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Sigmoid-based refined composite multiscale fuzzy entropy and t-SNE based fault diagnosis approach for rolling bearing

Jinde Zheng[a,b,*], Zhanwei Jiang[a], Haiyang Pan[a]

[a] Engineering Research Center of Hydraulic Vibration and Control, Ministry of Education, Maanshan, Anhui 243032, China
[b] School of Mechanical Engineering, Anhui University of Technology, Maanshan, Anhui 243032, China

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A B S T R A C T

Multiscale fuzzy entropy (MFE) has been taken as a prevalent tool for complexity measure of time series. However, the entropy estimation of MFE is sensitive to the preset parameters and will cause an inaccurate and even undefined entropy when the data is not long enough. In this paper the Sigmoid-based refined composite multiscale fuzzy entropy (SRCMFE) is proposed to improve the performance of MFE for complexity measure of short time series. The proposed SRCMFE method is compared with MFE and Sigmoid-based multiscale fuzzy entropy by analyzing Gaussian white noise and 1/f noise to verify its effectiveness and the analysis result indicate that SRCMFE method holds a better distinguish capacity and robustness and can reflect more complexity information of time series. Then SRCMFE is used to the dynamical complexity analysis of mechanical vibration signals and based on that a new fault diagnosis approach for rolling bearing is put forward by combining SRCMFE with t-distributed stochastic neighbor embedding (t-SNE) for feature dimension and the recently proposed variable predictive models based class discrimination (VPMCD) method for fault pattern recognition. In the proposed method, firstly, SRCMFE is utilized to extract the complexity characteristic related with fault information from vibration signals of rolling bearing. Then the feature dimension reduction method named t-SNE is adopt to obtain a low dimensional manifold features of rolling bearing. Next, the VPMCD method is employed for multi-fault classifier construction to fulfill an intelligent fault diagnosis according to the intrinsic inner relationships hidden in the fault features. Finally, the proposed fault diagnosis approach is applied to the experimental data analysis of rolling bearing and is compared with the same kinds of fault diagnosis methods through experiment data analysis. The analysis and comparison results indicate that the proposed method is very effective in distinguishing the fault categories of rolling bearings and can get a higher identifying rate than the contrast methods.

1. Introduction

Rolling bearing is an very important part of many rotating machines and plays a key role in lots of equipment and industrial sector. Once the rolling bearing works with failure, it will lead to the entire mechanical system breakdown and even accidents. It is pressing and necessary to develop advanced and effective health monitoring and fault detection approaches for rolling bearing. The vibration signal analysis have been the most significant methodology in machinery health monitoring and fault diagnosis because of its advantages of easy data acquisition and implementation, accurate positioning and wide range of applications [1]. Generally, the vibration signals acquired from rolling bearings in most cases are nonlinear and non-stationary due to the complex working conditions including variable speed, loading and friction and thus many traditional linear signal analysis methods will inevitably have some limitations in analyze these kinds of signals [2].

In recent years, the nonlinear dynamics and its applications have achieved rapid development and lots of nonlinear dynamic approaches have been widely applied to mechanical fault diagnosis areas and get much better diagnostic effects than the traditional linear analysis methods [3]. As a most often used nonlinear dynamic parameters for complexity measure of time series, approximate entropy (AppEn) was introduced to machine fault diagnosis field by Yan et al. [4] and the research indicate that AppEn is an effective diagnostic method of machine health monitoring. To improve the performance of AppEn, sample entropy (SampEn) was proposed by Richman et al. [5], however, it cannot capture the long-term structures in the multiple time scales and the estimated entropy in a single scale may cause contradictory or

* Corresponding author.
E-mail address: lqdlzheng@126.com (J. Zheng).

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misleading findings. Then multiscale entropy (MSE) was proposed by Costa et al. [6] and has been one of the most effective approaches to reveal the inherent complexity of time series over different scales. In literature [7], MSE is applied to the fault feature extraction of rolling bearings and the result indicate that MSE based fault diagnosis method can get a better diagnosis performance than the traditional linear signal analysis methods. However, the entropy of MSE at larger scales may be undefined when the data length of time series or coarse graining time series is not long enough. To overcome this, recently, the sample entropy used in MSE was replaced by fuzzy entropy [8,9], and based on that, the multiscale fuzzy entropy (MFE) [10,11] was proposed for complexity measure of time series and applied to the fault feature characterization and extraction of rolling bearings and the results showed MFE had much better performance in fault class identification than the MSE based and other fault diagnosis methods [12,13].

However, MFE also has some drawbacks, i.e. the length of coarse grained time series will decrease with the increase of scale factor, which causes that the estimated MFE curve fluctuates heavily at the larger scale factors and even have no definition when analyzing shorter coarse grained time series. In this paper, Sigmoid-based refined composite multiscale fuzzy entropy (SRCMFE) is put forward to enhance the performance and robustness of MFE for complexity measure of time series. Besides, SRCMFE is compared with MFE and Sigmoid-based multiscale fuzzy entropy (SMFE) through analyzing simulation signals and the results indicate that SRCMFE is more reasonable and less dependency on the data length and the entropy values have stronger relative consistency than MFE and SMFE methods. Based on the above, SRCMFE is utilized to extract the complexity features related with fault information from vibration signals of rolling bearing over different temporal scales.

