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Intelligent Bearing Diagnostics Using Wavelet Support Vector Machine

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Abstract. This paper deals with implementation of intelligent system for fault diagnostics of rolling element bearing. In this work, the proposed intelligent system was basically created using support vector machine (SVM) due to its excellent performance in classification task. Moreover, SVM was modified by introducing wavelet function as kernel for mapping input data into feature space. Input data were vibration signals acquired from bearings through standard data acquisition process. Statistical features were then calculated from bearing signals, and extraction of salient features was conducted using component analysis. Results of fault diagnostics are shown by observing classification of bearing conditions which gives plausible accuracy in testing of the proposed system.

Introduction

Condition monitoring of rolling element bearings for early detection and diagnostics of faults to prevent catastrophic failure is important in industry. As main component in rotating machine, rolling element bearing needs good attention from maintenance operator to guarantee their reliability when the machines operate. Industry may loss their profit if they deny the procedure of bearing condition monitoring dan fault diagnostics.

Condition monitoring and faults diagnostics are multi-disciplinary and integrated technology. It consists of the knowledge of intelligent system and the other parts such as analysis of vibration signal, current, temperature or even all of acquired signal from data acquisition. So it depends on how and which parts the intelligent knowledge will be dealt with. Developing intelligent system, combining modern signal analysis and soft computing theory, data mining, realizing the real-time, online dynamic monitoring, is a developmental direction to reach relatively best performance in condition monitoring and faults detection of machine.

Recently, many advanced technology and intelligent methods have been developed such as the use of support vector machine (SVM) combining with wavelet transform [1], neural network [2], and genetic algorithm [3] to perform faults detection. However, the research in this area is still open issue. The use of SVM [4] as intelligent classifier tool becomes popular due to its good performance. Compared with artificial neural network (ANN), SVM do not have some problem such as local minimization, the number selection of nodes in hidden layer and the dimension disaster. SVM which is based on statistical learning theory (SLT) is widely gaining application in the area of machine learning, data classification and pattern recognition because of the high accuracy and good generalization capability [5].

In this paper, a relatively new kernel trick using wavelet function is proposed. In this method, wavelet function is performed as kernel function and then inducing in SVM theory. The researchers who contribute the theoretical development of wavelet kernel are reported in references: reproducing wavelet kernel [6], construction of support wavelet network [7], application wavelet support vector to regression [8, 9], least square wavelet support vector [10]. However, the application is still rare in faults detection and classification of rolling element bearing. So it becomes a chance to built and establish an intelligent faults detection and classification of rolling element bearing using wavelet support vector machine called W-SVM.

In addition, this paper also introduced the use of component analysis using independent component analysis, principal component analysis and their kernel for feature reduction and extraction. This method is performed to overcome the huge of dimensionality phenomenon that tends to decrease the performance of classifier. Finally, a new intelligent faults detection and classification method called W-SVM was established. This method is used to rolling element bearing for faults detection based on vibration signal. The results show that this method can well classify and separate each condition of faults in rolling element bearing based on experimental work.

Wavelet Support Vector Machine (W-SVM)

SVM is a kind of machine learning based on statistical learning theory. The basic idea of applying SVM to pattern classification can be stated as follows: first, map the inputs vectors into one features space, possible in higher space, either linearly or nonlinearly, which is relevant with the kernel function. Then, within the feature space from the first step, seek an optimized linear division, that is, construct a hyperplane which separates two classes. It can be extended to multi-class. SVMs training always seek a global optimized solution and avoid over-fitting, so it has ability to deal with a large number of feature. A complete description about SVMs is available in Vapnik [4].

In the linear separable case, there exists a separating hyperplane whose function is

$$\mathbf{w}\cdot\mathbf{x} + b = 0, \tag{1}$$

which implies

$$y_i(\mathbf{w}\cdot\mathbf{x} + b = 0) \geq 1, \quad i = 1, \ldots, N. \tag{2}$$

By minimizing $\|\mathbf{w}\|$ subject to this constrain, the SVM approach tries to find a unique separating hyperplane. Here $\|\mathbf{w}\|$ is the Euclidean norm of $\mathbf{w}$, and the distance between the hyperplane and the nearest data points of each class is $2/\|\mathbf{w}\|$. By introducing Lagrange multipliers α_i, the SVMs training procedure amounts to solving a convex quadratic problem (QP). The solution is a unique globally optimized result, which has the following properties

$$w = \textstyle\sum_i^N \alpha_i y_i x_i \,. \tag{3}$$

Only if corresponding $\alpha_i > 0$, these $\mathbf{x}_i$ are called support vectors.

