Fault Analysis of Engine Timing Gear and Valve Clearance Using Discrete Wavelet and a Support Vector Machine

Jian-Da Wu, Jian-Bin Chain, Chen-Wei Chung, and Hao Yu

***Abstract*—An engine fault diagnosis method based on discrete wavelet transform and a support vector machine using engine vibration and sound signals is proposed in the present study. The use of mechanical vibration and sound signals for fault analysis in rotating machinery has grown significantly due to the progress of digital signal processing algorithms and implementation techniques. In general, the conditions of rotating machineries can be monitored by measuring the mechanical vibration and sound signals. In the present study, both the vibration and sound signals are used to find faults in the engine timing gear and valve clearance. The diagnosis system consists of feature extraction using the discrete wavelet transform and fault classification using the artificial neural network technique with the support vector machine method. In the experimental work, an electronic fuel injection scooter engine is used for simulating six working conditions in the faults of timing gear and intake-exhaust valves. The experimental results indicated the proposed technique is effective in fault diagnosis for experimental cases.**

***Index Terms*—Discrete wavelet transforms, Expert system, Fault diagnosis system, Support vector machine.**

I. Introduction

Mechanical system such as the internal combustion engine of a motorcycle can be monitored by measuring the vibration and sound signals for early fault diagnosis. Motorcycle is a popular vehicle in Taiwan, which provides the convenience of personal traffic. One of the most important motorcycle parts is the engine, which produces and controls the power for a motorcycle. The engine is consisted of cylinder head, cylinder, piston, valve train, timing gear and crankshaft. Both of the valve train and timing gear are important parts of engine. The valve train provides a passageway that allows air-fuel mixture into the cylinder and allows exhaust gas to pass out. The timing gear of engine is used to operate the intake and exhaust valves. In the previous study, reported that many faults of engine may be on the valve train [1]. For an internal combustion engine, the timing-gear angle is an important factor for determining the air-fuel mixture of engine combustion. The engine timing gear is the most important part of the engine which provides valve train work for correctly time of engine combustion. In traditional engine fault diagnosis, the technician depends on the experience and will introduce many subjective senses to diagnose the fault in the engine. Unfortunately, to correctly classify when the engine is operating the traditional procedure is not a precise approach. For a technology point of view, it is necessary to design an expert system to detect the engine of valve train and timing gear damage so that the expert system can be identified replaced parts in time. This study build up a fault diagnosis system using discrete wavelet transform (DWT) and support vector machine (SVM) for engine of valve train and timing gear fault diagnosis.

Recently, several useful signal processing techniques have been developed on fault diagnosis, such as fast Fourier transform (FFT) [2], short time Fourier transform (STFT) [3], adaptive order-tracking techniques [4], Wigner-Ville distribution (WVD) [5], and wavelet transform (WT) [6]. Although these analysis methods are often applied in sound and vibration signal processing, however, these analysis techniques are not suited to the valve train and timing gear of sound and vibration signals. Although the WVD and STFT methods have better performance in time-frequency analysis, the drawbacks of the time window are fixed. In view of the steadily, DWT method proposed a significant tool in signal analysis and processing [7]. It has a good solution simultaneously in both frequency and time domains, it can extract more information in the time domain at different frequency bands [8].

Recently, for increasing accuracy and reducing the diagnosis error rate, many machinery diagnosis systems with intelligent classification have been developed. There are several useful intelligent diagnosis methods used in machinery, such as artificial neural network techniques [9] and the support vector machine (SVM) [10]. The support vector machine is a network algorithm originally developed by Vaplink and coworkers. It is a powerful classification tool for problems with small sampling, nonlinear, high dimensions, and local minima. Therefore, SVM has been widely used for many kinds of applications, such as pattern identification [11], multi-regression [12] and fault detection [13].

