889. Using combination of lifting wavelet and multiclass SVM based on global optimization class strategy for fault pattern identification

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Abstract. This paper presents a new method based on lifting wavelet for obtaining a fast multiclass SVM classification based on global optimization class strategy for fault diagnosis of roller bearing. Decision making was performed in two stages: feature extraction by computing the lifting wavelet coefficients and classification using the multiclass SVM classifiers trained on the extracted features. Experiments demonstrate that in comparison to discrete wavelet transform the lifting wavelet feature extraction can speed up the identification phase as well as achieve higher accuracy of multiclass SVM that is based on global optimization class strategy. Experimental results also reveal that the proposed multiclass SVM of global optimization is better than strategy of one against one and DAGSVM.

Keywords: roller bearing, fault diagnosis, lifting wavelet, multiclass SVM, global optimization class strategy.

1. Introduction

The present study attempted to develop a novel computational approach for fault pattern identification of roller bearing that may be useful for machinery fault diagnosis [1]. Conventionally, machinery diagnosis is highly dependent on subjective interpretations. These methods have many limitations and are highly prone to diagnostic errors for roller bearing. Computer-based analysis and classification of machinery fault can be very helpful in diagnostics. In this paper, we propose a new method using combination of lifting wavelet and multiclass SVM based on global optimization class strategy for fast and accurate diagnosing of machinery faults.

Roller bearings [2-3] are important and frequently encountered components in the rotating machines that find widespread industrial applications. The process of roller bearing fault diagnosis includes the acquisition of information, extracting feature and recognizing conditions. Vibration measurement of the roller bearing can be carried out using some acceleration sensors that are placed on the bearing house [4]. In accordance with the practical application, the lifting wavelet is presented and applied in a roller bearing system. It is demonstrated that this lifting wavelet can be effectively used in extracting features of vibration signal [5].

Different bearing conditions have been found to be very efficient in solving machinery fault diagnosis problems. High generalization ability of SVMs is ensured by special properties of the optimal hyperplane that maximizes the distance between the closest training samples of each class and the separating hyperplane [6]. In order to discriminate machinery fault signals, multiclass support vector machine [7-10] combined with lifting wavelet preprocessing was implemented (Fig. 1). The multiclass SVM for machinery fault diagnosing of roller bearing exhibited great performance since it maps the features to a higher dimensional space.

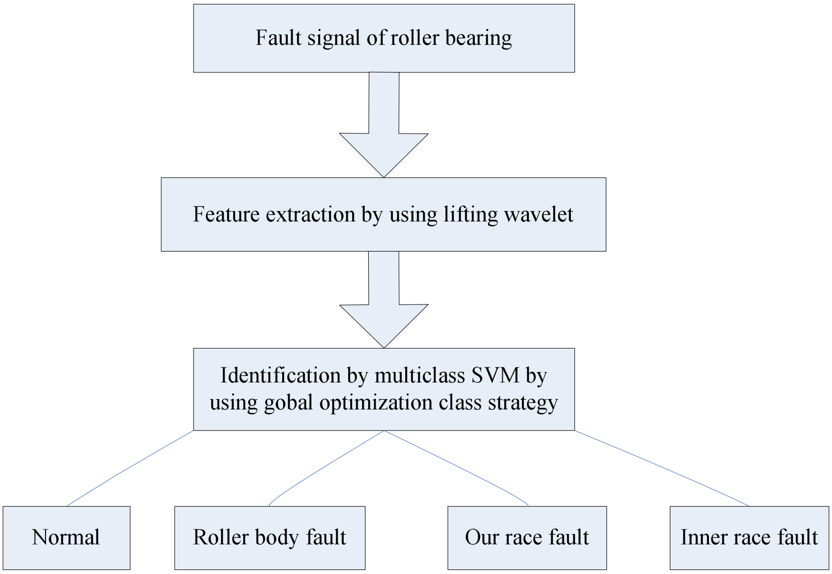

Fig. 1. Feature extraction method and identification method for machinery fault diagnosis

The wavelet transform (WT) [11-13] can be applied to extract the wavelet coefficients of discrete time signals. This procedure makes use of multirate signal processing techniques. The multiresolution feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The WT provides very general techniques which can be applied to many tasks in signal processing [14]. Machinery fault signal, consisting of many data points, can be compressed into a few parameters which characterize the behavior of the machinery fault signal. This feature of using a smaller number of parameters to represent the machinery fault signal is particularly important for identification and diagnostic purposes.

