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Fault diagnosis of roller bearings based on Laplacian energy feature extraction of path graphs

Lu Ou, Dejie Yu *

State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body, Hunan University, Changsha 410082, PR China

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ABSTRACT

Feature extraction of roller bearing is always an intractable problem and has attracted considerable attention for a long time. The vibration signal of roller bearing can be treated as the path graph in a manifold perspective. Generally, vibration signals of roller bearings with different faults have different correlation matrices of path graphs which including different adjacency matrices and Laplacian matrices. Therefore, as a complexity feature of the path graph, the Laplacian energy (LE) can be employed to analyze the roller bearing vibration signals. In this paper, LE is introduced as the fault feature of bearing vibration signals from graph spectrum domain and then a new fault diagnosis method based on the LE single feature extraction and Mahalanobis distance (MD) criterion function is proposed and applied to the analysis of roller bearing vibration signals. Experimental analysis results show that the proposed method can identify the roller bearing faults accurately and effectively only with a small amount of sampling points and training samples.

1. Introduction

Roller bearings are key parts of mechanical systems and play a crucial role in the modern manufacturing industry, and their failure is one of the most common causes of the mechanical breakdowns in engineering applications. Usually, vibration signals are used to detect the faults of machine components and reduce the damage of machinery by applying fault diagnosis methods [1–4]. The essence of fault diagnosis is the pattern recognition and classification. Naturally, feature extraction is a critical section in pattern recognition.

The conventional feature extraction methods include time-domain methods, frequency-domain methods, and time–frequency methods [1]. Time-domain methods are based on the time waveform index, e.g. peak amplitude, root-mean-square amplitude, variance, kurtosis and entropy [5–7]. Frequency-domain methods are based on the transformed signals in frequency domain, i.e. Fourier spectrum, cepstrum analysis, and envelope spectrum [8–10]. Time–frequency methods investigate signals in both the time and the frequency domains, such as the wavelet transform (WT), the empirical mode decomposition (EMD) [11–14] etc. These methods extracted the features either from the time domain, the frequency domain or the time–frequency domain. Nonetheless, these methods often produce unsatisfactory results because of their respective drawbacks when used to analyze complex roller bearing vibration data [15–17]. Accordingly, there is a need to develop new methods for feature extraction from other domains, such as from graph spectrum domain.

In the last few years, techniques based on the spectrum graph theory [18,19] provide a "frequency" interpretation of graph data and have been proven to be quite popular in some application areas [20–22]. Additionally, a growing amount of research works have been dedicated to extending and complementing the spectrum graph techniques, leading to the emergence of the Graph Signal Processing (GSP) [23]. Shuman [23,24] outlined the main challenges of the area, discussed different ways to define the graph spectrum domain, which is the analogue to the classical frequency domain, and highlighted the importance of incorporating the irregular structures of graph data domains when processing signals on graph. Agaskar [25,26] justified the use of the graph Laplacian's eigenbasis as the surrogate of the Fourier basis for graphs, defined the notions of "spread" in the graph and spectrum domains, and investigated the uncertainty principle and localization of a graph signal in different domains. Zhu [27] provided a detailed theoretical analysis on why the graph Laplacian eigenbasis can be regarded as the Fourier transform of graphs and discussed whether the Laplacian eigenvectors are meaningful basis vectors for all graphs. Sandryhaila [28–30] extended Discrete Signal Processing (DSP) to

* Corresponding author.
E-mail address: djyu@hnu.edu.cn (D. Yu).

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"DSP on graphs", including transform, impulse response, spectrum representation, Fourier transform, frequency response, and illustrated DSP on graphs by classifying blogs, linear predicting and compressing data from irregularly located weather stations and so on.

Obviously, the main targets of these studies are generally the case for all class graphs, but the study of a particular class graph is ignored, namely the path graph. Generally, a path graph is a sequence of vertices which is connected by edges in sequence, while a path graph signal is a function defined on the set of vertices of the path graph. Path graph is one type of graph with the simplest and most intuitive structure, such as harmonic signals, mechanical vibration signals, and ECG signals, which are time series signals with the structure of path graph. As the time series signal is one class of path graph signal, it is of important significance to introduce the path graph signal analysis into the time series analysis. Meanwhile, there are structural corresponding relationships between the time-series and the path graph, which are the sequence structure of time-series signal correspond to the graph structure of path graph and the function value of time-series signal correspond to the graph signal value of path graph. The roller bearing vibration signals are time-series signals and the signal processing in fault diagnosis is actually the signal processing in time-series [31], hence the path graph can be used to analyze the roller bearing vibration signals.

In fact, vibration signals of roller bearings with different faults have different path graph structures, and thus the characteristics of its Laplacian matrix are different. The eigenvalues of the Laplacian matrix contain the most important characteristics of a graph in graph spectrum domain, and then these eigenvalues could reflect the internal structure information of the path graph. Consequently, the Laplacian energy (LE) [32], which is calculated from the eigenvalues of the Laplacian matrix, can be used as a measure of graph complexity in many areas. LE of a graph has a clear connection to chemical problems [33] and there are some known results in the mathematical literature [34,35]. Song [36–38] introduced component-wise LE to filter image description hierarchies. Livi [39–41] applied LE in the characterization of graphs for protein structure modeling and recognition of solubility. Zhao [42] proposed a new high-resolution satellite image classification and segmentation method which applies LE as a generic measure to reduce the number of levels and regions in the hierarchy. Zhang [43] proposed a new hierarchical segmentation method that applies graph LE as a generic measure for segmentation in hierarchical remote sensing image analysis. Ayyalasomayajula [44] used topological clustering of LE segmentation algorithm in text binarization. In general, LE is a powerful tool for uncovering the structural characteristics of graphs. With the present of relationship between the time-series and the path graph, LE can be used to discover the intrinsic structure of path graph from roller bearing vibration signals.

