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Vibration Gear Fault Diagnostics Technique Using Wavelet Support Vector Machine

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Abstract. Intelligent diagnostics tool for detecting damaged bevel gears was developed based on wavelet support vector machine (WSVM). In this technique, the existing method of SVM was modified by introducing Haar wavelet function as kernel for mapping input data into feature space. The developed method was experimentally evaluated by vibration data measured from test rig machinery fault simulator (MFS). There were four conditions of gears namely normal, worn, teeth defect and one missing-teeth which has been experimented. Statistical features were then calculated from vibration signals and they were employed as input data for training WSVM. Fault diagnostics of bevel gear was performed by executing classification task in trained WSVM. The accuracy of fault diagnostics were evaluated by testing procedure through vibration data acquired from test rig. The results show that the proposed system gives plausible performance in fault diagnostics based on experimental work.

Introduction

Gearboxes are important component in machinery due to their function to power trasnmission with high efficiency. The gearboxes are widely spreaded in use such as helicopter and airplane, ships, automobiles and manufacturing machineries. Since their function is very important, a gearbox monitoring system is needed as reliable tool for quality control of power transmission. Early detection and fault diagnostics of gear is critical for guarantee the functional availability of power transmission. In addition, this will be a maintenance tool that enables the establishsment of a maintenance program based on early warning and automated fault diagnostics.

Intelligent fault diagnostics of rotating machinery component such as gearboxes is sequential process involving three steps: 1) feature calculation for finding salient feature; 2) feature extraction that represents the symptom; and 3) pattern classification (for diagnostics task). Feature extraction refers to mapping process from iput space to feature space which usually employs special functions such as kernel functions. Salient features that represent charateristics features assicoated with the conditions of gearboxes are usually extracted using approriate signal processing technique.

Pattern classification or sometimes called pattern recognition is the process of classifying the features into different categories. This procedure is augmented by intelligent technique through a knowledge-based paradigms [1, 2]. This technique is adopted in this work due to existing of many difficulties when deriving mathematical model for very complex system such as gear. The great efforts has been reported in using knowledge-based diagnostics as intelligent tools for diagnostics such as neural network [3, 4], fuzzy logic [5, 6], sinergetic schemes [7] and support vector machine [8].

In this paper, a relatively new kernel trick using Haar wavelet function is proposed. In this method, wavelet function is performed as kernel function for mapping input data in SVM theory. The theoretical development of wavelet kernel are reported in references: reproducing wavelet kernel [9], construction of support wavelet network [10], application wavelet support vector to regression [11, 12], least square wavelet support vector [13]. However, the application is still rare in faults detection and classification of gearboxes. Therefore, this study is aimed to evaluate the performance of WSVM in diagnosing gearboxes.

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 [14].

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:

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

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

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

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. 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 [14].

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

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

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 $||\phi_i||_{L2}=1$, then kernel function $K(\mathbf{x}, \mathbf{x}')$ can be expanded as

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

and must satisfy the positivity condition

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

In the case of building a new kernel using wavelet, it is helpful to refer the frame theory [15] 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

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

Experimental Work

Data acquisition was conducted on test rig of machine fault simulator (MFS) with operating speed 1000 rpm that driven by induction motor of 1 HP, 220 volt, 3 poles as shown in Fig. 1. Two accelerometers were used to pickup vibration signal at gearbox in vertical direction. 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. The maximum frequency of the signal acquisition and the number of sampled data were 2 kHz and 40,960, respectively. The acquired signals are presented in Figs. 2 and 3.