When SVM are trained, the decision function can be written as

$$f(x) = sign(\textstyle\sum_{i=1}^N \alpha_i y_i (x.x_i) + b). \tag{4}$$

For a linear non-separable case, SVMs perform a nonlinear mapping of the input vector $\mathbf{x}$ from the input space into a higher dimensional Hilbert space, where the mapping is determined by kernel function. Typical kernel functions are linear, polynomial and Gaussian RBF kernels. According to the different classification problems, the different kernel function can be selected to obtain the optimal classification results [4]. The decision function in Eq. (4) contains dot product and can be replace using kernel function $K(\mathbf{x}, \mathbf{x}') = K(\langle \mathbf{x}\cdot\mathbf{x}' \rangle)$. In the SVM theory, any function can serve a kernel function if satisfy the Mercer's condition [5].

Suppose $K \in L(R^N \times R^N)$, such that integral operator $T_K : L_2(R^N) \to L_2(R^N)$

$$(T_K)f(\cdot) = \textstyle\int_{R^x} K(\cdot, x) f(x)\, dx. \tag{5}$$

is positive. Let $\phi_i \in L_2(R^N)$ be the eigenfunction of T_k associated with the eigenvalue $\lambda_i \geq 0$ and normalized in such way $\| \phi_i \|_{L_2} = 1$, then kernel function $K(\mathbf{x}, \mathbf{x}')$ can be expanded as

$$K(x, x') = \textstyle\sum_{i=1}^{\infty} \lambda_i \emptyset_i(x) \emptyset_i(x'). \tag{6}$$

And must satisfy the positivity condition

$$\textstyle\iint_{L_2 \otimes L_2} K(x, x') f(x) f(x') dx\, dx' \geq 0, \forall f \in L_2(R^N). \tag{7}$$

In the case of building a new kernel using wavelet, it is helpful to refer the frame theory [11] which is an extension of the normalized orthogonal basis. In frame theory, one can reconstruct perfectly a function f in a Hilbert space H from its inner product $\langle\ ,\ \rangle$ with a family vectors $\{\psi_k\}$ if satisfy the condition which exists two constant $0 < A \leq B < \infty$ such that

$$A\|f\|^2 \leq \sum_k |\langle f, \bar{\Psi}_k \rangle|^2 \leq B\|f\|^2. \tag{8}$$

with $\langle\ ,\ \rangle$ and $\|\ \|$ denoting the standard inner product and norm, respectively. Any function in Hibert space can be decomposed as follows

$$f = \sum_k \langle f, \bar{\Psi}_k \rangle \Psi_k = \sum_k \langle f, \Psi_k \rangle \bar{\Psi}_k. \tag{9}$$

where $\bar{\psi}_k$ is the dual frame of ψ_k. In $L_2(R^N)$, if $f = \{\psi_i\}$ is a frame and $\{\lambda_i\}$ is a positive increasing sequence, a function $K(\mathbf{x}, \mathbf{x}')$ can be given by

$$K(x, x') = \sum_{i=1}^{\infty} \lambda_i \Psi_i(x) \Psi_i(x'). \tag{10}$$

Eq. (10) is similar to Eq. (6) in satisfying the condition for kernel function. A mother wavelet $\psi_{a,b}(x)$ is called a frame wavelet if $\psi \in L_2(R^N)$, $a > 1$, $b > 0$ and the family function $\{\psi_{mn}\} = \{D_{am}\, T_{nb}\, \psi\}$ where D and T are unitary dilatation operator and unitary translation operator, respectively, while a is scale parameter and b is translation parameter. A wavelet kernel function can be constructed by any mother wavelet which can generate frame wavelet. When a frame is used to construct a kernel function, the Mercer's condition in Eq. (7) must be satisfied. In addition, beside the inner product, there exists a kernel called translation–invariant kernel such that $K(\mathbf{x}, \mathbf{x}') = K(\langle \mathbf{x} - \mathbf{x}' \rangle)$.

If translation–invariant kernel is admissible in SVM kernel function, so the necessary and sufficient condition of Mercer's theorem must be satisfied. Thus, the Fourier transform is written as

$$F[K](\omega) = (2\pi)^{-N/2} \int_{R^N} exp\big(-j(\omega \cdot x)\big) K(x)\, dx. \tag{11}$$

is non-negative. Based on the mother wavelet, the wavelet kernel which satisfies the translation-invariant theorem can be given as

$$K(x, x') = K(x - x') = \prod_{i=1}^{N} \Psi\left(\frac{x_i - x'_i}{a_i}\right). \tag{12}$$

Experimetal Work

A test rig was designed for bearing vibration signal acquisition through vibration sensors and DAQ device. The test rig has capabilities to simulate several conditions of rolling element bearings with various load application. The effect of unbalance to bearing signals can also be simulated using this test rig. The prime mover of this test rig is 3 phase induction motor with 1 horse power (HP). The rotating speed (RPM) of induction motor is controlled by inverter that used programmable logic control (PLC) to possible control the desired rotating speed. The presentation of test rig during experimental work is shown in Fig. 1.