Four types of vibration signals of roller bearing (normal, rolling body fault, out-race fault and inner-race fault) were analyzed. Machinery fault signals were decomposed into time-frequency representations using lifting wavelet and wavelet coefficients were calculated to represent the signals. The aim of the study is the classification of machinery fault by the combination of wavelet coefficients and multiclass SVM. The purpose is to determine an optimum classification scheme for machinery fault diagnosis problem and also to infer clues about the extracted features. The present research demonstrated that the wavelet coefficients are the features, which well represent the machinery fault signals and the multiclass SVM trained on these features achieved high classification accuracies.

This paper is organized as follows: next section introduces the feature extraction method of lifting wavelet. Section 3 presents the multiclass SVM based on global optimization class. Classification experiments are performed in Section 4. Section 5 provides the main conclusions from this work.

2. Feature extraction by lifting wavelet

Because of the time-frequency localization feature and fast waveform convergence [5], the wavelet transform is an effective method for vibration signal feature detection. The recent method for detecting machinery vibration signal is based on the lifting wavelet.

Wavelet transform based on lifting algorithm is called the second generation wavelet transform. Lifting scheme classify the first generation wavelet transform as the following three phase: split, predict and update.

(1) Split. The input signal s_i was divided into two small subset s_{i-1} and d_{i-1}. d_{i-1} is also called wavelet subset. The most simple method is classify the input signal s_i into two group according to their parity. Wavelets given from this method are named as "lazy wavelet". Decomposition process can be expressed as $F(s_i) = (s_{i-1}, d_{i-1})$. And $F(s_i)$ is the process of decomposition.

(2) Predict. According to relation of the original data, predicting value $P(s_{i-1})$ of even sequence s_{i-1} is used to predict the odd sequence d_{i-1}. In practice, we can not predict subset d_{i-1} from subset d_{i-1} accurately. $P(s_{i-1})$ can give an approximate compatible solution to d_{i-1}. The new value d_{i-1} can be obtained from the following equation $d_{i-1} = d_{i-1} - P(s_{i-1})$. Original signal is defined as the smaller subset s_{i-1} and wavelet subset d_{i-1}. Repeating the process of decomposition and predicting, after *n* steps, original signal is given as below $\{s_n, d_n, \ldots, s_1, d_1\}$.

(3) Update. For containing the global feature of the original in the subset s_{i-1}, we can use the wavelet subset d_{i-1} which is already calculated to update s_{i-1}. It is necessary to construct a operator U to update s_{i-1}. The equation is given as:

$$s_{i-1} = s_{i-1} + U(d_{i-1}) \tag{1}$$

3. Multiclass SVM based on global optimization class strategy

Input patterns [15-16] have been studied extensively for machinery fault diagnosis. SVM maps the machinery fault signal into a higher dimensional feature space through some nonlinear mapping chosen a priori. A linear decision surface for fault diagnosis is then constructed in this high-dimensional-feature space. Thus, SVM is a linear classifier in the parameter space, but it becomes a nonlinear classifier as a result of the nonlinear mapping of the space of the input machinery fault signal into the high-dimensional feature space. SVM training became a quadratic-optimization problem. The construction of a hyperplane is performed so that the margin between the hyperplane and the nearest point is maximized and can be posed as the quadratic-optimization problem [17]. SVM can provide high-generalization ability for machinery fault diagnosis. The SVM is a binary classifier, which can be extended into a multiclass classifier. In this paper, we use multiclass SVM [18-19] based on global optimization class for fault signal diagnosis.