In the present study, an engine timing gear and valve clearance fault diagnosis system based on the discrete wavelet transform technique for feature extraction and classification using SVM has been developed. In the DWT, the db4 Daubechies wavelet coefficients are used [14]. In

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order to achieve intelligent fault diagnosis system, the BPNN and SVM are used to classify the following six engine fault conditions using engine vibration and sound emission signals: idle without fault, timing gear advance 5 degree, timing gear delay 5 degree, intake valve clearance is 0.2 mm, exhaust valve clearance is 0.2 mm, intake and exhaust valves clearance both are 0.2 mm.

II. Principles of Feature Extraction

In 1986, in the field of harmonic analysis, found that wavelet function [15], part of mathematical and physical earthquake researchers began focusing on this issue. Generally, wavelet transform in time domain and frequency domain are localized functions. From the application point of view, any filter can not be simultaneously in the time domain and frequency domain has a high accuracy. Wavelet transform also be limited. However, in this limitation can be designed with high efficiency filters by wavelet transform. Development so far, wavelet transform in terms of mathematics, computer science, physics and engineering have their importance. Present wavelet transform for signal analysis has provided a complete framework.

The principle of DWT is improved from CWT. The CWT is defined as follow, for any function $\varphi(t) \in L^2(R)$, the CWT can be defined as

$$CWT(a,r) = |a|^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t)\varphi^*\left(\frac{t-r}{a}\right)dt \qquad (1)$$

where a is the scale parameter, r is the shift parameter, φ is the wavelet function and φ^* represents the complex conjugate of φ. Because continuous wavelet transform has redundancy and impracticality of the two restrictions. The DWT can be defined as:

$$DWT(a,r) = 2^{-\frac{j}{2}} \int_{-\infty}^{+\infty} f(t)\varphi^*\left(\frac{t-2^j k}{2^j}\right)dt \qquad (2)$$

where a represent 2^j and r represent $2^j k$, $(k,j) \in Z^2$. This is the most common binary DWT. In fact, the DWT works like a band pass filter and its can decide DWT for a signal several levels. DWT filters composed of a high-pass filter and lower-pass filter. The high frequency bands [Details (D_j)] is analyzed by high-pass filter. Conversely, the low frequency bands [Approximations (A_J)] is analyzed by low-pass filter. The signal *X(t)* is decomposed into high and low frequencies shows in Fig. 1, the original signal *X(t)* can be defined as:

$$X(t) = A_J + \sum_{j \le J} D_j \qquad (3)$$

where A_J represent the approximation signal and D_j is the detail signals of the *J*th level. In case the sample rate is 10k Hz, the original signal can be analyzed 2^n down-sampling in frequency domain. The frequency distribution of approximations and details are summarized in table I and table II.

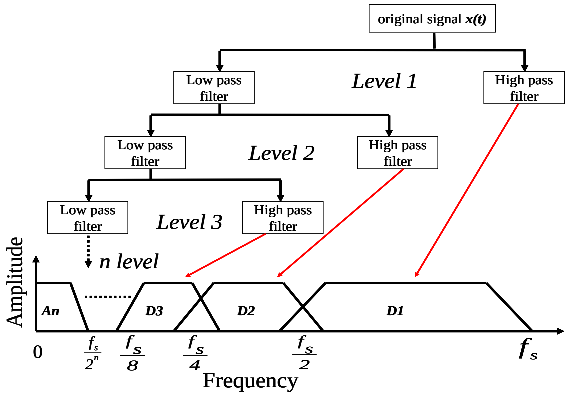

Fig. 1. Original signal decomposition processing and frequency domain representation of DWT

TABLE I: Frequency Distribution of Details

High pass filters (Details)		
Level	Samples(f_s =10kHz)	Frequencies
1	$f_s/2 - f_s$	5000-10000 Hz
2	$f_s/4 - f_s/2$	2500-5000 Hz
3	$f_s/8 - f_s/4$	1250-2500 Hz
4	$f_s/16 - f_s/8$	630-1250 Hz
5	$f_s/32 - f_s/16$	320-630 Hz
6	$f_s/64 - f_s/32$	160-320 Hz
7	$f_s/128 - f_s/64$	80-160 Hz
8	$f_s/256 - f_s/128$	40-80 Hz
9	$f_s/512 - f_s/256$	20-40 Hz