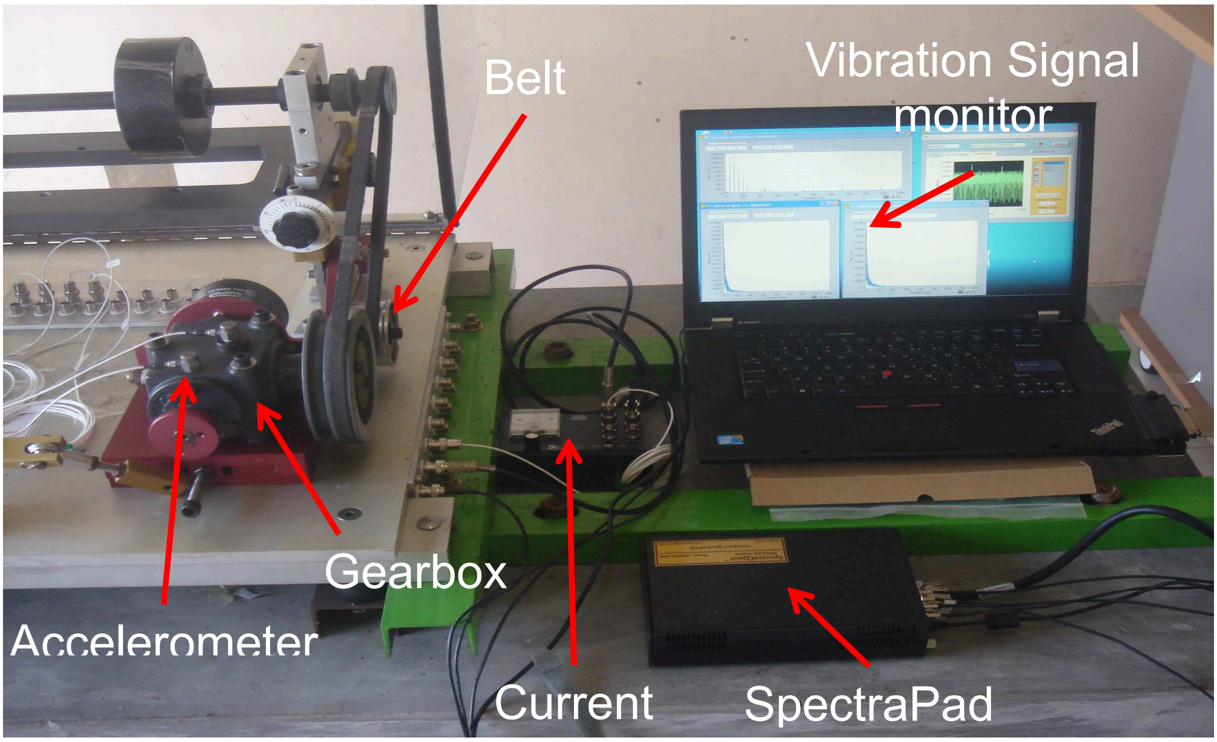

Fig. 1 Data acquisition process

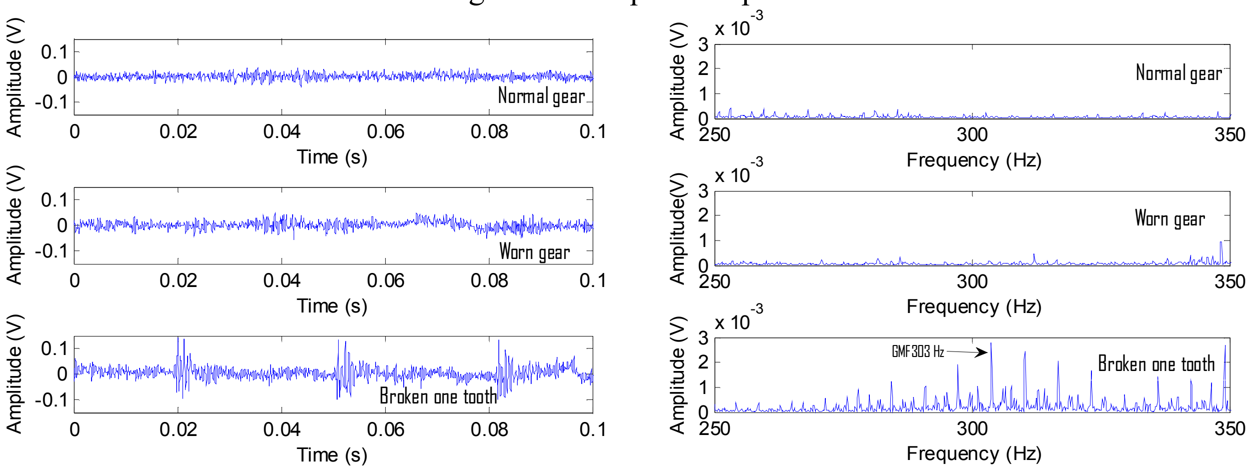

Fig. 2 Vibration signal in time and frequency domain

Fig. 2 shows the acquired vibration signal of gearbox in three conditions: normal, worn and broken gear. Gear mesh frequency (GMF) and their sidebands are clearly presented in signal frequency domain that shows the fault was detected occur in the gearbox. In statistical poin of view, the broken tooth condition give significant different value of mean, rms and kurtosis of time domain signal as presented in Fig. 3.

The conditions of experimented gearboxes are worn, normal, broken 1 tooth and chipped. Each condition is labeled as class from 1 to 4. Feature