Comparing with the method of combination of binary classifier, the method of global optimization class tries to construct a discriminant function to classify the unknown data once.

The main idea of this algorithm is similar to the one against all algorithm: construct *k* two-level schematizations. The m^{th} function $\omega_m^T \varphi(x) + b$ classifies the data samples of m^{th} level from other data samples. Hence, we need *k* discriminant functions.

The multiclass problem is solved by the solution of optimization problem as follows:

$$\min_{\omega_m \xi_i} \frac{1}{2} \sum_{m=1}^{k} \omega_m^T \omega_m + C \sum \xi_i \omega_{y_i}^T \varphi(x_i) \;-\; \omega_m^T \varphi(x_i) \geq e_i^m \;-\; \xi_i,\; i = 1,\ \ldots,\ l \tag{2}$$

$$e_i^m \equiv 1 - \delta_{y_i, m} \tag{3}$$

$$\delta_{y_i,m} \equiv \begin{cases} 1, & y_i = m \\ 0, & y_i \neq m \end{cases} \tag{4}$$

The discriminant function is defined as:

$$\underset{m=1,\ldots,k}{\arg\max}\left(\omega_m^T \phi(x)\right) \tag{5}$$

Only l variables is used to substitute ξ_i^m for interval of two classes. The maximum k variables ξ_i are:

$$\xi_i = \left(\max_m \left(\omega_m^t \phi(x_i) + e_i^m\right) - \omega_{y_i}^T \phi(x_i)\right)_+ \tag{6}$$

where $(\bullet)_+ \equiv \max(\bullet, 0)$.

The quadratic programming problem is described as follows:

$$\xi_i = \left(\max_m \left(\omega_m^t \phi(x_i) + e_i^m\right) - \omega_{y_i}^T \phi(x_i)\right)_+ \tag{7}$$

$$\min f(\alpha) = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} k_{ij}\alpha_i^T \alpha_j + \sum_{m=1}^{l}\alpha_i^T e_i \sum_{m=1}^{k}\alpha_i^m = 0,\ i = 1,\ldots,l \tag{8}$$

$$\begin{cases} \alpha_i^m \le 0 & y_i \neq m \\ \alpha_i^m \le C & y_i = m \ (i = 1,\ldots,l; m = 1,\ldots,k) \end{cases} \tag{9}$$

where $k_{ij} = \varphi(x_i)^T \varphi(x_j)$.

The discriminant function is expressed as below:

$$\underset{m=1,\ldots,k}{\operatorname{argmax}} \sum_{i=1}^{l} \alpha_i^m k(x_i, x) \tag{10}$$

4. Experimental results

4. 1. Data selection

Rolling bearing is mounted on the motor driven experiment system. Accelerating sensors are mounted on the motor driven end to obtain the bearing vibration signal. The sampling frequency is 10000 Hz. The schematic diagram of experimental signal acquisition apparatus is shown in Fig. 2.

There are four types of vibration signals that are characteristic to roller bearings: normal (T1), rolling body fault (T2), out-race fault (T3) and inner-race fault (T4). In our research, 3503 samples were used in the experiment, 1644 for training and 1859 for testing. The composition of training data set and testing data set is presented in Table 1. We used Matlab 7.0 for our experiments.

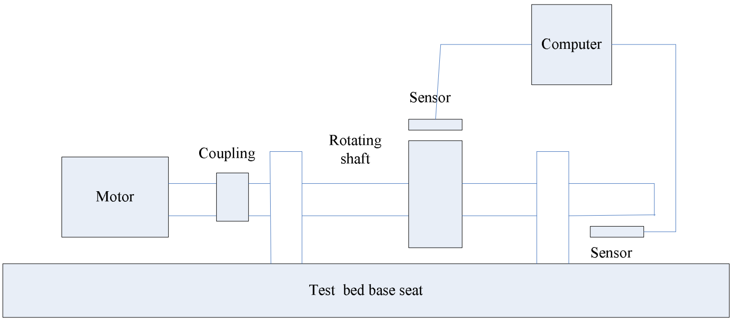

Fig. 2. Schematic diagram of experimental signal acquisition apparatus

Table 1. The composition of training data set and testing data set

	Normal (T1)	Rolling body fault (T2)	Out-race fault (T3)	Inner-race fault (T4)
Training data set	433	387	405	419
Testing data set	486	402	417	554

