Journal of Sound and Vibration 428 (2018) 72–86

Contents lists available at ScienceDirect

Journal of Sound and Vibration

journal homepage: www.elsevier.com/locate/jsvi

Early fault diagnosis of rolling bearings based on hierarchical symbol dynamic entropy and binary tree support vector machine

Yongbo Li [a], Yuantao Yang [b], Xianzhi Wang [c], Binbin Liu [a], Xihui Liang [d,*]

[a] School of Aeronautics, Northwestern Polytechnical University, Xi'an, Shanxi 710072, China
[b] Department of Astronautical Science and Mechanics, Harbin Institute of Technology, Harbin 150001, China
[c] School of Mechanical Engineering, Northwestern Polytechnical University, Xi'an, Shanxi 710072, China
[d] Department of Mechanical Engineering, University of Manitoba, Winnipeg, Manitoba R3T 5V6, Canada

A R T I C L E I N F O

Article history:
Received 9 December 2017
Revised 23 March 2018
Accepted 27 April 2018
Available online XXX
Handling Editor: K. Shin

Keywords:
HSDE
Complexity measurement
Rolling bearing
Fault diagnosis
SVM

A B S T R A C T

Early fault diagnosis of rolling bearings is crucial to operating and maintenance cost reduction of the equipment with bearings. This paper aims to propose a novel early fault feature extraction method based on the proposed hierarchical symbol dynamic entropy (HSDE) and the binary tree support vector machine (BT-SVM). Multiscale symbolic dynamic entropy (MSDE) has been recently proposed to characterize the dynamical behavior of time series. MSDE has several merits comparing with multiscale sample entropy (MSE) and multiscale permutation entropy (MPE), such as high computational efficiency and robustness to noise. However, MSDE only utilizes the fault information in the low frequency components and consequently the fault information hidden in the high frequency components is discarded. To address this shortcoming, a new method, namely HSDE, is proposed to extract the fault information in the high frequency components. Then, the BT-SVM is utilized to automatically complete the fault type identification. The effectiveness of the proposed method is validated using simulated and experimental vibration signals. Meanwhile, a comparison is conducted between MPE, hierarchical permutation entropy (HPE), MSE, hierarchical sample entropy (HSE), MSDE and HSDE. Results show that the proposed method performs best to recognize the early fault types of rolling bearings.

1. Introduction

Effective early fault diagnosis of rolling bearings can help reduce maintenance cost and enhance the reliability of machines [1]. Therefore, early fault diagnosis of rolling bearings has become a research hotspot. Generally, the fault diagnosis scheme of bearings can be summarized into three stages: data collection, fault feature extraction and fault pattern identification. Among these three stages, fault feature extraction is most challenging. If a localized bearing damage occurs, periodic impulsive signals should occur. However, the impulse signal is very weak at the early fault stage. It is easily submerged by the strong environment noise leading to the difficulty in fault feature extraction [2].

Entropy is a powerful and effective tool to extract fault features, which has been widely applied in the bearing fault diagnosis of rotating machinery [3–5]. The vibration signal collected from a healthy rolling bearing generally has a large entropy value due

* Corresponding author.
E-mail address: Xihui.Liang@umanitoba.ca (X. Liang).

https://doi.org/10.1016/j.jsv.2018.04.036
0022-460X/

to its high irregularity, while that collected from a damaged rolling bearing has a small entropy value due to its low irregularity. Therefore, many researchers have utilized entropy to extract the fault features of rolling bearings [6–8]. The most widely used entropy includes sample entropy (SE) [9–11] and permutation entropy (PE) [12–14]. However, SE is not fast enough especially in the analysis of long time duration signals [15]. PE, though faster than SE, only utilizes the amplitude information of the time series. A small change in amplitude by noise will affect the value of PE and hence PE is relatively sensitive to the noise [16]. To overcome these deficiencies, Li et al. [17] introduced a new method, namely symbolic dynamic entropy (SDE), to fit the dynamical characteristics of a vibration signal. The SDE can effectively remove the background noise using the symbolization procedure and also reserve the fault information using the probability of state pattern and the state transition [17]. SDE has been demonstrated to have better performance in the analysis of vibration signals using both amplitude and frequency information. SDE has obvious advantages, such as higher calculation efficiency and more robust to noise. In addition, SDE is extended to multiscale process, namely multiscale symbolic dynamic entropy (MSDE) [17] for comprehensive analysis of vibration signals. However, MSDE may discard the fault information hidden in the high frequency components because the multiscale analysis in MSDE only considers the fault information in the low frequency components. To overcome this drawback of multiscale analysis, Jiang et al. [18] introduced the hierarchical decomposition and proposed the hierarchical sample entropy (HSE). Hierarchical decomposition has been demonstrated to be more effective than multiscale analysis [19,20].