representation for training and classification is adopted from previous work as mentioned in [16]. There are totally 21 features calculated from vibration signals and 40 data calculated from 4 conditions, 10 measurements. In addition, feature extraction using principal component analysis (PCA), independent componen analysis (ICA) and their kernel (KPCA and KICA) were also employed for feature reduction based on eigenvalue of covariance matrix.

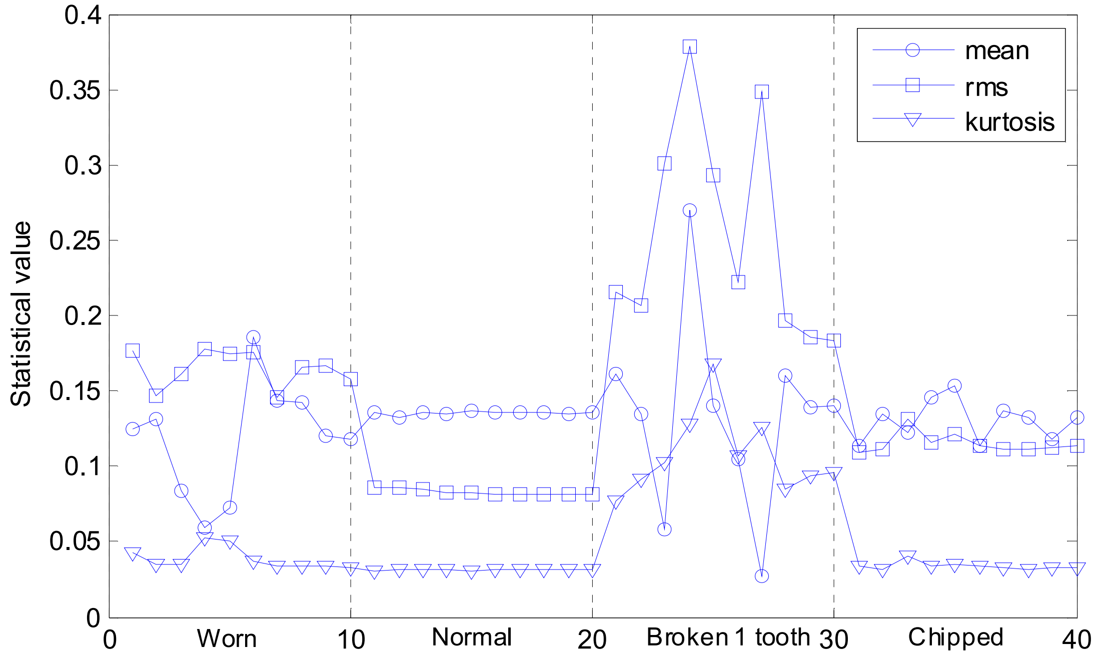

Fig. 3 Feature of mean, rms and kurtosis extracted from time domain signal

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 [18]. 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 Haar 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.

