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Fault diagnosis of rolling element bearings based on Multiscale Dynamic Time Warping

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ABSTRACT

A fault recognition method for rolling element bearings based on Multiscale Dynamic Time Warping (MDTW) is proposed in this paper. After preprocessing using Empirical Mode Decomposition (EMD), CWs are extracted from vibration signals. The normalization of CWs is necessary to eliminate the influence of amplitude variations before using MDTW. Following this process, one CW of the normal condition is selected as a template to calculate the distance of DTW (DDTW) with other CWs. The calculated DDTW results can then be utilized to classify the bearing conditions since different conditions have different DDTW bands. The proposed method is validated by the data from Bearing Data Centre of Case Western Reserve University. The analysis results indicate that the influence of variable speed and different defect sizes can be effectively eliminated by DTW.

1. Introduction

Rotating machines are prime movers of process industry. With challenging demands to extent their useful life and increase production capacity, modern rotating machineries are required to operate at high-speeds and are usually large in size. These machines have many rotating parts and a fault in one of the components can lead to catastrophic failure of the whole system which will affect the safety of operation and subsequent production loss. Rolling element bearings are critical components of rotating machinery and are confronted with vulnerability due to unsteady loads and speeds, and the corrosive effects of the working environment.

Conventional fault diagnostic techniques of rolling element bearings utilized vibration, acoustic, temperature and oil measurements to assess the condition of the bearings [1]. These techniques are effective if the operating characteristics do not change significantly during operation. Vibration diagnostic technique, which is commonly used in bearings fault diagnosis, provides an effective and easy approach in analyzing the signals obtained from the sensors [2]. The key step of fault recognition of rolling element bearings based on vibration analysis is to process the measured signal correctly to extract the fault characteristics, which is directly related to the theoretical calculations of the bearing dynamics with an assumed constant rotating speed. In order to extract the fault pattern of roller bearings, the measured frequency components are compared with the theoretical values. However, the vibration signals of rotating machinery are non-stationary and have nonlinear characteristics. Thus, it is difficult to directly extract fault information from the original measured signals. With the progress of computing capability, bearing fault diagnosis technology has become an integrated discipline of computer, digital signal processing, artificial intelligence and other technologies.

Compared with the conventional methods, current researches have focused on the following techniques: Continuous Wavelet Transform [3] which focused on the selection of real wavelet and complex wavelet according to the Maximum Energy to Shannon Entropy ratio and Maximum Relative Wavelet Energy criterion is used to extract the statistical properties of the wavelet coefficients of raw vibration signals and finally exploit these statistical properties as inputs of machine learning techniques to achieve fault diagnosis of rolling element bearings. Expert System [4] is established to verify the correctness of the algorithm utilizing the processed data and gathered a large number of fault features from the vibration signals to build an experienced database. It combines the algorithm with the database to complete the fault diagnosis. Fuzzy Diagnosis [5] deals with the change of inherent complexity of the vibration waveform when a fault has occurred in a roller bearing. Fuzzy entropy is used to measure the complexity and the self-similarity of the time series in fault diagnosis. Neural Network

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[6,7] obtained the mode network signals through the study of known samples to accomplish the pattern recognition task of rolling element bearing faults. This identification process is essentially to match the unidentified data with the prior data. The neural network classifier has the same problem as the traditional pattern recognition methods, which requires a significant amount of learning samples. Unfortunately, in most practical situations, it is difficult to obtain typical fault samples, which is one of the limitations of the techniques. Different types of rolling element bearings exhibit different characteristics which can be extracted directly in the time domain signals. Compared with characteristic statistics (such RMS and impulse index), the time-domain Characteristic Waveform (CW) is intuitive, clear physical representation, and comprehensive reflection of the inherent characteristics of bearing vibration. Compared with transformed feature (characteristic frequency, wavelet coefficients, etc.), it is easy to access and does not need any space transformation. Hence, fault diagnosis of rolling element bearings based on time-domain CW signal matching [8,9] is an attractive area of research.