As the fault features obtained by using SRCMFE often consist of fuzzy entropies in different scales, which may contain redundant information and cannot be able to reflect the fault information precisely. Thus, a feature dimension reduction method is needed to select the most important features that are closely related to fault information and improve the efficiency of fault diagnosis. Manifold learning is a kind of dimension reduction method that based on the concept of topological manifold, which mainly includes linear and nonlinear manifold learning algorithms. Among them, t-distributed stochastic neighbor embedding (t-SNE) algorithm proposed recently by Laurens et al. [14] is a nonlinear visualizing dimensionality reduction method with deep learning, by using which a low dimensional manifold structure can be obtained from the high dimensional fault feature sets. At present, t-SNE method has not been applied to mechanical fault diagnosis widely and we will plan to utilize it to reduce the extracted fault feature dimension of rolling bearing with high dimension in the paper. After that, a multi-fault classifier should be designed for an automatic working condition identification of rolling bearing of different fault classes. The most often used fault mode identification method in mechanical fault diagnosis mainly falls into two major categories, i.e. neural network based methods [15] and support vector machines (SVMs) related approaches [16]. However, they both have a common limitation, i.e. the intrinsic relationship among the features is ignored for classification. As generally there are some inherent linear or nonlinear relations hidden in the used features that can be utilized for helping fault pattern recognition. In view of this consideration, the variable predictive models based on class discrimination (VPMCD) was proposed in [17] to fully make use of the intrinsic relationship between the input features for classification. In VPMCD method, the mathematical prediction models for revealing the intrinsic relationships of features are established for different fault categories according to the features of training samples and then the features of testing samples are predicted by using these mathematical models and the squares sum of prediction error is taken as a criterion for a discriminating classification and further pattern recognition. Based on the above advantages, VPMCD is employed to the fault feature classification problems of rolling bearing and then a new fault diagnosis approach for rolling bearing is put forward based on RCMFE, t-SNE and VPMCD. Finally, the proposed fault diagnosis method is compared with the existing other methods in the fault feature extraction, feature selection and fault mode identification through experiment data analysis. The results have shown the validity and superiority of the proposed method.

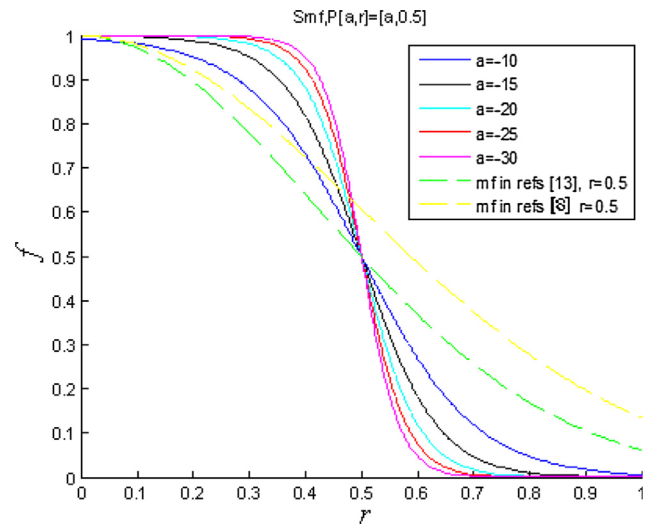

Fig. 1. The influence of parameter a on fuzzy function $f(x)$.

The rest of this paper is organized as follows. SRCMFE and its related methods are reviewed and proposed in Section 2. Comparison study of SRCMFE with MFE and SMFE is given in Section 3. The new SRCMFE based fault diagnosis method for rolling bearing is put forward in Section 4, as well as experiment data analysis. The conclusion is given in the final section.

2. SRCMFE and its related methods

2.1. Sigmoid-based fuzzy entropy

Similar with FuzzyEn defined in [8,13], the steps for Sigmoid-based fuzzy entropy (SFE) computation can be described as follows.

(1) If we consider the time series $\{u = u(1), u(2), u(3), ..., u(i), ...u(N), 1 \leqslant i \leqslant N\}$ with length N, the vectors can be formed as $X_i^m = \{u(i), u(i+1), ..., u(i+m-1)\} - u_0(i)$, $i = 1, 2, ..., N-m+1\}$ for given embedding dimension m and similar tolerance r, where

$$u_0(i) = m^{-1} \sum_{k=0}^{m-1} u(i+k) \tag{1}$$

and X_i^m represents m consecutive u values from the ith point removing $u_0(i)$.

(2) The distance d_{ij}^m between X_i^m and X_j^m is defined as

$$d_{ij}^m = d[X_i^m, X_j^m] = \max_{k \in (0, m-1)} \{|[u(i+k) - u_0(i)] - [u(j+k) - u_0(j)]|\}, \tag{2}$$

where $i, j = 1, 2, ..., N-m$, $i \neq j$.

(3) The similarity degree D_{ij}^m of X_i^m and X_j^m is calculated by using $\mu(d_{ij}^m, a, r)$ as

$$D_{ij}^m = \mu(d_{ij}^m, a, r) \tag{3}$$

(4) Then the probability function $\varphi^m(a, r)$ is defined as