TABLE II: Frequency Distribution of Approximations

Low pass filters (Approximations)		
Level	Samples(f_s =10kHz)	Frequencies
1	$0 - f_s/2$	0-5000 Hz
2	$0 - f_s/4$	0-2500 Hz
3	$0 - f_s/8$	0-1250 Hz
4	$0 - f_s/16$	0-630 Hz
5	$0 - f_s/32$	0-320 Hz
6	$0 - f_s/64$	0-160 Hz
7	$0 - f_s/128$	0-80 Hz
8	$0 - f_s/256$	0-40 Hz
9	$0 - f_s/512$	0-20 Hz

III. Principle of Classifiers for Proposed System

In the present study, fault classification using the artificial neural network technique with back-propagation neural network (BPNN) and SVM method is proposed. Neural network is an imitation of the operation of the human brain developed a mathematical model, which consists of many artificial neurons connected to mimic the ability of human neural network. In an expert system, one of the popular multi-layer perception algorithms is back-propagation neural network. The most representative BPNN algorithm is proposed by the Rumelhart in 1986 [16]. The BPNN is a supervised learning network and most commonly encountered problem has local minimum, need to decide hidden layer and neuron number, over training and under training, and unable convergence. However, if a good adjustment so that still have good recognition rate. The basis architecture of the BPNN is shown in Fig. 2. The basic structure has input layer, one to multi-hidden layer, and the final output layer. Feed-forward stage is input vector into input layer, hidden layer by conduction to output layer, and calculate the network output value. Back-propagation stage, the target output value minus network output value to obtain the error signal, and then back to this error signal back propagation network, then neurons to amend weights makes the network's output on target output value.

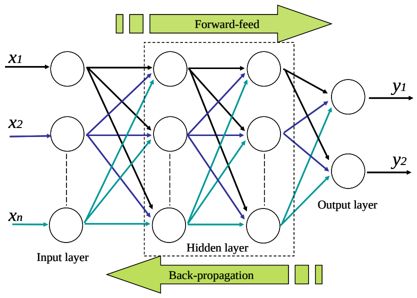

Fig. 2. Architecture of back-propagation neural network.

The basis architecture of the SVM is in high dimensional space to find a super-hyperplane level as divided into the two class, in order to ensure have minimum classification error rate [10]. SVM is a set of similarity supervised learning methods. Advantage of SVM is able to process the no-linear separable case. The main distinction is that using the separating hyperplane separated by two or more of the feature is not the same class to process the information to carve class of data mining problems. The Fig. 3 and Fig. 4 illustrate the training of a linear separable SVM. In the input training data, find data can be separated by a maximum margin distinction hyperplane. One of the important reasons for the wide application is SVM capacity to handle nonlinearly separable data.

Assumed known training examples represented as input vector $\{x_i, y_i\}, i = 1,2,...., n$ correspond with labels $x_i \in R^d, y_i \in \{+1,-1\}$. For linearly separable data, exists a separating hyperplane and its function is as

$$f(x) = \omega^T x + b = 0 \tag{4}$$

where ω is an n-dimensional vector, x is the input vector training data, b is scalar value. To find a line, $f(x) = \omega^T x + b = 0$ which will make dots on the $y_i = -1$ fall on the side of $f(x) < 0$. Moreover, this line will also make all dots on the $y_i = +1$ fall on the side of $f(x) > 0$. Based on the positive and negative sign of $f(x) > 0$, we can distinguish and make sure that this dot belongs to one dot which is between the two sets. For each i either

$$\begin{aligned} &\omega \cdot x_i - b \geq +1 \quad \text{for } x_i \text{ of the first class} \\ &\omega \cdot x_i - b \leq -1 \quad \text{for } x_i \text{ of the second class} \end{aligned} \tag{5}$$

