Journal of Sound and Vibration 399 (2017) 330–344

Contents lists available at ScienceDirect

Journal of Sound and Vibration

journal homepage: www.elsevier.com/locate/jsvi

Sparse discriminant manifold projections for bearing fault diagnosis

Gang Chen*, Fenglin Liu, Wei Huang

College of Mechanical Engineering, Chongqing University, Chongqing 400044, PR China

ARTICLE INFO

Article history:
Received 11 January 2016
Received in revised form
18 February 2017
Accepted 24 March 2017
Handling Editor: I. Trendafilova
Available online 1 April 2017

Keywords:
Sparse discriminant manifold projections
Dimensionality reduction
Feature extraction
Fault diagnosis

ABSTRACT

The monitored vibration signal of bearing is usually nonlinear and nonstationary, and may be corrupted by background noise. Thus, it is very difficult to accurately extract sensitive and reliable characteristics information from the vibration signal to diagnose bearing health conditions. This paper proposes a novel bearing fault diagnosis method based on sparse discriminant manifold projections (SDMP). The SDMP was developed based on sparsity preserving projections, and sparse manifold clustering and embedding. The SDMP can effectively extract the meaningful low-dimensional intrinsic features that hidden in a high-dimensional feature dataset. After dimensionality reduction with the SDMP, the least squares support vector machine (LS-SVM) is utilized to classify the different low-dimensional feature data for fault recognition. The effectiveness and superiorities of the proposed method are demonstrated through several comparative experiments with other three manifold learning methods. The experimental results validate that the SDMP is more effective than the other three manifold learning methods for implementation bearing fault diagnosis, and it is more robust when deal with noise interference signal.

1. Introduction

Rolling element bearing play an important role in various rotating machinery. When faults occur in bearing, it may bring about fatal damage to machine, and lead to huge economic losses [1]. Fault diagnosis technique is utilized to detect hidden defects of machinery. It can give an early-warning before faults deteriorate to a series of fatal breakdown. Furthermore, it is significant for the modern mechanical industry. Nowadays, fault diagnosis has been an extremely important research field in the machinery engineering [2].

The vibration signal that collected from rolling bearing through sensors contains abundant useful information about bearing health condition [3]. The crucial fault information of defective bearing can be excavated from the monitored signal through proper signal processing techniques. Through analyzing these vibration signals to detect bearing latent faults is reliable, and it has proved to be the principal and effective method [4]. However, it is a great challenge to extract sensitive and reliable fault features from vibration signal for performing accurate fault diagnosis [5]. In order to obtain the effectively fault information which hidden in the data that relevant to operating machinery, many time–frequency features need to be extracted from the monitored signal [6]. However, there are always a number of redundant information in the high dimensionality feature datasets, it is difficult to excavate the useful information that can accurately evaluate the bearing

* Corresponding author.
E-mail address: cqdxcg@126.com (G. Chen).

http://dx.doi.org/10.1016/j.jsv.2017.03.029
0022-460X/

health condition from these redundancy data [7]. Therefore, it is a great necessary to develop a proper feature extraction technique for extracting the dominant feature information to obtain more accurate fault recognition results.

For fault feature extraction, the traditional linear dimensionality reduction methods, including principal component analysis (PCA) [8], linear discriminate analysis (LDA) [9], multidimensional scaling (MDS) [10], and neighborhood preserving embedding (NPE) [11], etc. However, these methods are effective only when high-dimensional feature dataset is linear or near linear. Owing to the intrinsic non-stationary and non-linear property of machine vibration, the multi-domain feature dataset that extracted from the monitored vibration signal is non-linear [12]. Thus, it is difficult to utilize these linear methods to extract the dominant fault features from the non-linear dataset, and obtain accurate fault diagnosis results.

