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Weighted local and global regressive mapping: A new manifold learning method for machine fault classification

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ABSTRACT

This article studies if machine faults can be effectively determined in a reduced dimensional space. When faults occur in machines, machine vibration signals will deviate from its normal signal pattern. Such changes can be reflected in the features constructed from the machine signals. In this article, 13-dimension feature data set is constructed to represent different health conditions of machines, and unsupervised learning algorithms are introduced to deal with feature data sets for feature extraction and fault classification. A weighted local and global regressive mapping (WLGRM) algorithm is proposed for machine fault classification. Two synthetic fault data sets and two experimental data sets are employed to validate the effectiveness of the proposed approach. Comparative analysis with other unsupervised learning algorithms, such as local and global regressive mapping, locality preserving projection, Isomap, principal component analysis, and Sammon mapping, are reported. The results show that different machine faults can be classified, the degree of fault severity can be captured, and WLGRM can achieve better performance than other algorithms in most cases of machine fault classification.

1. Introduction

Machine faults are behaviors in machines that do not correspond to well-defined notion of its normal behaviors. Generally, it is easier and less costly to obtain behavior data from a machine that is functioning normally than from a machine that is known to be faulty. Machine fault data are scarce because they usually have to be collected from seeded fault experiments, data log of anomaly behaviors, simulations and theoretical calculations, etc. Indeed, getting a labeled set of machine fault data is difficult. Based on the types and availability of labeled data, techniques for machine fault classification can be categorized into supervised and unsupervised approaches (Chandola et al., 2009). When the priori information of machine normal behaviors and fault conditions is available, a supervised method can be used to distinguish the normal and abnormal classes; when no prior information is available, an unsupervised method is effective for detecting the anomalies. The unsupervised techniques take the priority when there is little or even no known information about the anomaly, which happens often in reality.

When faults occur in machines, faults will cause the machinery signals to deviate from the normal ones. Sensor-based technologies are successfully used to indicate the health conditions of machines. Vibration signals are widely used to diagnose the faults in bearings, induction motors, gearboxes, etc. (Yan and Gao, 2009; Jin et al., 2012; Chow and Hai, 2004; Miao et al., 2011). Wang (2007) developed a model to predict the wear in aircraft engine using oil-based information. Acoustic noise (sound pressure level) was a good precursor to indicate new and degraded fans (Oh et al., 2012). Acoustic emission signals were used to detect gear fault and predict the tool wear condition (Li and He, 2012; Zhou et al., 2011). Motor current signals were used to diagnosis of faults in induction motors (Casimir et al., 2006; Lebaroud and Clerc, 2009; Hu et al., 2011; Riera-Guasp et al., 2012; Weber et al., 2012). Among these afore-mentioned methods, the vibration signal analysis is the most reliable, effective, powerful, popular method for machine fault diagnosis.

Generally, many approaches based on vibration signals can be taken for machine fault diagnosis, such as time domain analysis (Jin et al., 2012; Martin and Honarvar, 1995; Heng and Nor, 1998), frequency domain analysis (Miao et al., 2011; Courrech, 2000) or time–frequency domain analysis (Goumas et al., 2001; Yan and

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Gao, 2009; Chow and Hai, 2004; He et al., 2009). Pattern recognition technique, neural networks, and neuro-fuzzy approach using features constructed from machine signals are also being developed for machine fault diagnosis (Tse et al., 1996; Jin and Chow, 2013; Li et al., 2000; Wang et al., 2013; Wu and Chow, 2004; Zio and Gola, 2009; Zio and Popescu, 2007, Jin et al., 2014, Zhao et al., 2014). This paper transforms machine fault classification into a pattern classification way. A 13-dimensional feature data set was constructed from vibration signals to represent different health conditions of machines. Then, unsupervised learning algorithms, which project high-dimension data set into a low-dimensional data set by reserving the original data topology and characteristics, are used for fault clustering and classification.

Many unsupervised dimensionality reduction methods have been proposed for machine fault diagnosis. Typical methods include principle component analysis (PCA) and local preserving projection (LPP). Georgoulas et al. (2013) propose a PCA based fault diagnosis system, which is to detect the broken rotor bar in asynchronous machine. However, PCA is a global method; it cannot grasp the intrinsic local information in the data. Yu (2011, 2012a, 2012b) utilize LPP to extract features from vibration signals for bearing fault prognosis, which can overcome the drawback of PCA by preserving the local structure of data manifold. Recently, Yang et al. (2010) propose a novel manifold learning framework, namely, local and global regressive mapping (LGRM), which employs local regression models to grasp the manifold structure and a global regression term to learn the global projection matrix. As a result, both PCA and LPP can be the special cases in LGRM. In this work, we propose a new manifold learning method, which aims to reduce the bias reduction of LGRM as well as grasp the local geometrical structure, and apply it for machine fault classification.

The contribution of this paper can be summarized as: (1) Unsupervised learning algorithms, which are proposed in pattern recognition, are extended for machine fault classification; (2) a weighted version of LGRM algorithm, referred as WLGRM, is proposed for machine fault classification, in which the bias reduction of LGRM is reduced; (3) synthetic fault data sets and experimental data sets are employed to validate the effectiveness of the proposed scheme for machine fault classification; (4) results show that different machine faults can be classified successfully, and the degree of fault severity can also be captured.

