HEALTH MONITORING OF VEHICLE STRUCTURE BY USING PVDF SENSORS

Akihisa Tabata*, Yoshio Aoki*
***Nihon University**

Keywords: *PZT Sensor, Health Monitoring, Wavelet Transform, Support Vector Machines, Statistical Treatment*

Abstract

A vehicle's vibration response contains information about the vehicle's structure and the environment that it is used in. This information is useful for diagnosing the structural health of a vehicle. To monitor the vehicle's vibration response, we used the PVDF sensor attached to the frame of a vehicle. Then A highly accurate technique for detecting and analyzing structural changes is thus required. So we investigate and evaluate the Support Vector Machines method, which is based on a statistical technique, by using it to diagnose structural health by applying the technique to the vibration response of vehicles.

1 Introduction

To prevent serious accidents involving mechanical structures, it is important to detect structural changes early. These structural changes are indicative of damage or functional deterioration. Because they are used in various situations and under various conditions, many mechanical structures have complex deterioration and wearing processes, and their working loads have probabilistic and statistical properties. Since it is difficult to accurately predict the occurrence of deterioration or failure, it is necessary to continually monitor structures during their use to detect any structural changes at an early stage.

Structural health monitoring is used for this purpose. In structural health monitoring, the response signals from sensors built into a structure are used to monitor the condition of the structure. When strain, vibration, sound, and infrared sensors are used for monitoring real structures, they are generally affected by environmental and load changes, often resulting in a nonlinear relationship between phenomena and the response signals. Since the response signals from a vehicle-like structure that continually experiences vibration contain information about the vehicle's operating conditions and environment, a highly accurate technique for monitoring and analyzing the vehicle's structure is required to interpret changes in the response signal accurately.

In order to predict the occurrence of phenomena, we need to create a model that relates the response signals to the phenomena. Strong generalization capabilities are required for highly accurate predictions. General learning tools can be used for modeling. The learning processes employed by these techniques enable the creation of a complicated nonlinear model, but they require defining the various learning parameters appropriately. Even a model capable of classifying learning data correctly may yield only a local solution. In order to obtain a model that has great generalizability, the learning parameters must be determined by trial and error.

In this study, therefore, we apply the Support Vector Machines (SVM) method, which uses a statistical technique for learning and estimating, to structural health diagnosis. Since the method for creating a model of great generalizability based on the theory of statistical learning is clearly an optimization problem, SVM is expected to allow highly accurate prediction of phenomena. We investigate and evaluate SVM by applying it to the vibration response, which is dependent on various factors, and using it to diagnose the structural health of a vehicle.

2 Health Monitoring of a Vehicle

Figure 1 shows the vehicle monitoring system we developed.

Health diagnosis was conducted on the compact electric car shown in Figure 2. A piezoelectric polymer sensor was attached to the support frame of the right front wheel of this vehicle to monitor the vibration response while it was running.

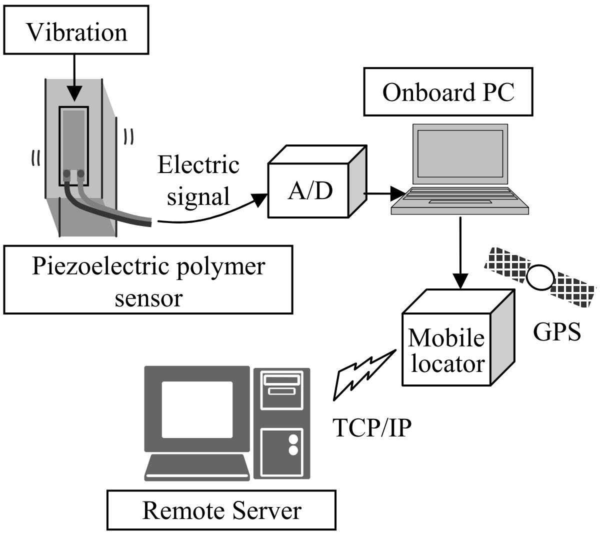

Fig. 1. Schematic diagram of vehicle monitoring system

Fig. 2. The experimental vehicle and the sensor

The piezoelectric polymer sensor was a differential sensor made of polyvinylidene fluoride, which is a piezoelectric material. This sensor was employed to detect changes in the vibration response to a high degree of accuracy. Signals from this sensor were processed by an amplifier and an AD converter and collected by an onboard PC.

The vibration response waveform was processed to extract useful information for predicting phenomena. The signal processing method used was discrete wavelet transform (DWT), which is capable of efficient extraction of features from vibration response waveforms.

