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Generalized composite multiscale permutation entropy and Laplacian score based rolling bearing fault diagnosis

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ABSTRACT

Multiscale permutation entropy (MPE) is a recently proposed nonlinear dynamic method for measuring the randomness and detecting the nonlinear dynamic change of time series and can be used effectively to extract the nonlinear dynamic fault feature from vibration signals of rolling bearing. To solve the drawback of coarse graining process in MPE, an improved MPE method called generalized composite multiscale permutation entropy (GCMPE) was proposed in this paper. Also the influence of parameters on GCMPE and its comparison with the MPE are studied by analyzing simulation data. GCMPE was applied to the fault feature extraction from vibration signal of rolling bearing and then based on the GCMPE, Laplacian score for feature selection and the Particle swarm optimization based support vector machine, a new fault diagnosis method for rolling bearing was put forward in this paper. Finally, the proposed method was applied to analyze the experimental data of rolling bearing. The analysis results show that the proposed method can effectively realize the fault diagnosis of rolling bearing and has a higher fault recognition rate than the existing methods.

1. Introduction

Rolling bearing plays an important part in the rotating machines and even modern manufacturing industry. Hence, it is of practical significance to study the fault detection techniques and diagnosis methods of rolling bearings. The kernel of rolling bearing fault diagnosis is to extract the fault feature information from the vibration signals. Since the equipment usually inevitably runs with friction, vibration and impact, the vibration signals will show a certain nonlinear and non-stationary characteristics. Therefore, many linear and stationary analysis methods will have some limitations in dealing with the vibration signals, while the nonlinear analysis methods own their special advantages in extracting the nonlinear fault feature hidden in the vibration signals [1]. In recent years, many nonlinear dynamic methods, such as fractional dimension [2], approximate entropy (ApEn) [3], sample entropy (SampEn) [4], multiscale entropy (MSE) [5], permutation entropy (PE) [6] and multiscale permutation entropy (MPE) [7], have been applied to mechanical fault diagnosis for their being able to extract the nonlinear fault feature from the vibration signal that cannot been extracted by the linear analysis methods. For example, in [1], the ApEn was seen as a diagnostic tool for machine health monitoring by Yan et al. In [8,9] the MSE was employed to the fault diagnosis of rolling bearing and the results show that MSE was a promising tool for extracting much more diagnostic information than the traditional single scale-based entropy. In [10] PE was employed to the status

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characterization monitoring and fault information extraction of rotary machines by Yan et al. In [11,12], MPE was used to the fault diagnosis of rolling bearing and some effective fault diagnosis methods were proposed.

PE is a nonlinear dynamics parameter for measuring the randomness and dynamic change of time series and has been applied to analyze EMG and heart rate signals [13,14]. In literature [10] PE was applied to fault feature extraction of rotary machines and is compared with approximate entropy and L-Z complexity and the results show that PE can effectively detect the dynamic change and represent the working features of vibration signal of rolling bearing under different conditions. However, PE only analyzes time series by single scale and many useful fault information riding in other scales will be ignored. To overcome this, the concept of multiscale permutation entropy (MPE) was proposed by Aziz and Arif [7] and was compared with PE and MSE through analyzing physiological signals and the results show that MPE was more robust than MSE. However, MPE still has some problems. First of all, since the calculation of PE depends on the length of data and the length of each coarse-grained time series equals the length of original data dividing the scale factor, the length of coarse-grained time series will shorten with the increasing of scale factor and correspondingly the deviation of PE will increase. Secondly, in coarse graining process a time series is divided into equal non-overlapping fragments and then the mean value of all data points in each fragment is calculated. Since the mean value is calculated of each coarse graining time series in different scales, which inevitably will cause much potentially useful information be lost. Moreover, the averaging algorithm will counteract the dynamics changes of original data and make the estimated entropy smaller than the desired one. To decrease the deviation of MPE caused by the data length shortening, the mean of PEs of all coarse-grained time series in the same scale factor are seen as the final PE. Secondly, by referring the idea of [15], the first-order moment used in the coarse graining procedure is expanded to the second-order moment (unbiased variance). Based on this, a new nonlinear method called generalized composite multiscale permutation entropy (GCMPE) is put forward for randomness measuring and dynamic change detection of time series.

Then GCMPE is employed to extract fault feature from vibration signals of rolling bearing. Since the vibration of normal rolling bearing is random, the randomness and dynamic behavior of vibration signal will change once the rolling bearing has local failure. Not only that, due to the background noise and the complexity of mechanical system, the information associated with failure is often distributed in different time scales of vibration signal and correspondingly, the dynamics change of vibration signal will occur over different scales. Therefore, GCMPE can effectively extract the fault features from vibration signal of rolling bearings. After obtaining GCMPE from vibration signals of rolling bearing, Laplacian score (LS) for feature selection is utilized to reduce the dimension of features and improve the efficiency of fault diagnosis [16]. Meanwhile, in order to realize an intelligent fault diagnosis of rolling bearing, particle swarm optimization based support vector machine classification (PSO-SVM) [17,18] is applied to automatic recognition of failure modes. Then a new fault diagnosis method for rolling bearing is proposed based on the GCMPE, LS and PSO-SVM. Also the proposed method is applied to rolling bearing experiment data analysis and the results show the effectiveness of the proposed method.

This paper is organized as follows. Section 2 reviews the theories of permutation entropy and multiscale permutation entropy. The generalized composite multiscale permutation entropy is proposed in Section 3. A new rolling bearing fault diagnosis method and its experimental evaluation is given in Section 4. Finally, conclusions are drawn in Section 5.

2. PE and MPE algorithms

2.1. PE algorithm

PE was introduced for measuring the randomness and detecting the dynamic changes of time series. It is based on the comparison of neighboring values without considering the size of values and thus has a simple and fast calculation. It has been verified that PE is a particularly useful and robust tool in the presence of dynamic or observational noise [15]. The algorithm of PE can be described as follows.

For the time series $\{x(i),\ i = 1, 2, \ldots, N\}$, it can be reconstructed in phase space as

$$\begin{cases} X(1) = \{x(1), x(1+\lambda), \ldots, x(1+(m-1)\lambda)\} \\ \vdots \\ X(i) = \{x(i), x(i+\lambda), \ldots, x(i+(m-1)\lambda)\} \\ \vdots \\ X(N-(m-1)\lambda) = \{x(N-(m-1)\lambda), x(N-(m-2)\lambda), \ldots, x(N)\} \end{cases} \tag{1}$$

where m is the embedding dimension and λ is the time delay.

For a given but arbitrary i, the m real values: $\{x(i), x(i+\lambda), \ldots, x(i+(m-1)\lambda)\}$ contained in each $X(i)$ can be rearranged in an increasing order as

$$X(i) = \{x(i+(j_1-1)\lambda) \leqslant x(i+(j_2-1)\lambda) \leqslant \cdots \leqslant x(i+(j_m-1)\lambda)\} \tag{2}$$

If there exist two elements in $X(i)$ having the same value, e.g. $x(i+(j_{i1}-1)\lambda) = x(i+(j_{i2}-1)\lambda)$, then we order the quantities x according to the values of their corresponding j's. Namely, if $j_{k1} < j_{k2}$, we set $x(i+(j_{i1}-1)\lambda) \leqslant x(i+(j_{i2}-1)\lambda)$. Therefore, any vector $X(i)$ can be mapped onto a group of symbols as