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A New Method for Fault Diagnosis of Mine Hoist based on Manifold Learning and Genetic Algorithm Optimized Support Vector Machine

Sunwen Du
College of Mining Technology, Taiyuan University of Technology,
Yingze Street, 79#, Taiyuan 030024, Shanxi, P. R. China, e-mail: wendu_sun@163.com

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Introduction

Mine hoist is one of the most important equipments in mine industry. Known as the *mine throat*, the mine hoist has been used for the coal gangue ascension, materials transmission, and personnel and equipment lift. Hence, the normal operation of the mine hoist has great significance for ensuring the security of the mining. The safety problem has been accepted considerable attentions. However, grave accidents occurs time after time [1], leading to huge economic lost and severe casualties. Therefore, it is imperative to monitor the mine hoist conditions to detect the faults at the early stage.

The failures caused by the crucial components of the mine hoists, i.e. the drive motors and gear transmissions, account for a large proportion in general malfunctions of mine hoists. The brake failure, pulleying and sliding, overspeed of the hoist are the main faults of mine hoists. In recent years, the monitoring methods based on the vibration signal of the mine hoists have been put forward [2]. Advance signal processing methods can evaluate the situation of mine hoists through the analysis of the vibration signal generated by the crucial components of the mine hoists. A lot of effective methods have been proposed, including the wavelet transform [2] and empirical mode decomposition [3], etc. These methods have been combined with intelligent classifiers (e.g. artificial neural network (ANN)) to provide accurate fault diagnosis. However, the problem is that due to the lack of the training fault samples, the networks are prone to fall into local minimum. This disadvantage restricted the applications of the ANNs. However, owning to the strong generalization ability, the support vector machine (SVM) can work well even when the training data is very small [4]. Hence, the SVM may overcome the shortcomings of the neural networks.

On the other hand, the data fusion of multiply sensors is essential for reliable fault feature extraction. The vibration signals are often submerged in a large amount of redundant data. As a result, the extracted feature vector contains some useless features, which may influence the fault detection. Hence, it needs to eliminate these useless ones. The problem is that it is difficult to select the distinguished features from a set of data. The principal component analysis (PCA) has been proven to be effective for the feature selection [2]. However, the nonlinear properties of the original feature space decline PCA's ability [5]. Fortunately, the manifold learning algorithms can deal with the nonlinear dimensionality reduction. The representative algorithms include locally linear embedding (LLE), Isomap, and Laplacian eigenmap [5]. Compared with the PCA, the manifold learning projects the original high-dimensional data into a lower dimensional space and keeps the nonlinear characteristics of the original data. Thus, the applications of the manifold learning have got many attentions in the field of mechanical fault diagnosis. Jiang [6] proposed the supervised Laplacian eigenmap (S-LapEig) for feature extraction of rotational machinery. Wang [7] adopted the supervised kernel locality preserving projection to extract distinct features in the DC motor system. Li [5] proposed the adaptive LLE for the fault diagnosis of rotor systems. The manifold learning was effective for fault feature selection in these studies. Hence, it is worth investigating the manifold learning for feature selection in the fault diagnosis of mine hoists.

This paper aims to deal with the fault diagnosis of mine hoists. In order to enhance the fault detection rate, a new approach is presented based on the integration of LLE and SVM. The features of the vibration signals of the mine hoist were firstly extracted by the wavelet packet analysis [8]. Then the LLE was used to eliminate the useless features to form a new feature space. Lastly, the least square SVM (LS-SVM) was used to learn the new feature space that matches with the hoist operation states. To speed up the training and learning, the genetic algorithm (GA) was adopted to optimize the SVM parameters. Experiments have been conducted in a mine hoist test rig to show the effectiveness of the proposed method.

Fault diagnosis method

A brief description of the proposed fault diagnosis method is presented in Fig. 1. The theories of the LLE and GA-SVM are given in this Section, and the details of the wavelet packet transform can refer to [8].

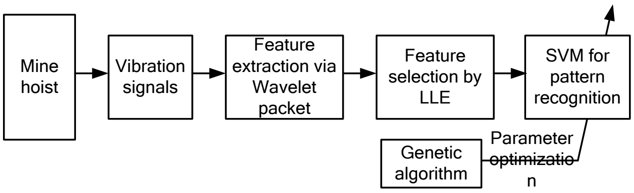

Fig. 1. The workflow of the proposed diagnosis procedure

A. The locally linear embedding (LLE). Given a high-dimensional dataset $S=[\mathbf{s}_1 \quad \mathbf{s}_2 \quad \cdots \quad \mathbf{s}_n]\in R^p$, where n is the total sample number and p the dimensionality, the objective of LLE is to reconstruct a nonlinear mapping to project S into a low dimensionality space $S_r=[\mathbf{s}_{r1} \quad \mathbf{s}_{r2} \quad \cdots \quad \mathbf{s}_{rn}]\in R^q$ (q<<p). The LLE algorithm can be described as follows [5]:

1. Compute neighbourhoods of every sample using the Euclidean distance.
2. Compute the local reconstruction weight matrix W by minimizing a cost function

$$\min \varepsilon(W)=\sum_{i=1}^{n}\left|s_i - \sum_{j=1}^{k} w_j^i s_{ij}\right|^2, \tag{1}$$

where k is the number of nearest neighbours and w_j^i is the weights ($\sum_{j=1}^{k} w_j^i=1$). If s_i and s_j are not neighbours, $w_j^i=0$.

