors.

- Calculate the marginal relative frequencies by using

$$p\left(\pi_{v_0 v_1 \cdots v_{m-1}} \right) = \sum_{c=1}^{P} p\left(\pi_{v_0 v_1 \cdots v_{m-1}}^{c} \right) \tag{9}$$

- At last, according to the definition of Shannon entropy, mvDE is defined below:

$$mvDE(x, m, r, d) = -\sum_{\pi=1}^{r^m} p\left(\pi_{v_0 v_1 \cdots v_{m-1}} \right) \cdot \ln\left(p\left(\pi_{v_0 v_1 \cdots v_{m-1}} \right) \right) \tag{10}$$

where r denotes the number of classes. Eventually, normalized dispersion entropy (NDE) is written as below

$$mvDE_{norm}(x, m, r, d) = mvDE(x, m, r, d) / \ln\left(r^m \right) \tag{11}$$

3. Developed fault identification strategy

The detailed steps of the presented bearing fault identification strategy are given below:

- The multi-channel data is synchronously measured under different conditions.
- The proposed MvHDE is used to extract fault information from the multi-channel signal.
- MvHDE values of the training samples are employed to train the ELM classifier.
- MvHDEs of the testing samples are input into the trained ELM to automatically recognize bearing health conditions.

4. Experiment validation

This section adopts the benchmark dataset [5] provided by the Bearing Data Center of CWRU to evaluate the proposed scheme to identify different bearing health conditions. The bearing fault types consist of ball fault, inner race fault, and outer race fault with diameters of 0.178 mm, 0.356 mm, and 0.533 mm. Moreover, the multi-channel signal would be collected by three accelerometers fixed on the drive end and fan end of the motor housing and the motor supporting base plate, and the sampling frequency is 12,000 Hz. In the benchmark dataset, the data with nine different fault types were selected as the analyzed data. For different fault types, the collected time series would be divided into 100 non-overlapping samples with the size 3×1024.

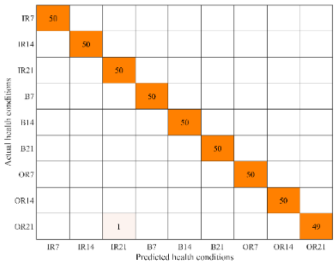
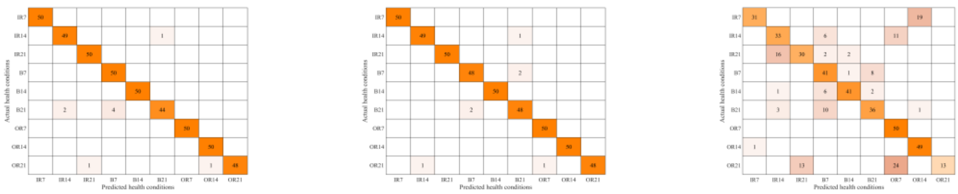


Fig. 1. Classification accuracy of the presented strategy.

At first, we randomly chose fifty samples for different fault patterns as training samples, and the remaining dataset was adopted for testing. Then, the mvHDE approach is adopted to extract the fault features of the whole dataset. In the parameter settings, the hierarchical layer $k=3$, symbol number ε=3, and embedding dimension $m=2$ in the mvHDE. Subsequently, we use the MvHDE values of the training dataset to train the ELM classifier. Finally, mvHDEs of the testing samples would be input into the well-trained ELM, and the final result of the developed algorithm is depicted in Fig.1. From Fig. 1, only one sample with outer race fault is misdiagnosed as inner race fault, and other fault patterns have been perfectly-recognized. For comparison, some state-of-the-art dispersion entropy-based feature extraction methods such as dispersion entropy (DE), hierarchical dispersion entropy (HDE), and multi-scale dispersion entropy (MDE) are respectively used to process the same measured samples. We also adopt the ELM classifier to identify the fault features extracted by those comparison schemes, and the final identification rates are given in Fig. 2. By comparing the results plotted in Fig. 1 and Fig. 2, the developed MvHDE has the highest identification rate among those four strategies. It preliminary suggests that the presented MvHDE can capture richer fault information than the existing dispersion entropy-based extractors in bearing fault identification.

Eventually, we set the range of percentages of training samples as $[10\%,50\%]$ with a stride of 10% to evaluate the influence of different percentages of training samples on the developed strategy. In each case, we conducted ten trials to restrict the influence of randomness on the identification rate, and



(a) MDE (b) HDE (c) DE

Fig. 2. The classification results of other comparison methods.

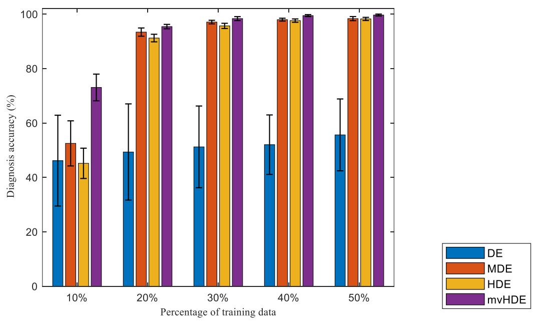


Fig. 3. Average classification accuracies of the four methods over twenty trials with different percentages of training dataset.

the diagnosis rates are given in Fig. 3. As seen in Fig. 3, the presented strategy has the highest classification rate and the lowest standard deviation among those four strategies. The above results confirm that the presented scheme has higher identification accuracy than the existing dispersion entropy-based fault extraction algorithm.

5. Conclusion

This paper presents a new collaborative algorithm based on mvHDE and ELM to achieve bearing fault diagnosis automatically. The CWRU-bearing dataset is adopted to confirm the superiority of the developed scheme. The above analysis suggests that the developed strategy has a higher identification rate than the existing dispersion entropy-based bearing fault identification strategies.

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