The maximum value of the two parallel lines margin $= 2/\|w\|$ is obtained. This type of learning process is termed structural risk minimization (SRM), intended to make the classifier find the minimum expected risk. For the relationship between the categories of training data, the equation can be re-organized to

$$y_i(\omega^T x + b) \geq 1 \qquad i = 1,2,..., n \tag{6}$$

The target is to maximize the m, therefore, the following constraints are grouped as

$$\text{Minimize} \frac{1}{2}\|W\|^2 \text{ subject to } y_i(\omega^T x_i + b) \geq 1 \quad \forall i \tag{7}$$

By introducing the Lagrange Multiplier Method for the constraint, Equation (7) can be changed to

$$\begin{aligned} &\text{Maximize } W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1, j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\ &\text{subject to } \alpha_i \geq 0 (i = 1,2,..., n), \sum_{i=1}^{n} \alpha_i y_i x_i = 0 \end{aligned} \tag{8}$$

Quadratic Programming can find all the content Equation (8) of α_i sets and $W(\alpha) = \sum_{i=1}^{n} \alpha_i y_i x_i$, if $\alpha_i > 0$, and all x_i are termed support vectors (SVs). Suppose there are P support vectors in total. Therefore, re-ordering equation $W(\alpha) = \sum_{k=1}^{P} \alpha_k y_k x_k$ gives a boundary equation as

$$f(x) = \omega^T x + b = \sum_{k=1}^{P} \alpha_k y_k (x_k \cdot x) + b \tag{9}$$

The discrimination function can be given by

$$f(x) = sign\left(\sum_{k=1}^{P} \alpha_k y_k (x_k \cdot x) + b \right) \tag{10}$$

where P is the number of SVs. This equation makes all dots on $y_i = +1$ fall on the side of $f(x) > 0$. Otherwise, the line will also make all dots on $y_i = -1$ fall on the side of $f(x) < 0$.

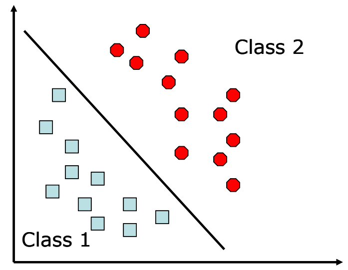

Fig. 3. SVM arbitrary classification boundary.

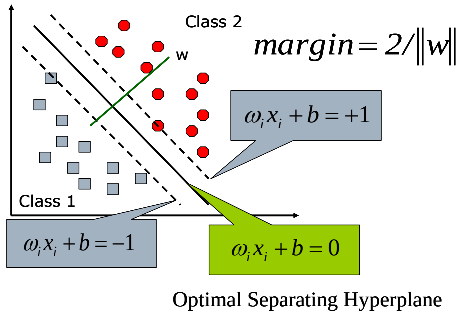

Fig. 4. SVM optimal classification plane.

IV. Experimental Investigation and Analysis

A. Experimental Set-up

In the experiment, to estimate the proposed discrete wavelet transform with the SVM in the fault diagnosis system, an engine platform was used to measure the engine timing gear and valve clearance fault signal for the diagnosis system. The fault diagnosis system mainly used engine vibration and sound signals as the diagnostic basis. This system was divided into two parts. One was the signal dealing, and the other was fault classification. Fig. 5 shows the engine vibration and sound emission signals were analyzed to verify the proposed fault diagnosis system. In the signal analysis, the DWT can decompose the signals to n-levels, and use the energy distribution to detect faults. The purpose of SVM is to find the different engine fault conditions in an idle condition.

Figure 6 shows the flowchart representing the action of signal processing in the engine fault diagnosis system. In the experiment, a scooter with an electronic fuel injection system, single-cylinder, four-stroke, 125 c.c internal combustion engine is used. The vibration and sound emission signals are extracted by an accelerometer (PCB 357B03) and condenser microphone (PCB 37B11). The signals are recorded using NI-compact (NI-DAQ 6024E) and the sampling frequency is chosen to be 10 kHz. In the experiment, there are six work conditions, including idle without fault, timing gear advance 5 degree, timing gear delay 5 degree, intake valve clearance is 0.2 mm, exhaust valve clearance is 0.2mm, intake and exhaust valves clearance both are 0.2 mm fault. The engine is operated in an idle condition.