3. Map the original dataset into the embedded coordinates. Compute the reconstructed q-dimensional manifold space S_r by minimizing the following constraint

$$\min \varepsilon(S_r)=\sum_{i=1}^{n}\sum_{j=1}^{n} m_j^i s_{ri}^T s_{rj}=\mathrm{tr}(S_r M S_r^T), \tag{2}$$

where function $\mathrm{tr}(\cdot)$ is used to calculate matrix trace, $s_{ri,\,j}$ are the projection vector of $s_{i,\,j}$ in the embedded coordinates and the cost matrix M is

$$M=(I_{n\times n}-W)^T(I_{n\times n}-W). \tag{3}$$

Hence, the minimization of (2) can be reduced to an eigenvalue problem, and S_r could be determined by the q smallest nonzero eigenvectors of M.

B. GA optimized SVM. The SVM algorithm is briefly described, a more detailed description of SVM can refer to Ref. [4]. For a given sample set $T=\{x_l, y_l\}_{l=1}^{n}$ (n is the sample number), the SVM model can be described as [9]

$$\sum_{l=1}^{n}\boldsymbol{\omega}\mathbf{x}_l+b=0, \tag{4}$$

where, $\boldsymbol{\omega}$ denotes the weight matrix, and b is the threshold. Eq. (4) satisfies the following constrains:

$$\min\{\frac{1}{2}\left\|\boldsymbol{\omega}\right\|^2+C\sum_{l=1}^{n}\xi_l\}, \tag{5}$$

$$\text{s.t.}\begin{cases} y_l(\boldsymbol{\omega}\mathbf{x}_l+b)\ge 1-\xi_l, \\ \xi_l\ge 0, \end{cases} \tag{6}$$

where ξ_l (l=1, 2, …, n) are the relaxation factors, and C a penalty constant.

The classification decision function of the LS-SVM can be expressed as [9]

$$y(x)=\mathrm{sgn}(\sum_{i,\,j=1}^{n}\alpha_i\varphi^T(x_i)\varphi(x_j)+b), \tag{7}$$

where x_i and x_j are the SVM inputs, y is the output, α_i is the Lagrange multiplier, and $\varphi(\cdot)$ is the nonlinear transform.

The Kernel trick is used to simplify the inner product, i.e. define the Kernel $K(x_i, x_j)=\varphi^T(x_i)\varphi(x_j)$. Popular kernel is [9]

$$K(x_i, x_j)=\exp(-\left\|x_i-x_j\right\|/2\sigma^2), \tag{8}$$

where σ is the kernel coefficient. The kernel parameter σ and the SVM decision boundary C have great influence on the classification performance of the SVM. So the GA was used to optimize the two parameters. The energy entropy based individual selection procedure [10] was employed in the GA searching processing in this work.

The following fitness function was used

$$F=\frac{1}{e(o)}, \quad \text{and } e(o)=\frac{1}{2}\sum_{m}(R_m-G_m)^2, \tag{9}$$

where o (o = 1,…,N) is the chromosome number, m is the training samples, G_{m} is desired SVM output, and R_{m} is the real SVM output.

Experiments

The vibration signals of man-seeded faults were collected on a mine hoist fault test rig. Fig. 2 shows the experimental test rig. The test rig is driven by two motors. The gear transmission system is used to propel the friction wheel. The tooth numbers of the gears are: Z1=Z3=24, and Z2=145. The motor shaft misalignment, the gear tooth broken and their coupled fault were investigated in the experiments. The faults were seeded in driver 1 and gear Z2. Two accelerators mounted on the flat surface of the driver 1 and gear Z2 were used to measure the vibration signals. The motor speed was 600 rpm. Hence the foundation frequencies of the motor shaft and the gear Z2 were 10.0 Hz (1X) and 1.65 Hz (1R), respectively.

