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Machine health monitoring based on locally linear embedding with kernel sparse representation for neighborhood optimization

Chuang Sun [a], Peng Wang [b], Ruqiang Yan [a], Robert X. Gao [b,*], Xuefeng Chen [a]

[a] School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China
[b] Department of Mechanical and Aerospace Engineering, Case Western Reserve University, Cleveland, OH 44106, USA

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ABSTRACT

Manifold is considered to be a low dimensional surface embedded in a high dimensional vector space, and manifold learning is to find this surface based on data points sampled from this vector space. Neighborhood construction is a critical step in manifold learning to retain local relationship of data, i.e., neighbors and the connection weights. Current methods for manifold learning, including locally linear embedding, locality preserving projection, etc., assume fixed and linear neighborhood, thus lacking in adaptability for handling nonlinear system states caused by variations in machine condition or operation. To overcome this limitation, an enhanced manifold learning method is developed by utilizing kernel sparse representation to determine data neighbors and connecting weights. This enhanced manifold learning method maps data into a feature space where a kernel function is adopted to represent data by its neighbors nonlinearly. The number of data neighbors and connecting weights are determined adaptively by kernel sparse representation. It is found that the developed method enables state-related feature fusion and redundant feature elimination, thus is more effective for dimensionality reduction and feature extraction than traditional manifold learning. Analysis using vibration data measured on a gearbox with multiple faults of varying severity degrees confirmed the performance of the developed method.

1. Introduction

Vibration analysis has been widely applied to mechanical system health monitoring due to the accessibility to vibration sensors. Over the past decades, analysis methods in the time domain [1,2], frequency domain [3–6] and time-frequency domains [7–9] have been developed to analyze characteristics of vibration signals and extract features with structural defects in bearings and gearboxes, for machine health monitoring, root cause diagnosis, and remaining useful life prognosis [10–13]. Considering the interrelationship of the features and their respective sensitivity relative to the severity of defects, dimensionality reduction techniques are often needed to eliminate redundant information and fuse multiple features to improve the effectiveness and efficiency machine health monitoring [14].

* Corresponding author.
E-mail address: Robert.Gao@case.edu (R.X. Gao).

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Duo to the nonlinearity in degradation process of machine, vibration signals sampled during the degradation process formed a nonlinear and curved surface [15], which is considered to be a manifold. Manifold is a low dimensional surface embedded in a high dimensional vector space, and it can be discovered by manifold learning method. As an emerging method for dimensionality reduction, manifold learning has demonstrated improved nonlinear feature extraction ability over other methods such as principal component analysis (PCA) and linear discriminant analysis (LDA) for data compression [16]. Variants of manifold learning methods, such as Laplacian eigenmaps (LE) [17], locality preserving projection (LPP) [18,19], locally linear embedding (LLE) [20–23], neighborhood preserving embedding (NPE) [24], local tangent space alignment (LTSA) [25,26] and isometric feature mapping (IsoMap) [27] have been investigated for machine health monitoring. Manifold learning aims to keep the local relationship among data points gathered as part of feature vectors of vibration signals. By doing so, data that are similar in original feature space will remain close to each other in the feature space after dimensionality reduction.

While the effectiveness of manifold learning has been demonstrated in the literature, several limitations still exist. Firstly, local linearity is assumed on a manifold, and local patch of a manifold is considered to be a linear surface. Given that a manifold is a curved surface, linear distance such as the Euclidean distance will inherently not be a suitable metric to measure the distance between the points on a data manifold. Secondly, local neighborhood of the data is characterized by the number of neighbors and connecting weights. The number of neighbors and the function used to calculate connecting weights are assumed to be fixed in current methods. This means that fixed neighborhood expression is forced to be used for the mechanical states with or without fault. However, due to impulse component caused by mechanical fault and random component caused by fault propagation, data monitored from varying machine states are associated with different structures. Taking bearing as an example, distribution of the data from fault-free state is stable without fluctuation, while impulse and randomness caused by bearing fault make the data fluctuate in a large range. This can be seen in the features of bearing data monitored in its whole life-cycle, and fluctuation in amplitude of vibration signal caused by the bearing fault can be obviously observed [14,28,29]. Hence, adaptive neighborhood is needed for manifold learning to make it more effective and flexible to describe characteristics of data from different mechanical states.

A critical issue in adaptive neighborhood construction is to represent data adaptively without need to set a fixed neighborhood. Sparse representation is an adaptive method for data representation, and sparse-based dimensionality reduction method, i.e., the sparsity preserving projection [30], has been presented. The sparse representation can be extended as kernel sparse representation (KSR) by combining it with kernel function for nonlinear data representation in machine health monitoring. To improve performance of manifold learning in dealing with nonlinearity and adaptability, an enhanced manifold learning method is presented by introducing KSR into manifold learning in this paper. LLE is taking as an example and the enhanced manifold learning method is given by leveraging KSR to solve the number of neighbors and connecting weights in LLE. This enhanced manifold learning is termed as kernel sparse locally linear embedding (KS-LLE). To validate effectiveness and advantage of the KS-LLE for machine health monitoring, a case study on fault severity assessment of a gearbox is considered.

The rest of this paper is organized as follows: kernel sparse representation-based adaptive neighborhood, which is the first step in manifold learning, is introduced in Section 2. In Section 3, the KS-LLE method is described. Case study on gearbox diagnosis by utilizing the KS-LLE method is shown in Section 4. Discussion of characteristics of the KS-LLE method is presented in Section 5 and some conclusions are summarized in Section 6.

2. Kernel sparse representation-based adaptive neighborhood

2.1. Neighborhood in manifold learning

Manifold learning is a neighborhood-based method, and neighborhood that determines data neighbors and connecting weights plays a fundamental role in manifold learning methods, including LE, LPP, LLE, NPE and IsoMap. Though objective functions are different, a common issue in these methods is construction of data neighborhood. Methods for neighborhood construction fall into two categories: k-nearest neighbor (knn) and ε-neighborhood. In knn method, k samples with the smallest distance to sample $\boldsymbol{x}_i,\ i = 1,\cdots,n$ are chosen from all the n samples to form a k-nearest neighborhood of $\boldsymbol{x}_i$, and sample $\boldsymbol{x}_j,\ j = 1,\cdots,n$ is connected to $\boldsymbol{x}_i$ if it is one of the k-nearest neighbors of $\boldsymbol{x}_i$. In the ε-neighborhood method, a sample $\boldsymbol{x}_j$ is treated as a neighbor of $\boldsymbol{x}_i$ if their Euclidean distance is smaller than a threshold, expressed mathematically as $\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2 < \varepsilon,\ i,j = 1,\cdots,n$ with $\varepsilon > 0$ denoting the threshold.

After neighbors are identified, the next step is to calculate connecting weight of the neighbors. In LE and LPP, the weight between for the neighbors is assigned by a heat kernel [31], which is described as

$$w_{ij} = \exp\left(-\frac{\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{t}\right),\ i,j = 1,\cdots,n \tag{1}$$

where w_{ij} is the weight, and t is a parameter in the heat kernel. If these two samples are not neighbors, the weight is set to be 0. In IsoMap, weight between neighboring points $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ is defined by the Euclidean distance, that is $d(\boldsymbol{x}_i, \boldsymbol{x}_j) = \|\boldsymbol{x}_i - \boldsymbol{x}_j\|$. In