Result and Discussion

The diagnostics of gearbox is presented in Fig. 4 using classification strategy of one-agains-all. The performance of WSVM using Haar wavelet function in classification gearbox conditions is contrasted with common SVM using RBF kernel function. In this work, WSVM can accurately recognize the conditions of gearbox from all input data except data kernel IC with 85% accuracy of training and testing. White circle in Fig. 4 refers to support vectors that represent correct recognition of gearbox conditions in SVM using kernel wavelet and RBF functions.

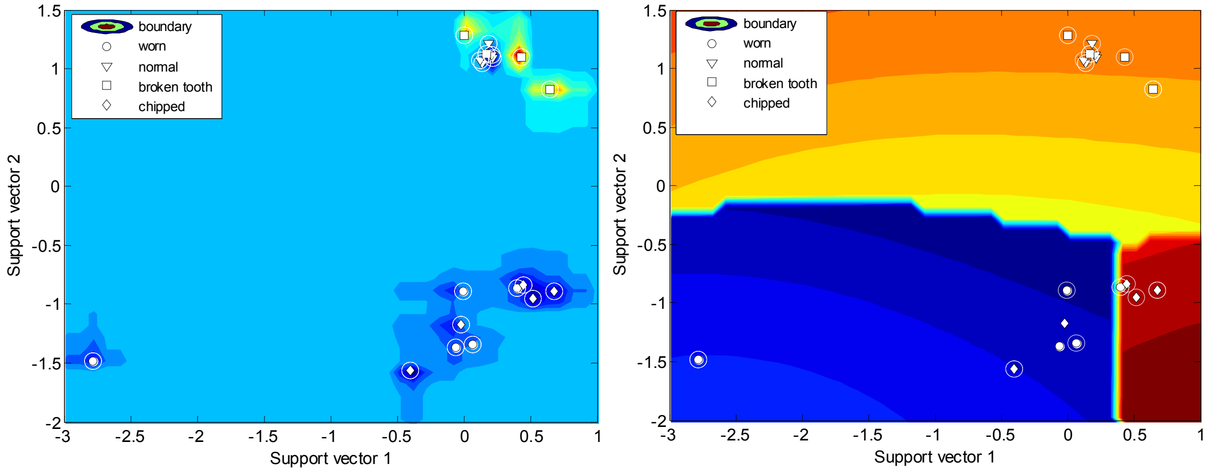

Fig. 4 Classification of gearbox conditions in SVM using kernel wavelet and RBF functions

The performance of classification process is summarized in Table 1. All data set come from component analysis are accurately classified using Haar wavelet kernel and SVM. SVM using RBF kernel function with kernel width $\gamma = 0.5$ is also performed in classification for comparison with Haar wavelet kernel. The results show that the performance of WSVM approaches SVM using RBF kernel functions, those are 85% in accuracy of training and testing, respectively.

Table 1: Results of classification for gearbox fault diagnostics

Kernel	Accuracy (Train/Test) [%]			
	IC	PC	Kernel IC	Kernel PC
Wavelet Haar	100/100	90/90	85/85	100/100
RBF-Gaussian ($\gamma = 0.5$)	100/100	100/100	100/100	100/100

Conclusions

The study of gearbox fault diagnostics using vibration signals and wavelet SVM has been proposed to approach the existing method of common SVM using RBF kernel function. The proposal of introducing wavelet Haar as kernel function in SVM is highlighetd as relatively new trick for mapping input data into feature space. In this work, the proposed method is validated by using vibration signal acquired from gearbox for fault diagnostics purpose. The results show that the performance of WSVM using Haar wavelet is good in training and testing process. Introducing wavelet function as kernel for mapping input data in SVM and its application to gearbox fault diagnostics is significant in intelligent machine fault diagnostics research field.

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