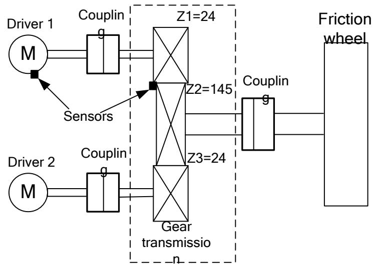

Fig. 2. The experimental test rig of the mine hoist

The time and frequency spectra of the hoist vibration under normal and faulty conditions are shown in Figs. 3-6. For the motor shaft, energy peaks may appear at low frequency band around 1X under normal state while at higher frequency band when a misalignment occurs. These characteristics can be observed in Figs. 3 and 4. In Fig. 5, the harmonics of the foundation frequency 1R appear when the gear tooth broken down. The impact of the gear meshing can be observed obviously.

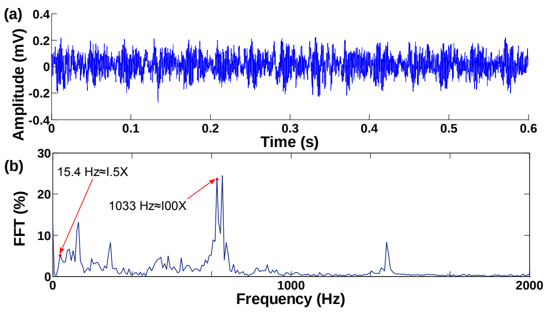

Fig. 3. Under the normal state

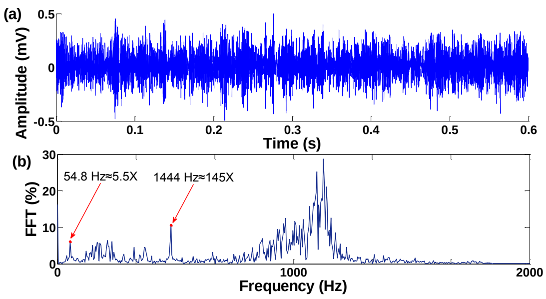

Fig. 4. Under the motor shaft misalignment

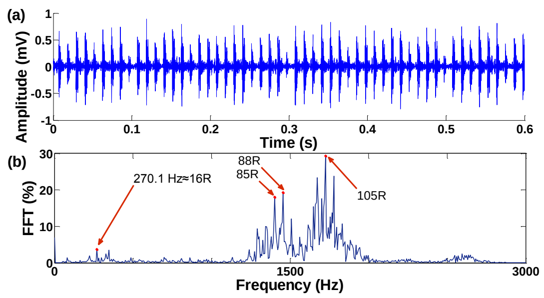

Fig. 5. Under the gear tooth broken

In Fig. 6, when the misalignment and gear tooth broken were coupled, the impact energy of the gear meshing becomes stronger than the single gear tooth broken, and energy peaks appear at the coupled frequency of 1X and 1R (e.g. 7(X+R) in the figure). Hence, the spectra reflect the characteristics of the hoist vibration under different operation conditions. However, it is not applicable diagnose the faults using the time-frequency plots directly. Thus, the proposed method in this paper was used to identify the hoist faults.

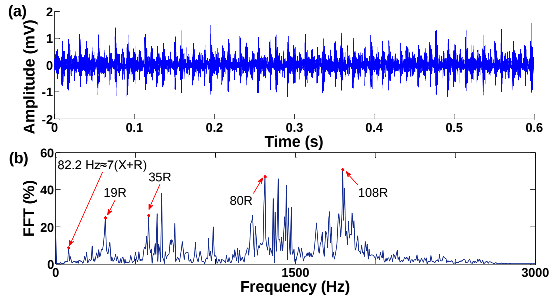

Fig. 6. Under the coupled fault

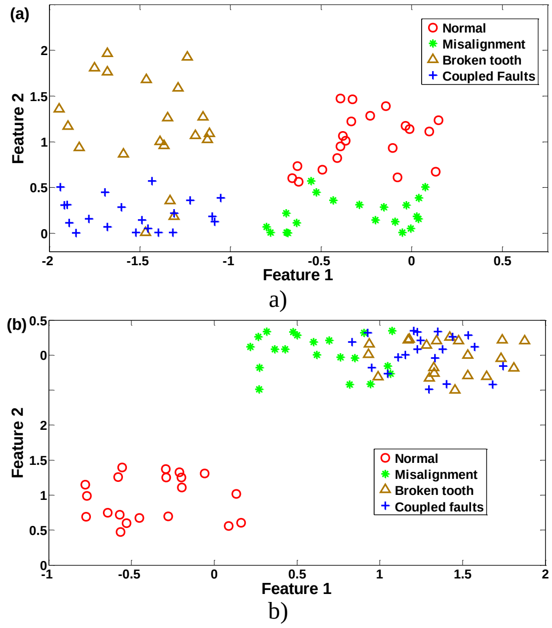

Fig. 7. The feature selection results: (a) by LLE, and (b) by PCA

In the fault diagnosis procedure, the vibration signals were firstly decomposed by the Daubechies 16 (db16) wavelet function to 3 levels. The Root-Mean-Square (RMS), kurtosis and peak fact values of the 3rd wavelet band were extracted as the feature vector. Hence, the feature vector contained 24 elements, i.e. 8 RMS values, 8 kurtosis values and 8 peak fact values. Then the LLE was employed to fuse the original feature space from 24 dimensions into 2 dimensions. 20 samples of each condition were analyzed and there were 80 samples in total. Fig. 7 gives the feature selection performance. The PCA method was compared here. It can be seen that the selected features using the LLE can be categorized into four groups, though there are some overlaps between the normal and misalignment states, and the gear tooth broken and coupled faults conditions. In contrast, the PCA cannot distinguish the three faulty states of the hoist in Fig. 7(b). Thus, the LLE outcomes the PCA in the selection of intrinsic features.