Manifold learning, an effective nonlinear feature extraction method, has attracted more and more attention in recent years. It can effectively discover the low-dimensional intrinsic structure of high-dimensional dataset. Thanks to its nonlinear dimensionality reduction capability, it can extract the crucial fault feature information from high-dimensional feature dataset for fault recognition. At present, the representative manifold learning methods, including isometric mapping (Isomap) [13], locally linear embedding (LLE) [14], Laplacian eigenmaps (LE) [15], local tangent space alignment (LTSA) [16], etc. Many signal processing methods that based on manifold learning were utilized to perform machinery fault diagnosis in recent years [1,17–22]. However, these traditional manifold learning algorithms are sensitive to noise, because noise may change the intrinsic structure of a manifold, lead to obtain incorrect low-dimensional feature dataset [23]. The measurement signal unavoidable containing background noise, and the noise is one of the major barriers when handle the monitored vibration signal to obtain accurate fault recognition results [24]. The robustness of an algorithm would have influences on its performance of implementation of fault diagnosis. Moreover, all of these manifold learning methods need to select an appropriately neighborhood size for building neighborhood graph before clustering and dimensionality reduction. However, it is difficult to find the optimal neighborhood parameter to build the optimum neighborhood graph, especially when the interference noise is extremely strong.

In this paper, we introduce a novel algorithm, which called SMCE (sparse manifold clustering and embedding) [25], and ameliorate it for performing bearing fault diagnosis. SMCE can adaptively select adjacent points with sparse representation techniques to build a neighborhood graph and simultaneously obtain corresponding weights. The SMCE has better performance of dimensionality reduction than those traditional manifold learning methods, particularly when deal with the challenging situations that the nearest neighbors of a point come from different manifolds. However, SMCE is an unsupervised learning method, and suffers from the out-of-sample problem. Moreover, it does not give an explicit projections matrix, this leads to some disadvantage when utilize it to perform fault diagnosis. For improvement the performance of SMCE, a new approach that called SDMP (sparse discriminant manifold projections) is proposed, which is based on SMCE and SPP (sparsity preserving projections) [26]. In the implementation progress of fault diagnosis, the SDMP can take advantage of the class label information of training samples to guide dimensionality reduction of high-dimensional feature dataset. The experimental results indicate that the SDMP has better performance than other three manifold learning methods for bearing fault diagnosis, especially when the vibration signals are contaminated by strong background noise.

The remainder of this paper is organized as follows. Section 2 summarizes the foundation theory about sparsity preserving projections, and sparse manifold clustering and embedding. In Section 3, we propose a sparse discriminant manifold projections algorithm, which is based on SMCE and SPP. Section 4 introduces the implementation progress of bearing fault diagnosis with sparse discriminant manifold projections. In Section 5, some experiments with the proposed method were implemented, and the experimental results show the effectiveness and advantage of SDMP compared to the LLE, LTSA and SMCE. Finally, Section 6 gives the conclusion and summary of this paper.

2. Fundamental theories of SPP and SMCE

It is assumed that there exist a set of data $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\} \in R^{D\times N}$ with the i-th high-dimensional vector is $\boldsymbol{x}_i \in R^D$, $i = 1, \ldots, N$. The goal of dimensionality reduction is to find a low-dimensional intrinsic representation of $\boldsymbol{X}$ by mapping the D-dimensional dataset to a low-dimensional subspace R^d. The N data points in the low-dimensional subspace are $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_N$, let $\boldsymbol{Y} = \{\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_N\}$. Definition $\boldsymbol{V}$ is the projections matrix, so that $\boldsymbol{Y}$ can be represented as $\boldsymbol{Y} = \boldsymbol{V}^T\boldsymbol{X}$.

2.1. Sparsity preserving projections

Sparsity preserving projections can preserve the sparse reconstruction relationship of a data set from high-dimensional space to low-dimensional subspace [26]. This program corresponds to the solution of the following optimization problem, and the objective function is defined as

$$\min_{\boldsymbol{V}} \sum_{i=1}^{n} \left\| \boldsymbol{V}^T\boldsymbol{x}_i - \boldsymbol{V}^T\boldsymbol{X}\boldsymbol{s}_i \right\|^2 \tag{1}$$

where $\boldsymbol{V}$ is the projections matrix, $\boldsymbol{s}_i$ is the sparse reconstructive coefficient. Through some simple algebraic formulation, the objective function can be simplified to