Based on the advantages of SDE and hierarchical decomposition, we propose a new bearing fault feature extraction method called hierarchical symbolic dynamic entropy (HSDE). HSDE method can extract the fault features hidden both in the high frequency component and low frequency component. After the fault extraction, a widely used classifier BT-SVM is employed to identify the fault types. There are two steps in the proposed method. First, the HSDE is applied to extract the fault information from bearing vibration signals corresponding to different health conditions. Second, BT-SVM is employed to complete the fault diagnosis. The experimental data collected from the Case Western Reserve University (CWRU) are used to validate the effectiveness of the proposed method. Experimental results demonstrate that the proposed method has the best fault extraction performance among MPE, HPE, MSE, HSE, MSDE and the proposed HSDE.

The organization of the rest of this paper is as follows: Section 2 describes the fundamentals of HSDE; Section 3 shows the steps of the proposed method based on HSDE and BT-SVM. Section 4 applies the proposed method to classify rolling bearing early faults. A conclusion is drawn in Section 5.

2. Proposed hierarchical symbol dynamic entropy

In this section, the theoretical background of the SDE and MSDE briefly described, respectively. Meanwhile, the concept of hierarchical symbol dynamic entropy (HSDE) is introduced.

2.1. Symbol dynamic entropy

Let $X = \{x_1, x_2, \ldots, x_n\}$ represents a given time series with length N. The calculation procedure of the SDE method can be summarized as follows:

Step 1. Conduct the symbolization. Since the maximum entropy partitioning (MEP) has the advantage of adaptive segmentation [21], MEP is applied to convert the time series into a symbol time series. Detailed application of the MEP method is available in Ref. [21].

Step 2. Construct the template vectors $Z_j^{m,\lambda}$ with embedding dimension m and time delay λ using the symbol time series according to Eq. (1):

$$Z_j^{m,\lambda} = \{z(j), z(j+\lambda), \ldots, z(j+(m-1)\lambda)\}, j = 1, 2, \ldots, N-(m-1)\lambda \tag{1}$$

Step 3. Calculate the probability of each state pattern. For a symbol time series with embedding dimension m and symbol number ε, there are ε^m state mode patterns. The probability of each state pattern $q_a^{\varepsilon,m,\lambda}$ can be calculated using Eq. (2):

$$P(q_a^{\varepsilon,m,\lambda}) = \frac{\|\{j : j \le N-(m-1)\lambda, type(Z_j^{\varepsilon,m,\lambda}) = q_a^{\varepsilon,m,\lambda}\}\|}{N-(m-1)\lambda} \tag{2}$$

where $type(.)$ denotes the map from symbol space to state pattern space.
$\|.\|$ denotes the cardinality of a set.

Step 4. Construct the state mode matrix using the probability of state pattern $q_a^{\varepsilon,m,\lambda}$ as $[P(q_1^{\varepsilon,m,\lambda}), P(q_2^{\varepsilon,m,\lambda}), \ldots, P(q_n^{\varepsilon,m,\lambda})]_{1\times\varepsilon^m}$.

Step 5. Calculate the probability of state transitions using Eq. (3) as follows:

$$P(\sigma_b \mid q_a^{\varepsilon,m,\lambda}) = \frac{\|\{j : j \le N-m\lambda, type(Z_j^{\varepsilon,m,\lambda}) = q_a^{\varepsilon,m,\lambda}, z(j+m\lambda) = \sigma_b\}\|}{N-m\lambda} \tag{3}$$

where ε is the number of symbols, ε^m is the number of states, $a = 1, 2, 3, \ldots, \varepsilon^m$ and $b = 1, 2, 3, \ldots, \varepsilon$. Note that there are total ε^{m+1} state transitions.