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A rolling bearing fault diagnosis method based on multi-scale fuzzy entropy and variable predictive model-based class discrimination

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ABSTRACT

A new rolling bearing fault diagnosis method based on multi-scale fuzzy entropy (MFE), Laplacian Score (LS) and variable predictive model-based class discrimination (VPMCD) is proposed in this paper. Compared with previous approximate entropy (ApEn) and sample entropy (SampEn), MFE has taken into account the dynamic nonlinearity, interaction and coupling effects among mechanical components and thus it provides much more hidden information in different scales of vibration signal. Hence, MFE is employed to characterize the complexity and irregularity of rolling bearing vibration signals. Besides, to fulfill an automatical fault diagnosis, the VPMCD, as a new classification approach, is employed to construct a multi-fault classifier for making decision. Also, Laplacian Score (LS) for feature selection is utilized to refine the feature vector by sorting the features according to their importance and correlations with the fault information to eschew a high dimension of feature vector. Finally, the proposed method is implemented to rolling bearing experimental data and the results indicate that the proposed method is able to discriminate the different fault categories and degrees effectively.

1. Introduction

In recent years, mechanical condition monitoring and fault diagnosis have been the research focus and have been attracting many scholars' attentions [1,2]. For rolling bearing is an important and frequently encountered part in the rotating machinery, many rolling bearing fault diagnosis methods have been proposed in succession. Among these methods, analysis of vibration signal has been the most common and important methodology [3,4]. Due to the factors such as instantaneous variations in friction, damping or loading conditions, clearances and non-linear stiffness of rolling elements, machine systems are often characterized by non-linear dynamic model, especially when the faults have occurred. Therefore, when the bearing operates in a fault condition, vibration signals collected from mechanical system often give expression to nonlinearity and non-stationarity, and the most often used signal processing methods that aimed for linear and stationary vibration signals, such as time and frequency domain techniques, or time–frequency analysis, may all exhibit limitations in different degrees [5]. On the other hand, the non-linear parameter estimation methods provide a good alternative to extract the defect-related features hidden in the measured vibration signals that may not be effectively extracted using other methods [5]. Hence, a number of non-linear parameter identification methods and theories, such as correlation dimension [6,7] and approximate entropy (ApEn) [5] have been investigated and introduced to mechanical fault diagnosis field. However, a very long data is needed to estimate the correlation dimension, and ApEn calculation depends heavily on the data length and the estimated value is often smaller than the

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expected one especially when the length of concerned data is short [8,9]. In 2000 Richman and Moorman [9] proposed the concept of sample entropy (SampEn) to overcome the shortcomings of ApEn. However, neither SampEn nor ApEn was defined to measure the irregularity and self-similarity of time series in a single scale. In 2002 multi-scale entropy (MSE) was introduced by Costa et al. [10,11] as an enhanced method to evaluate the irregularity and self-similarity of time series in several different scales and to characterize biological and physiological signals successfully. Zhang et al. [8] firstly introduced MSE into bearing fault diagnosis and proved that MSE could characterize the nonlinearity and complexity of bearing vibration signal, interaction and coupling effects between machine components more effectively in comparison to traditional single scale-based entropy.

Recently, an improved SampEn, i.e. fuzzy entropy (FuzzyEn) was developed by Chen et al. [12,13] by replacing the self-similarity function, Heaviside function, with a kind of fuzzy membership function. However, the membership function used by Chen et al. in FuzzyEn lacks physical meaning and statistical sense; thus, in this paper, we modified it and made it more reasonable in physical meaning and statistical sense. Based on this, multi-scale fuzzy entropy (MFE), i.e. the FuzzyEn of data in different scales, is developed to measure the complexity of time series. As the complexity of mechanical system, the single-scale base entropy could not reflect the hidden information effectively; fault information in other scales also plays important roles for fault feature extraction. Therefore, in this paper MFE is introduced to extract the fault features hidden in different scales from the vibration signals.

When we extracted the fault features using MFE, normally, the features constructed by MFE in different scales are used to achieve fault diagnosis. But, on one hand, the fault features extracted from bearing vibration signals in different scales are often of high dimension and with information redundancy, which will cause much training time, and on the other hand, it is hard to find out which feature is the most important to identifiably reflect the fault characteristics and which one is inessential without concern with fault information. Thus, it is our aim to reduce and refine the extracted features and to improve efficiency of rolling bearing fault diagnosis. In this paper, the Laplacian Score (LS) introduced by He et al. [14,15] recently is utilized to select the features by sorting feature elements with a series of scores from low to high according to their importance. Then the first several most important ones which contain the main fault information are seen as the new feature vector, which can not only reduce the dimension of the original feature vector but also improve the speed and efficiency of fault diagnosis greatly.

Naturally, after extracted the feature vector, a multi-fault classifier is needed to make the rolling bearing fault diagnosis automatically and make a reliable decision quickly on the working condition of machinery [8]. In recent years, various classical pattern recognition methods have been used to mechanical fault diagnosis, such as artificial neural networks (ANNs) [16,17], support vector machines (SVMs) [18–20] and adaptive neuro-fuzzy inference system (ANFIS) [8,21]. Though theories of these methods are already well established, some inherent limitations still exist. For example, the classification accuracy of ANN cannot be high enough due to the limitations of 'over-fitting', slow convergence velocity and relapsing into local extremum easily [22]. It is difficult for the SVM to select appropriate parameters and kernel function and the process for optimizing parameters also is time-consuming for a large quantity of data. In addition, SVM classification only is limited to be dimidiate [23]. ANFIS, which utilizes hybrid learning algorithm combined with ANN and fuzzy logic, is also easily fall into local extremum, and the training time and classification accuracy highly depend on the number of features in the feature vectors. Recently, a new classification approach named variable predictive models based on class discrimination (VPMCD) is proposed by Raghuraj and Lakshminarayanan [24,25]. As an alternate to existing classification methods, VPMCD is founded on the inter-relations among feature elements that can be exploited for distinguishing samples into specific classes. Also an efficient supervised learning algorithm, showing consistent and good performance with biological data sets, has been demonstrated. So far, VPMCD application to mechanical fault diagnosis has not been reported widely. Hence, in this paper VPMCD is introduced to rolling bearing fault diagnosis, and based on MFE, LS and VPMCD, a new fault diagnosis approach for rolling bearing is proposed.

The rest of this paper is organized as follows. Section 2 introduces a review of MSE and MFE. In Section 3 the Laplacian Score for feature selection is given briefly. The VPMCD method for classification is introduced in Section 4. A rolling bearing fault diagnosis method is proposed and experimental evaluation of the proposed method is given in Section 5. Finally, conclusions are drawn in Section 6.

2. Review of SampEn, FuzzyEn and MFE

2.1. Sample entropy

As an improvement of ApEn, sample entropy (SampEn) is defined as follows. For the sake of brevity only the main steps of the procedure are presented [7].

(1) For a time series of length N: $\{x(i)$: $1 \le i \le N\}$, an m dimension vector is formed as

$$X_i^{\,m} = \{x(i), x(i+1), \ldots, x(i+m-1)\}, i = 1, 2, \ldots, N-m+1. \tag{1}$$

Then a new vector series is obtained.

(2) For every $X_i^{\,m}$, define the distance $d[X_i^m, X_j^m]$ of $X_i^{\,m}$ from $X_j^{\,m}$ as

$$d_{ij}^m = d\left[X_i^m, X_j^m\right] = \max_{0 \le k \le m-1} \{|x(i+k)-x(j+k)|\}, i, j = 1, 2, \ldots N-m+1. \tag{2}$$