We employed data acquisition device (DAQ) hardware called SpectraPad from SpectraQuest Inc., which consists of 8 channels input and output from many sensors. This DAQ is capable to 24 bits analog-to-digital converter (ADC), 102.4 Ksamples/sec, and 40 kHz of analysis frequency range. The DAQ was controlled by VibraQuest Software that is an integrated data acquisition and analysis solution package designed for diagnosing rotating/reciprocating machinery malfunctions, structural dynamics analysis and acoustical analysis. This novel software includes proprietary advanced signal processing algorithms specially designed for diagnosing faults in drive train components such as gearbox, bearings and rotor cracks.

Data acquisition was conducted on test rig of rotating machine that was driven by induction motor of 1 HP, 220 volt, 3 poles as shown in Fig. 1. One accelerometer was used to pickup vibration signal at rolling element bearing housing in radial direction (Fig.2). The maximum frequency of the signal acquisition and the number of sampled data were 5 kHz and 16.384, respectively.

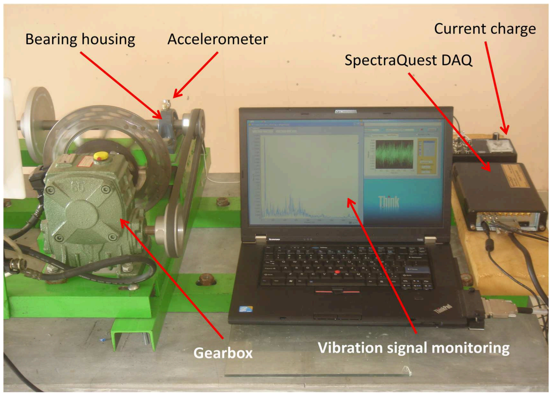


Fig. 1 Experimental work

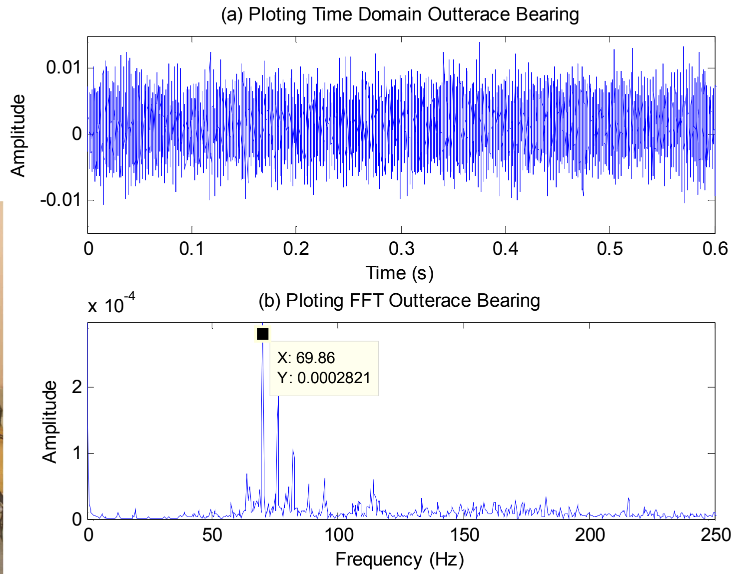


Fig. 2 Vibration signal of bearing outer race fault

Feature Extraction of Vibration Signal

The conditions of rolling element bearing are normal, outer race defect, inner race defect and ball defect. Each condition is labeled as class from 1 to 4. Feature representation for training and classification is adopted from previous work as mentioned in Ref. [12]. There are totally 21 features calculated from vibration signals and 80 data calculated from 4 conditions, 20 measurements.

Feature extraction means transforming the existing features into a lower dimensional space. Most of feature extraction techniques have based on linear technique such as principal component analysis (PCA) and independent component analysis (ICA) [13]. In this paper, non-linear feature extraction using kernel function which employed in linear feature extraction is proposed to extend the feature extraction process.Total of 21 original features consist of overlapping and disorder structures between each condition of rolling element bearing. It can be avoided and improved by employing feature reduction and extraction using component analysis. According to the eigenvalue of covariance matrix, the features were changed into component analysis and reduced only 5 component analysis which needed for classification process.