The rest of this paper is organized as follows. In Section 2 the basic concepts of PCA, LPP, and LGRM algorithm are briefly reviewed, and the WLGRM is introduced. The approach for machine fault classification is explained in detail in Section 3. Section 4 presents the four data sets (two simulated machine data sets and two experimental data sets) that are analyzed in the article. The effectiveness of proposed scheme for machine fault classification and the performance of six unsupervised learning algorithms based on these data sets are reported in Section 5. Finally, conclusions are drawn in Section 6.

2. Theoretical background

Suppose there is a set of N D-dimensional samples $X=\{x_1,x_2,\dots,x_N\}$, and each x_i belongs to one of c classes $\{X_1,X_2,\dots,X_c\}$.

2.1. Principal component analysis and locality preserving projection

PCA, also known as Karhunen–Loeve transform, aims to find a linear transformation matrix, $W_{\mathrm{PCA}} \in \mathbb{R}^{D\times d}$, mapping the original D-dimensional space onto a reduced d-dimensional feature space with $d<<D$, for which the scatter of all projected samples is maximized (Martinez and Kak, 2001). The new mapped feature vectors $y_i \in \mathbb{R}^d$ are defined as below

$$y_i = W_{\mathrm{PCA}}^T x_i \tag{1}$$

where $i=1,2,\dots,N$, and W_{PCA} is a matrix with orthonormal columns.

If the total scatter matrix, S_T, is defined as

$$S_T=\sum_{i=1}^{N}(x_i-\mu)(x_i-\mu)^T \tag{2}$$

$$\mu=\frac{1}{N}\sum_{i=1}^{N}x_i \tag{3}$$

The scatter of the transformed feature vectors by applying the linear transformation W_{PCA}^T is $W_{\mathrm{PCA}}^T S_T W_{\mathrm{PCA}}$. The objective of PCA is to find the optimal projection matrix $\widehat{W_{\mathrm{PCA}}}$ satisfying

$$\begin{aligned}\widehat{W_{\mathrm{PCA}}} &= \mathrm{argmax}_{W_{\mathrm{PCA}}} W_{\mathrm{PCA}}^T S_T W_{\mathrm{PCA}} \\ &= [w_1 \quad w_2 \quad \cdots \quad w_d]\end{aligned} \tag{4}$$

where $\{w_i | i=1,2,\dots,d\}$ is the set of D-dimensional eigenvectors of S_T corresponding to the d largest eigenvalues. One disadvantage of the PCA is that the optimal projection matrix is maximized not only by between-class scatter matrix that is useful for classification, but also by the within-class matrix that is the unwanted information for classification purpose (Martinez and Kak, 2001).

LPP is an alternative to PCA, aims to find a linear transformation, $W_{\mathrm{LPP}} \in \mathbb{R}^{D\times d}$, that optimally preserves local neighborhood information and intrinsic geometry of the original data set (He et al., 2005). The criterion of LPP is to minimize the following objective function by finding an optimal map under certain constraints (He and Niyogi, 2003)

$$\sum_{ij}(y_i-y_j)^2 S_{ij} \tag{5}$$

The similarity matrix S with S_{ij} is introduced to define the local neighborhood information as follows:

$$S_{ij}=\begin{cases}\exp(-\|x_i-x_j\|^2/t), & \|x_i-x_j\|^2<\varepsilon \\ 0 & \text{otherwise}\end{cases} \tag{6}$$

where $t \in \mathbb{R}$, is a parameter; ε is a small positive value (Belkin and Niyogi, 2001).

Suppose a is a transformation vector, that is $y^T=a^TX$. By simple algebra formulation and imposing a constraint $y^TDy=1$ ($a^TXDX^Ta=1$), the minimization problem reduces to finding

$$\mathrm{argmin}_{a^TXDX^Ta=1}\, a^TXLX^Ta \tag{7}$$

where $L=D-S$ is the Laplacian matrix, D is a diagonal matrix whose entries are row (or column, since S is symmetric) sums of S, $D_{ii}=\sum_j S_{ij}$.

The transformation vector that minimizes Eq. (7) is given by the minimum eigenvalues solutions to the generalized eigenvalue problem

$$XLX^Ta=\lambda XDX^Ta \tag{8}$$

Let the column vectors of $a_1,a_2,\dots,a_d$ be the solutions of Eq. (8), ordered by their eigenvalues as follows, $\lambda_1<\lambda_2<\cdots<\lambda_d$. Thus, the mapping is as follows.

$$y_i=W_{LPP}^T x_i,\ W_{LPP}=[a_1 \quad a_2 \quad \cdots \quad a_d] \tag{9}$$

2.2. Local and global regressive mapping

The objective of the LGRM algorithm is to find a low-dimensional representation Y of the data X as well as the projection matrix W_{LGRM} simultaneous (Yang et al., 2010). In LGRM, a local clique $X_i=\{x_i,x_{i1},\dots,x_{ik-1}\}$ is first constructed for each data