Recently, the study on time series has obtained widespread interest. One of the major applications of time series is in classification field. For example, two signals in the time domain having similar overall component shapes may be out of synchronization and generally are not of exactly the same length. In order to find the exact dissimilarity between these two signals and as a preprocessing step before comparing them, it is necessary to match them to an appropriate alignment. However, many methods have been applied using time domain waveform matching, which required the length, dimension and phase of two waveforms to be the same. These requirements can be hard to achieve which restrict its application and development. Dynamic Time Warping (DTW) is a well-known technique for measuring distance between two time sequences that are similar but locally out of phase through finding an optimal alignment. In the early stage, DTW was mainly used in the recognition of isolated words and speeches. Since then, it has been employed for clustering and classification in many domains: database index [10,11], handwriting recognition [12], in the field of biological engineering and biomedical informatics [13], and gene regulatory network [14]. In the field of computer vision, it was applied to gesture recognition and human activity recognition [15,16]. In addition, its application in signal processing [17,18], electrocardiogram analysis [19,20], and data mining [17] and process monitoring [21] have shown strong vitality. Recently, Zhen et al. [22] have explored its application in processing data from motors for condition monitoring and shown promising results. Dai et al. [23] have put forward a new fault diagnosis methodology for batch chemical processes, using a dynamic time warping-based artificial immune system and experiments show that it has the capability of fault diagnosis of batch processes. Zhao et al. [24] have studied a new online fault diagnosis system for full operating cycles of chemical processes and the dynamic artificial immune system based on dynamic time warping is used for fault identification in both the startup phase and the steady state, and shows it has high adaptation capability.

In this paper, DTW is applied for fault diagnosis of rolling element bearings using the vibration signals. Based on time waveform analysis of the vibration signals, CWs of different rolling element bearing conditions are extracted. After normalization and Empirical Mode Decomposition processing, different DDTW bands are obtained through calculating DTW of the template and other extracted CWs. Finally, fault recognition can be accomplished through matching the test CWs with the template. This technique has many advantages, among them, it ignores the diversity of lengths and phases of two waveforms. Furthermore, the influence of speed fluctuations and load conditions can be overcome during fault classification.

The rest of the paper will be organized as follows. Section 2, the theory of MDTW is briefly presented. Section 3 is dedicated to the resource of data collection, the methods of processing the vibration signals, and the proposed approach applied for fault diagnosis of rolling element bearings. Section 4, variable speed and different severity are discussed to present the properties of MDTW. Section 5 gives the conclusion.

2. Multiscale Dynamic Time Warping

DTW is a distance measurement technique which is ideal for comparing time series. It differs from Euclidean distance (ED) by allowing the vector components to compare with the "drift" from the corresponding exact positions. It is an algorithm for measuring similarity between two sequences (e.g. time series) which may vary in time or speed. The sequences are "warped" non-linearly in the time dimension to determine a measure of their similarity which is independent of non-linear variations in the time domains [25].

A time series is a sequence of observation which follows a certain order in time or space. For simplicity and without any loss of generality, we assume that time is discrete within a certain period.

The basic algorithm of DTW is as follows. Given two time series of lengths N and M

$$X = (x_1, x_2, x_3, \ldots, x_N) \tag{2-1}$$

$$Y = (y_1, y_2, y_3, \ldots, y_M) \tag{2-2}$$

where x_i and y_j are represented by the sequences of values at point i and j in series X and Y, respectively.

To align the two time series for comparison, a $N \times M$ distance matrix D is constructed first. The element of matrix D is the distance between the two points x_i and y_j which is represented by $d(x_i, y_j)$. Typically, the Euclidean distance is used to calculated the point-to-point distance by

$$d(x_i, y_j) = (x_i - y_j)^2 \tag{2-3}$$

Once the distance matrix is established, the path through the matrix with minimal cumulative distance between the time series can be calculated. DTW distance corresponds to the path with minimal warping cost:

$$DTW(x, y) = \min \sqrt{\sum\nolimits_{k=1}^{K} w_k} \tag{2-4}$$

where w_k is the matrix element that also belongs to the element of a warping path W.

$$W = (w_1, w_2, w_3, \ldots, w_K), \quad w_k = (n_k, m_k) \tag{2-5}$$

where$n_k = 1, 2, 3, \ldots, N; \quad m_k = 1, 2, 3, \ldots, M; \quad k = 1, 2, 3, \ldots, K;$ $\max(N, M) \leqslant K \leqslant N + M$

The warping path is subjected to three constraints:

(1) Boundary condition: $w_1 = (1, 1)$ and $w_K = (N, M)$ the starting and ending points of the warping path must be the first and the last points of the aligned time series.
(2) Monotonicity condition: Given $w_k = (n_k, m_k)$ then $w_{k-1} = (n_{k-1}, m_{k-1})$, where $(n_k - n_{k-1}) \geqslant 0$ and $(m_k - m_{k-1}) \geqslant 0$. This forces the points in w to be monotonically spaced in time.
(3) Continuity condition: Given $w_k = (n_k, m_k)$ then $(n_k - n_{k-1}) \leqslant 1$, $(m_k - m_{k-1}) \leqslant 1$, so the continuity condition is formulated as $w_k - w_{k-1} \in \{(1, 1), (1, 0), (0, 0)\}$