Using SVM learning, we created a discrimination unit for detecting phenomena from several data sets containing the feature amounts and the corresponding value for the phenomenon. The feature amounts from the vibration response waveforms collected at diagnosis were entered into the discrimination unit, and the phenomenon output values were then used to ascertain the vehicle conditions and the environment in which it was used.

The signal processing and the SVM discrimination were conducted by the onboard PC, and the results of diagnosis were transmitted to a remote server via a wireless TCP/IP network.

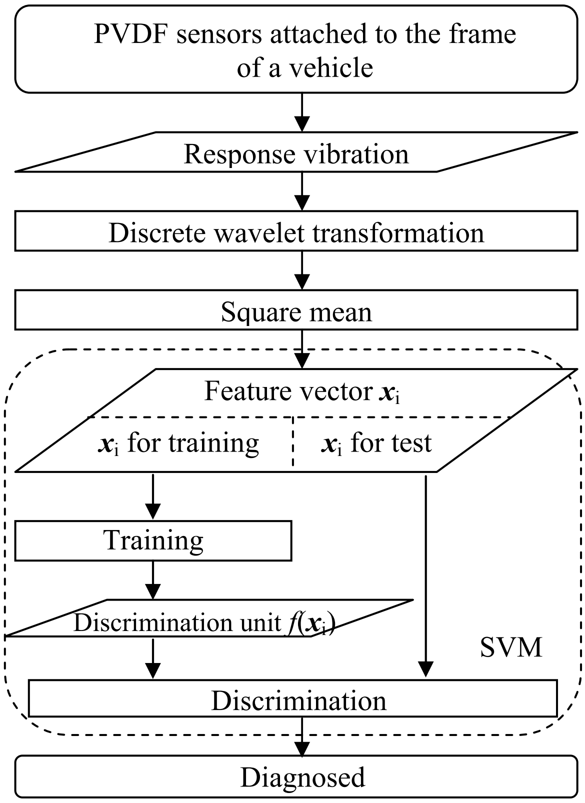

Fig. 3. Procedure of the vehicle health diagnosis

3 SVM

The Support Vector Machine is a linear discrimination unit of the perceptron type, and its indicator function $f(\mathbf{x}_i)$ is defined in terms of the feature amount vector $\mathbf{x}_i$ as follows:

$$f(\mathbf{x}_i) = \mathbf{w}^T \mathbf{x}_i + b \tag{1}$$

where $\mathbf{w}$ is the weight vector, and b is a bias term. Setting y_i as the class to which the feature amount vector belongs, the equation can be expressed using the following threshold function:

$$y_i = \mathrm{sign}\{\mathbf{w}^T \mathbf{x}_i + b\} \qquad y_i \in \{-1, 1\} \tag{2}$$

Learning is used to determine the boundary of the classes. SVM is a typical method to determine the boundary.

Suppose that data belonging to Classes A and B are distributed in n-dimensional space. In SVM, the minimum distance between the data of the two classes is called the margin, and the n-1-dimensional hyperplane where the margin is a maximum is found. At the center, a separating hyperplane is placed as a boundary between the two classes.

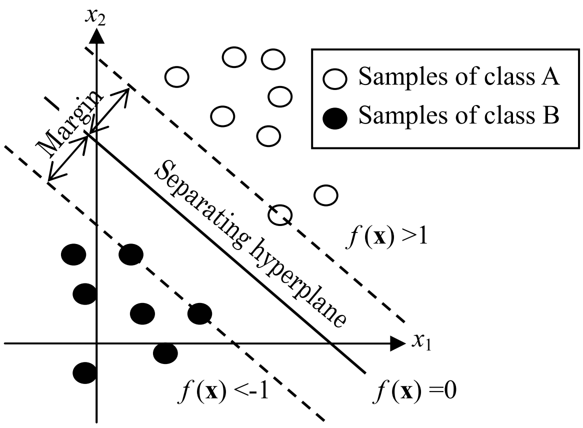

Fig. 4. The separating hyperplane of SVM

This is based on the structural risk minimization technique [1], which reduces the discrimination error rate of not only the learning data but also unknown data. Figure 4 shows an example where data is distributed in two-dimensional space, so that the feature vectors are two-dimensional. The separating hyperplane is thus linear, and a sample located on the broken line at the margin boundary is called a sample vector.