4. 2. Feature extraction method comparison between lifting wavelet and discrete wavelet transform

From the experimental testing result as shown in Table 2 and 3, it is illustrated that the feature extraction performance of lifting wavelet is better than in the case of discrete wavelet transform. The testing time of lifting wavelet is faster than discrete wavelet transform. As Table 2 and 3 indicates, fault pattern identification rate of lifting wavelet is 91.50 %, whereas, that of discrete wavelet transform is 90.05 %. Applying the feature extraction of lifting wavelet, 443 of actual T1 samples were identified as T1, the identification rate of 91.15 %. Three hundred and fifty eight of actual T2 samples were recognized as T2, the identification rate is 89.05 %. The identification rate of T3 samples is 91.85 %. Five hundred and seventeen of actual T4 samples were correctly classified with the identification rate of 93.32 %. It is therefore demonstrated that the lifting wavelet could be effectively applied in the vibration feature extraction for a roller bearing system.

Table 2. Confusion matrix of lifting wavelet feature extraction method combined with multiclass SVM based on global optimization class strategy

	T1	T2	T3	T4	Identification rate (%)
T1	443	4	17	22	91.15
T2	21	358	9	14	89.05
T3	19	0	383	15	91.85
T4	16	18	3	517	93.32
Testing time (s)	5.2				

Table 3. The confusion matrix of discrete wavelet transform feature extraction method combined with multiclass SVM based on global optimization class strategy

	T1	T2	T3	T4	Identification rate (%)
T1	435	8	14	29	89.50
T2	23	352	11	16	87.56
T3	26	3	375	13	89.92
T4	19	21	2	512	92.42
Testing time (s)	6.7				

As Table 2 and 3 indicates, the testing time of lifting wavelet and discrete wavelet transform are 5.2 s and 6.7 s, respectively. The discrete wavelet transform approach is not practical to application for machinery fault diagnosing of roller bearing since it leads to time-consuming testing. It is demonstrated that lifting wavelet feature extraction may be more suitable for practical use after comparing the identification speed with discrete wavelet transform.

4. 3. Performance comparison of multiclass SVM strategy with three methods

As Table 4 indicates, total identification rates of multiclass SVM strategy among one against one, DAGSVM and global optimization class are 90.53 %, 90.96 % and 91.50 %, respectively. Experimental results indicate that the multiclass SVM of global optimization class has higher identification rate than the strategy of one against one and DAGSVM. The performance of the strategy among one against one and DAGSVM was not as high as the global optimization class strategy. The results of the present paper demonstrated that using combination of lifting wavelet and multiclass SVM based on global optimization class strategy can be used in the classification of the machinery fault signals.

Table 4. Identification rate comparison of multiclass SVM strategy among one against one, DAGSVM and global optimization class

	One against one	DAGSVM	Global optimization class
T1 (%)	90.53	90.74	91.15
T2 (%)	88.81	88.31	89.05
T3 (%)	89.69	90.89	91.85
T4 (%)	92.42	93.14	93.32
Total identification rate (%)	90.53	90.96	91.50

5. Conclusion

In this paper, we proposed a lifting wavelet method to speed-up the SVM for machinery fault diagnosis problems. Each studied segment of the machinery fault signals under study was decomposed into multi-level low- and high-pass sub-bands by lifting wavelets, which were then input into the Multiclass SVM based on global optimization class for training and testing purposes. It was determined that the adopted approach may be faster than discrete wavelet transform in terms of test time, while the fault pattern identification rate is higher. We also compare with three types of multiclass SVM models. Experimental results indicate that higher accuracies were achieved by using the multiclass SVM trained on the wavelet coefficients by using strategy of global optimization class than that of one against one and DAGSVM.

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