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Self-adaptive bearing fault diagnosis based on permutation entropy and manifold-based dynamic time warping

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ABSTRACT

To make bearing fault diagnosis more systematic and effective with better operability and real-time capability, this study proposes an approach using permutation entropy and manifold-based dynamic time warping. First, the nonlinear and non-stationary vibration signals were decomposed into several mono-components by a self-adaptive time-frequency analysis method, such as empirical mode decomposition (EMD), local mean decomposition (LMD), and local characteristic-scale decomposition (LCD). Second, for each component, the permutation entropy (PE), which can reflect the data complexity with good robustness and fast computing ability, was calculated to act as the fault feature. Third, we propose a method called manifold-based dynamic time warping (MDTW), which was used to reasonably measure the similarity between the testing data and the template data. The proposed MDTW is a modified version of the classical dynamic time warping (DTW) algorithm by replacing Euclidean distance based similarity metric with manifold based similarity metric. To determine the optimal feature extraction scheme, EMD-PE, LMD-PE, and LCD-PE based schemes are compared in terms of both adaptability for variable working conditions and separability for different fault severities. Finally, a comparison among DTW, MDTW, and standardized DTW was conducted in terms of similarity measurement. Experimental results demonstrate that the proposed approach can effectively diagnose bearing faults under both variable working conditions and different fault severities.

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1. Introduction

Bearings are widely used in rotating machinery, bearings' health states directly influence the reliable operation of rotating machinery, and then influence the entire system [1]. Bearing fault diagnosis has become a hot topic in recent years, and many effective methods have been proposed based on the analysis of vibration signals [2–4], which contain rich information about bearing health states [5]. The process of bearing fault diagnosis mainly includes fault feature extraction and fault states determination [6,7]. In this study, we propose an approach to make the process more systematic and effective with better operability and real-time capability.

As for extracting effective fault features, the main problem is how to process the nonlinear and non-stationary bearing vibration signals [8]. Traditional time-domain or frequency-domain analysis methods are not applicative on this occasion

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Fig. 1. Example of the distances calculated by MDTW.

[9], while some time-frequency analysis methods have been proven to be effective [10], among which, several self-adaptive methods, such as empirical mode decomposition (EMD) [11], local mean decomposition (LMD) [12], and local characteristic-scale decomposition (LCD), have emerged in the past few years. EMD, first proposed by Huang et al. in 1998 [13], has been widely applied in machinery fault detection and diagnosis [14–17]. Then, in 2005, LMD was proposed by Smith for processing modulating signals [18]. Compared with EMD, LMD keeps better local characteristics of the original signals, avoids undershoot or overshoot, and provides more reasonable physical information for the decomposed components [12,19,20]. LCD was recently proposed by Cheng et al. [21], and it was proven to be better than EMD by reducing invalid components and mode mixing [8,22]. As EMD, LMD, and LCD are all typical self-adaptive signal analysis methods, we respectively employ them to decompose the original vibration signals into mono-components so as to make a comparison. Then, fault features can be extracted from these mono-components [2,7,23].

Recently, entropy-based methods, which can identify nonlinear parameters, have been introduced into fault detection and diagnosis, such as approximate entropy [24], sample entropy [25], fuzzy entropy [22], and multi-scale entropy [26]. However, approximate entropy is defective as it is heavily dependent on the record length and lower estimation value, while sample entropy is proposed on the Heaviside step function, which is discontinuous and mutational at the boundary [27]. Fuzzy entropy is based on the concept of membership function, which is difficult to be accurately determined [28]. Multiscale entropy is based on sample entropy and can analyze the signals under different scales [4]. To analyze the signals' complexity, permutation entropy (PE) was proposed by Bandit and Pompe [29]. With the advantages of simplicity, fast calculation, robustness, and invariance to nonlinear monotonous transformations, PE has been effectively applied in many fields [30–32]. Then, multi-scale permutation entropy (MPE) was proposed to calculate PE in multiple scale time series [33], but MPE cannot accurately reveal the characteristics of the signals' intrinsic time scales [28], while the mono-components obtained from EMD, LMD, or LCD can exactly reflect the local characteristics of the signals, mono-components based PEs can provide more accurate fault information, thus in this study, we calculate PEs of the mono-components to act as the fault features, and a comparison will be made among EMD-based PE, LMD-based PE, and LCD-based PE in terms of the ability to resist variable working conditions and to accurately separate different fault severities.

For fault state determination, the key is to accurately measure the similarity between the testing feature vector and the template feature vector. Dynamic time warping (DTW), first proposed for speech recognition in 1978 [34], is a popular pattern match technique and has been applied in many fields, such as fingerprint verification [35], human motion recognition [36], online signature verification [37], data mining, computer vision and computer animation [38], and process monitoring and fault diagnosis [39,40]. Compared with other pattern match methods, DTW is simple, easy and of good real-time capability [41]. However, in DTW, the similarity metric is based on square Euclidean distance, which cannot guarantee the separability of smaller distances, much less reflecting the global consistency. Thus, we proposed a method called manifold-based dynamic time warping (MDTW), in which Euclidean distance based similarity metric was replaced by manifold based similarity metric, in which the separability among different categories was strengthened. To demonstrate the effect, MDTW was compared with DTW and standardized DTW (SDTW) in terms of similarity measurement.

The outline of this paper is as follows. Section 2 introduces the methods of EMD, LMD, LCD, permutation entropy, DTW, SDTW, and MDTW. Then in Section 3, the proposed fault diagnosis approach is described and experimentally validated using bearing vibration signals. Finally, conclusions are drawn in Section 4.

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