The margin size is given by $1/\|\mathbf{w}\|$, and the determination of the separating plane becomes the quadratic programming problem expressed in Equation (3). Classifying the learning data correctly under restrictive conditions optimizes the weight vector $\mathbf{w}$ where the margin is maximized:

$$\begin{aligned} &\text{minimize} \quad \|\mathbf{w}\|^2 \\ &\text{subject to} \quad y_i\left(\mathbf{w}^T\mathbf{x}_i + b\right) \geq 1 \end{aligned} \tag{3}$$

The Support Vector Machine is initially a linear discrimination unit but it can be extended to a nonlinear discrimination unit using a technique known as the kernel trick. The kernel trick maps features from the input space of the discrimination unit where the features exist to a higher-dimension feature space which has linear dimensions in the feature space rather than nonlinear dimensions. Kernel functions are used for mapping the feature space. The following kernel functions were used:

$$K(\mathbf{x}, \mathbf{x}_i) = \mathbf{x}^T\mathbf{x}_i \tag{4}$$

$$K(\mathbf{x}, \mathbf{x}_i) = \tanh\left(\mathbf{x}^T\mathbf{x}_i\right) \tag{5}$$

$$K(\mathbf{x}, \mathbf{x}_i) = \exp\left(-\|\mathbf{x} - \mathbf{x}_i\|^2\right) \tag{6}$$

Equation (4) represents a polynomial kernel, Equation (5) represents a sigmoid kernel, and Equation (6) represents a Gaussian kernel.

Nonlinear discrimination using the kernel trick substitutes the feature vector $\mathbf{x}_i$ in Equations (2) and (3) with the kernel function $K(\mathbf{x}, \mathbf{x}_i)$ as follows:

$$y_i = sign\left\{\mathbf{w}^T K(\mathbf{x}, \mathbf{x}_i) + b\right\} \quad y_i \in (1, -1) \tag{7}$$

$$\begin{aligned} &\text{minimize} \quad \|\mathbf{w}\|^2 \\ &\text{subject to} \quad y_i\left(\mathbf{w}^T K(\mathbf{x}, \mathbf{x}_i) + b\right) \geq 1 \end{aligned} \tag{8}$$

4 Health Diagnosis Experiment

4.1 Diagnosing the Air Pressure of the Tire

The vibration response is the displacement of the road surface when the vehicle is being driven and is transmitted to the vehicle chassis through the tires. Therefore, the tire characteristics can be considered as one factor which always affects the vibration response of the vehicle. The damping characteristics of the tires are affected by the air pressure in the tires. A low air pressure may cause a standing wave phenomenon that could result in the tires blowing out. In this study, therefore, we decided to evaluate the SVM-based structural health diagnosis of the vehicle structure by diagnosing the air pressure of the tires from the vibration response. This leads to sequential diagnosis that identifies phenomena by successively collating various factors that affect the vibration response.

The vibration response waveform data was obtained from the vehicle shown in Figure 2, which was run under the experimental conditions given in Table 1.

Table 1. Experimental conditions

Speed	20 km/h
Road surface	Asphalt
Tire air pressure	130, 110, 90, 70, 50, 30 kPa
Sampling frequency	1 kHz

The recommended tire air pressure of the vehicle was 130 kPa. The air pressure of the right front tire was set to the recommended pressure or five lower pressures.

4.2 Vehicle Vibration Response

Figure 5 shows the vibration response waveforms at the air pressures of 130, 110, and 90 kPa. It is difficult to identify differences in the vibration responses from the initial waveforms. To make these features clearer, we extracted features using DWT. For DWT, the fifth mother wavelet of the most efficient feature extracted from the vehicle vibration response was selected from highly general Daubechies as a basis function for facilitating analysis of local vibration changes. Decomposition by DWT was performed in five pseudo-frequency bands, namely D1 (500 to 333 Hz), D2 (333 to 167 Hz), D3 (167 to 83 Hz), D4 (83 to 42 Hz), and D5 (41 Hz to 21Hz). Figure 6 shows the DWT processed waveform of the vibration response obtained at an air pressure of 130 kPa.