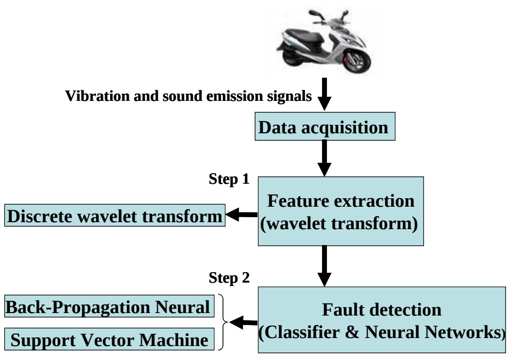

Fig. 5. Block diagram of engine timing gear and valve clearance fault diagnosis system.

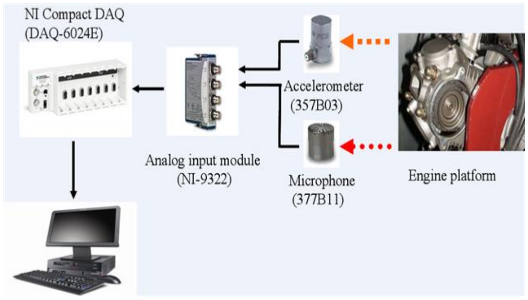

Fig. 6. Flow chart representation of engine fault signal processing procedure

Detecting the vibration and sound emission signals in the engine fault condition is very difficult using the time domain signal. In the present study, the feature extraction method in vibration and sound emission signals is processed by discrete wavelet transform and the energy distribution tendency. The DWT analysis could be decomposed into high and low frequency bandwidths. The BPNN and SVM adopting supervised learning so all experiment databases will be separated into training and testing parts. In the classification, each condition employs 60 items of data for training the networks and 120 items of data for testing the network in this classification work. In the case of fixed speed, 60 items of data are used to create a support vector machine classifier model, and a 120 item database is used for fault identification. Table 3 and Table 4 summarize the fault identification results, showing the fault identification rate can reach 96.6% for engine vibration signals and 100% for engine sound signals. The results indicate the fault diagnosis system based on DWT and SVM is a useful tool for fault identification in the experimental platform.

V. Conclusions

This study developed an engine timing gear and valve clearance fault diagnosis system based on the DWT technique for feature extraction and classification using SVM. DWT can used to detect the transient signals of faults in an engine platform. The experimental results show the proposed system can achieve effective fault diagnosis for an expert system. In fault identification, the classifier techniques both using BPNN and SVM were carried out and compared in the proposed systems. The experimental results show the performance of the identification rate in SVM is better than BPNN. The SVM achieved a fault identification rate over 96% in the experiment.

TABLE III: Recognition Rates In Various Fault Conditions Using Vibration Signals

Engine operation condition : Idle	Recognition rate of fault condition (%)	
	SVM	BP
Data training / test	60/120	60/120
Without fault	100	100
Timing gear advance 5 degree	100	80
Timing gear delay 5 degree	90	100
Intake valve clearance 0.2mm	100	75
Exhaust valve clearance 0.2mm	100	100
Intake and exhaust valve clearance 0.2mm fault	90	80

Average recognition rate	96.6	89.1

TABLE IV: RECOGNITION RATES IN VARIOUS FAULT CONDITIONS USING SOUND EMISSION SIGNALS

Engine operation condition : Idle	Recognition rate fault dition (%)	
	SVM	BP
Data training / test	60/120	60/120
Without fault	100	95
Timing gear advance 5 degree	100	95
Timing gear delay 5 degree	100	85
Intake valve clearance 0.2mm	100	60
Exhaust valve clearance 0.2mm	100	100
Intake and exhaust valve clearance 0.2mm	100	95
Average recognition rate	100	88.3

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