Training and classifiation

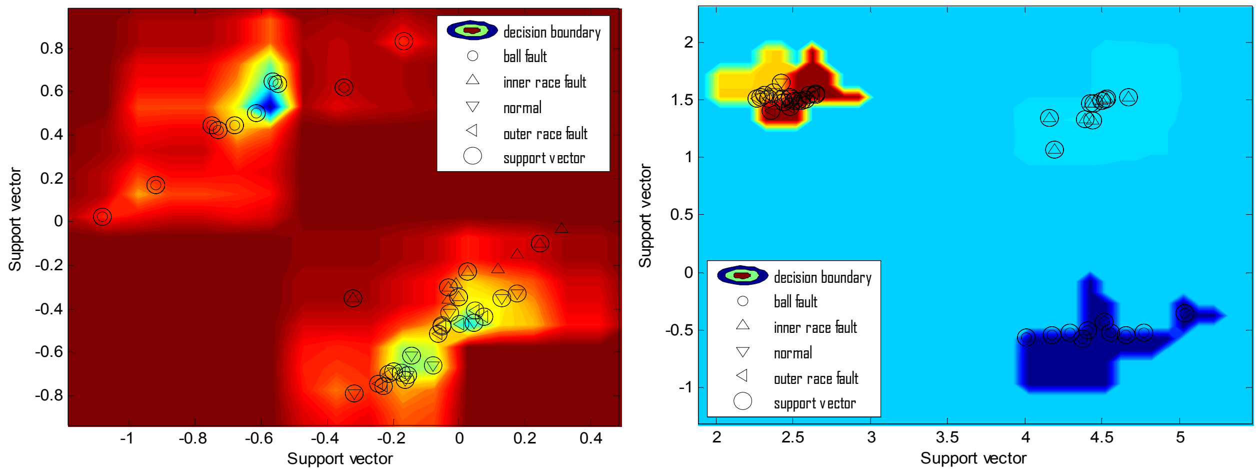
The SVM based multi-class classification is applied to perform the classification process using one-against-all methods [14]. To solve the SVM problem, Vapnik (1982) describes a method which used the projected conjugate gradient algorithm to solve the SVM-QP problem [15]. In this study, SVM-QP was performed to solve the classification problem of SVM. The parameter C (bound of the Lagrange multiplier) and (condition parameter for OP method) were 1 and 10^{-7}, respectively.

Wavelet kernel function using Daubechies series was performed in this study. The parameter δ in wavelet kernel refers to number of vanishing moment and is set 4. In the training process, the data set was also trained using RBF kernel function as comparison. The parameter γ for bandwidth RBF kernel was user defined equal to 0.5.

Results and Discussion

The classification process for fault diagnostics is presented in Fig. 3 from which the separation of W-SVM can be shown. In these figures, the circle refers to the support vector that states the correct recognition in W-SVM. Each condition of rolling element bearing is well recognized using Daubechies wavelet kernel. In the classification process using W-SVM, each condition of bearings can be clustered well. The good separation among conditions shows the performance of W-SVM in recognition of component analysis from vibration signal features.

The performance of classification process is summarized in Table 1. All data set come from component analysis are accurately classified using Daubechies wavelet kernel and SVM. SVM using RBF kernel function with kernel width $\gamma = 0.5$ is also performed in classification for comparison with Daubechies wavelet kernel. The results show that the performance of W-SVM approaches SVM using RBF kernel functions, those are 97% in accuracy of training and testing, respectively. In the case of number support vectors, SVM with RBF kernel function needs lower than W-SVM except kernel PCA.



(a) Daubechies wavelet with PC data (b) Daubechies wavelet with IC data

Fig. 3 Separation boundaries of W-SVM.

Table 1 Results of diagnostics

Kernel	Accuracy (Train/Test), %				Number of SVs			
	IC	PC	Kernel IC	Kernel PC	IC	PC	Kernel IC	Kernel PC
Wavelet Daubechies	100/100	97/97	100/100	97.5/97.5	35	39	39	17
RBF-Gaussian ($\gamma = 0.5$)	100/100	100/100	100/100	100/100	22	22	25	33

Conclusions

In this study, a new method of nonlinear kernel based on wavelet (W−SVM) is introduced. The kernel function transforms the data into higher dimensional space in order to make it possible to perform the separation process. Feature reduction and extraction using component analysis via PCA, ICA, KPCA and KICA are performed. The performance of W−SVM is validated by applying it to faults detection and classification of bearings based on vibration signals. The results show that W−SVM is well performed and reached high accuracy in training and testing process based on experimental work. Introducing nonlinear kernel using wavelets is concluded to significantly improve the SVM research fields.

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