In this paper, LE [32,45] and Laplacian-energy-like invariant (LEL) [46,47] are employed to represent the fault features of roller bearing vibration signals from graph spectrum domain. Since LE is a single feature that only contains one value, Mahalanobis distance (MD) criterion function [48] is employed to achieve fault classification. Accordingly, a fault diagnosis method of roller bearings based on the LE single feature extraction and MD classification is proposed. In the proposed method, the adjacency matrices and Laplacian matrices of the roller bearing vibration signals are firstly constructed. Then, LE is calculated by using eigenvalues which come from the standard orthogonal decomposition of Laplacian matrices. Finally, the fault characteristic vectors consisting of LE are input to the MD classifiers and the work condition and fault patterns of roller bearings can be identified. The analysis results from experimental signals with normal and defective roller bearings indicate that the proposed approach shows the effectiveness and availability for the fault diagnosis of roller bearings and have the characteristics of requiring only minute amounts of sampling points and training samples.

This paper is organized as follows. In Section 2, path graph and spectrum graph theory are introduced. In Section 3, the definitions of LE and MD are given briefly. In Section 4, the new approach for the fault diagnosis of roller bearings is proposed. In Section 5, the effectiveness of the proposed method is verified by the test results and the conclusions are given in Section 6.

2. Path graph and spectrum graph theory

A path graph is a sequence of vertices such that from each of its vertex there is an edge to the next vertex in sequence. A path graph P_{10} with 10 vertices is shown in Fig. 1. In Fig. 1, the vertex set is $\{v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9, v_{10}\}$, and the edge set is $\{v_1v_2, v_2v_3, v_3v_4, v_4v_5, v_5v_6, v_6v_7, v_7v_8, v_8v_9, v_9v_{10}\}$.

A signal or a function f defined on the vertices of a graph can be represented as a vector $f \in R^N$, where the ith component of the vector f represents the signal value at the ith vertex. As can be seen from the definition, the vector and the graph signal is the one-to-one correspondence, and this means that the sort order of graph signal is determined by the sort order of vertices.

Consider undirected, connected, weighted graph $G = (V, E, \boldsymbol{W})$, where V is a finite set of vertices with $|V| = N$, E is a set of edges with $|E| = M$, N and M are the number of vertices and edges respectively, and $\boldsymbol{W}$ is a weighted adjacency matrix. Let w_{ij} be the element of $\boldsymbol{W}$ at the ith row and jth column, if there is an edge e_{ij} connecting vertices i and j, then the element w_{ij} that represents the weight of e_{ij} is nonzero; otherwise, $w_{ij} = 0$. General definitions of nonzero w_{ij} are the following three ways [23]

$$w_{ij} = 1 \tag{1}$$

$$w_{ij} = \|x_i - x_j\| \tag{2}$$

$$w_{ij} = e^{-\frac{\|x_i - x_j\|^2}{2t^2}}. \tag{3}$$

where t is a suitable constant that indicates the thermonuclear width and x_i and x_j are the values of vertex i and vertex j, respectively. The degree matrix $\boldsymbol{D}$ is a diagonal matrix with the ith diagonal element $d_i = \sum_{j \neq i} w_{ji}$. The graph Laplacian matrix is defined as

$$L = D - W \tag{4}$$

As the graph Laplacian matrix $\boldsymbol{L}$ is a real symmetric matrix, it has a complete set of orthonormal eigenvectors $x_l, \{l = 0, 1 \ldots N-1\}$ and we denote eigenvector matrix by $X = [x_0, x_1, x_2 \ldots x_{N-1}]$. Without loss of generality, we assume that the associated real, nonnegative Laplacian eigenvalues are ordered as $0 = \lambda_0 < \lambda_1 \leqslant \lambda_2 \ldots \leqslant \lambda_{N-1} = \lambda_{\max}$, and we denote the graph Laplacian spectrum by $\sigma(L) = \{\lambda_0, \lambda_1, \lambda_2 \ldots \lambda_{N-1}\}$.

The Laplacian eigenvalues λ_l and Laplacian eigenvectors x_l can be obtained by the standard orthogonal decomposition of the graph Laplacian $\boldsymbol{L}$, which meets

$$Lx_l = \lambda_l x_l, l = 0, 1, \ldots N-1. \tag{5}$$

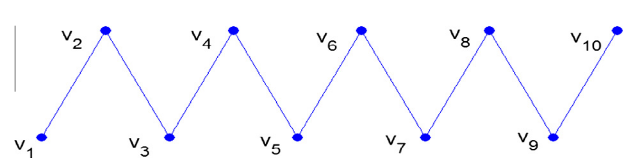

Fig. 1. A path graph P_{10} with 10 vertices.