Since there are overlaps in the new features space, the GA-SVM was further adopted to enhance the fault pattern identification. Fig. 8 compares the optimization performance using standard GA and the improved GA. Another 80 new samples were used to validate the diagnosis method. Table 1 gives the fault diagnosis results.

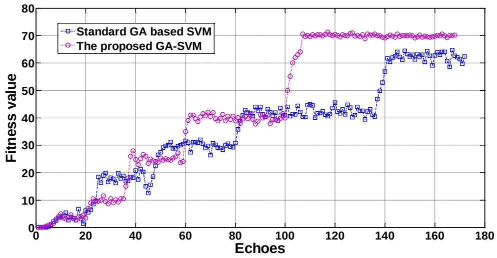

Fig. 8. The evolution performance for RBF optimization

Table 1. Fault diagnosis results of the mine hoist

Methods	Detection results
PCA and standard GA-SVM	87. 5%
PCA and improved GA-SVM	88.75%
LLE and standard GA-SVM	90.0%
The proposed method	92.5%

From Table 1, the LLE based methods are superior to the PCA based methods. This is because the nonlinear properties have been preserved by the LLE. Moreover, the improved GA can increase the fault identification rate. And the proposed method provides the best performance to the other three methods.

Conclusions

To detect the early failures of the mine hoist, a new fault diagnosis method is proposed in this paper. The contribution of the work is that the proposed method has adopted the manifold learning to extract the nonlinear properties embedded in the original data and employed the improved GA-SVM to recognize the fault patterns. Both single and coupled faults have been investigated in the experimental test. The analysis results demonstrate that the proposed method is feasible for the fault diagnosis of mine hoists. The fault detection of the proposed rate has been enhanced by 2.5% or better when compared with the PCA based feature selection methods. Hence, the proposed method has practice importance.

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Sunwen Du. A New Method for Fault Diagnosis of Mine Hoist based on Manifold Learning and Genetic Algorithm Optimized Support Vector Machine // Electronics and Electrical Engineering. – Kaunas: Technologija, 2012. – No. 7(123). – P. 99–102.

This paper reports a new development based on the manifold learning and intelligent classifier for the nonlinear feature extraction and fault pattern recognition of mine hoists. The wavelet packet was firstly used to extract the statistic characteristics of the hoist vibrations to obtain the original feature space. Then the locally linear embedding (LLE) was employed to learn the underlying nonlinear manifold in the original feature space to select distinct features. Following, the support vector machine (SVM) was applied to the fault pattern recognition. The energy-entropy based genetic algorithm was used to optimize the SVM parameters. The experimental vibration data measured on a mine hoist test rig was used to evaluate the proposed method. The diagnosis results show that the proposed method is efficient for the mine hoist and can increase the detection rate by 2.5% or better when compared with existing diagnosis approaches. Ill. 8, bibl. 10, tabl. 1 (in English; abstracts in English and Lithuanian).

Sunwen Du. Naujas šachtos keltuvo gedimų diagnostikos metodas, pagrįstas daugialypiu mokymusi ir optimizuotu atraminių vektorių mašinos genetiniu algoritmu // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2012. – Nr. 7(123). – P. 99–102.

Pateikiamas naujas metodas šachtos keltuvų gedimui aptikti, pagrįstas daugialypiu mokymusi ir intelektualiu klasifikatoriumi. Bangelių paketas pirmą kartą buvo panaudotas statistinėms keltuvo vibracijų charakteristikoms išskirti, siekiant gauti originalią ypatybių erdvę. Atraminių vektorių mašina (AVM) buvo pritaikyta gedimų struktūrai atpažinti. Energijos entropija pagrįstas genetinis algoritmas buvo panaudotas AVM parametrams optimizuoti. Siūlomas metodas buvo įvertintas naudojant eksperimentinius šachtos keltuvo duomenis. Diagnostikos rezultatai parodė, kad šis metodas yra efektyvus ir padidina detektavimo lygį 2,5% palyginti su esamais diagnostikos metodais. Il. 8, bibl. 10, lent. 1 (anglų kalba; santraukos anglų ir lietuvių k.).