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Supervised locally linear embedding projection (SLLEP) for machinery fault diagnosis

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ABSTRACT

Following the intuition that the measured signal samples usually distribute on or near the nonlinear low-dimensional manifolds embedded in the high-dimensional signal space, this paper proposes a new machinery fault diagnosis approach based on supervised locally linear embedding projection (SLLEP). The approach first performs the recently proposed manifold learning algorithm supervised locally linear embedding (SLLE) on the high-dimensional fault signal samples to learn the intrinsic embedded multiple manifold features corresponding to different fault modes, and map them into a low-dimensional embedded space to achieve fault feature extraction. For dealing with the new fault sample, the approach then applies local linear regression to find the projection that best approximates the implicit mapping from high-dimensional samples to the embedding. Finally fault classification is carried out in the embedded manifold space. The ball bearing data and rotor bed data are both used to validate the proposed approach. The results show that the proposed approach obviously improves the fault classification performance and outperform the other traditional approaches.

1. Introduction

Machinery fault diagnosis is essentially a kind of pattern recognition problem, in the process of which the feature extraction is fundamental and the recognition method is at the core. Sensors provide a large number of high-dimensional measurements, i.e. samples that contain much useful information for fault identification. For a measured vibration signal sample of length D, it can be treated as a data point in the high-dimensional signal space $\mathbb{R}^D$. Different fault classes usually have different data distributions in the signal space, according to which the fault recognition can be achieved. However, the ideal decision boundary between different fault classes in such signal space is often highly nonlinear. A classifier should therefore have many degrees of freedom, and consequently a large number of parameters. So applying a classifier directly on such high-dimensional data for fault recognition is quite complicated because too many parameters have to be estimated using a limited number of samples. This is the well-known "curse of dimensionality". A widely used way to attempt to resolve the problem is feature extraction, which aims to project the original high-dimensional data into a lower dimensional feature space that reflects the inherent structure of the original data and holds the useful information as much as possible. At last a suitable classifier is adopted to perform fault classification in low-dimensional space.

For fault feature extraction, principal component analysis (PCA) [1] and linear discriminate analysis (LDA) [2] are the classical dimensionality reduction methods. However, since they are linear, their performances degenerate for nonlinear data where the underlying low-dimensional structure has nonlinear manifolds (such as nonlinear curves and surfaces)

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