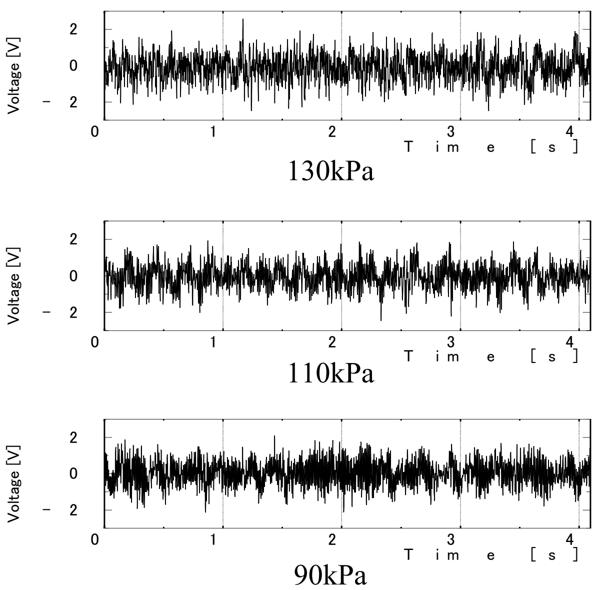

Fig. 5. The time-domain response in the driving test

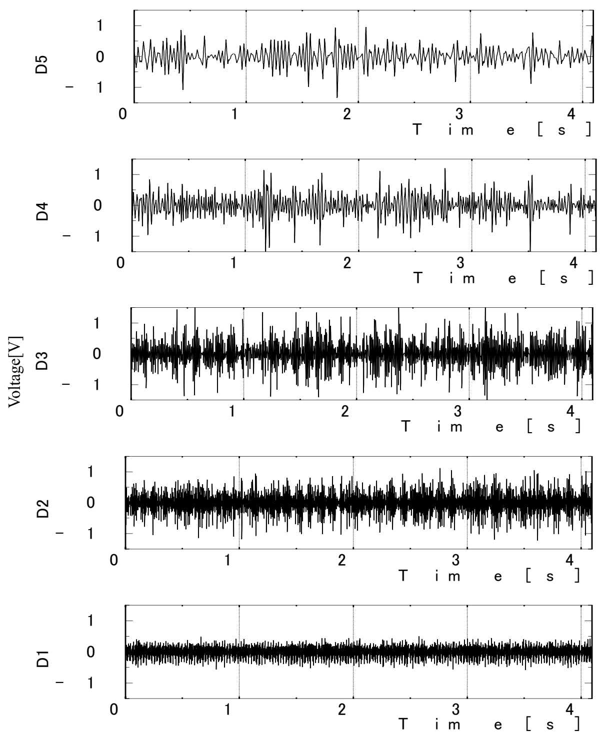

Fig. 6. The DWT-processed waveform of the vibration response (at 130 kPa)

4.3 SVM Application

As explained above, the features were extracted from the vibration response waveforms, and the air pressures of tires were distinguished by using the amplitudes of the pseudo-frequency bands from D1 to D5. Since SVM basically evaluates one status using one discrimination unit, we created one discrimination unit for each of the six air pressure levels and evaluated the discrimination performance.

The amplitude obtained by DWT analysis from the vibration response that is the input signal to the discrimination unit always varies, as shown in Figure 5. The square means of the fixed continuous times were calculated using Equation (9) for D1 to D5 and used as the components of the feature vector:

$$x_k = \frac{1}{n}\sum_{j=t_0}^{t_0+n}\sqrt{\left(d_k^{(j)}\right)^2} \quad \left(k = 1,2,\ldots,m\right) \qquad (10)$$

where $d_k^{(j)}$ is the amplitude at each sampling point, and n is the number of sampling points for the square mean or the measurement time required for obtaining the feature amount.

The length of time used in the feature amount calculation may affect the discrimination performance. We therefore investigated changes in the feature amount discrimination performance of the discrimination unit for the recommended air pressure level of 130 kPa when the number of sampling points was n (see Figure 7).

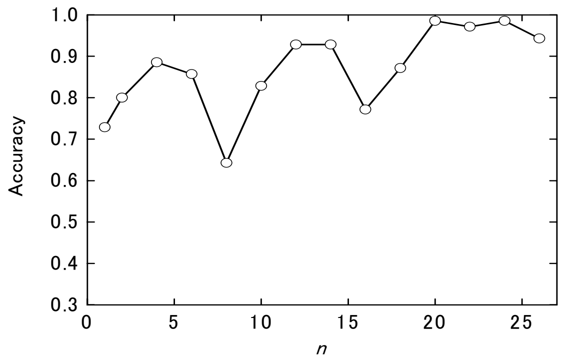

Fig. 7. The recognition accuracy versus number of samples

The discrimination unit was created from 120 items of randomly selected learning data. There were 60 positive data items corresponding to the recommended pressure and 60 negative items that did not correspond to the recommended pressure. The polynomial kernel in Equation (4) was used. To evaluate the discrimination performance, 70 items of test data were randomly selected for each air pressure level from 130 to 30 kPa.

The discrimination accuracy generally improved with larger numbers of sampling points and reached a peak of 98% or more when the number of sampling points was 20 to 24. Also, from the viewpoint of having a small calculation volume for diagnosis, it is preferable to reduce the number of sampling points. On this basis, was set to 20 in Equation (10) for the feature amount calculation in the subsequent air pressure diagnosis of the tires. This corresponds to a measurement time of 20 ms.

By using the method described above, we also created discrimination units for air pressure levels other than the recommended one and diagnosed the air pressure. Figure 8 shows the results. The discrimination accuracy was 99% for the discrimination unit whose prescribed pressure was 130 kPa. Initial changes of 15% to 30% lower than the recommended pressure, which are difficult for a driver to detect, can be detected with high accuracy.

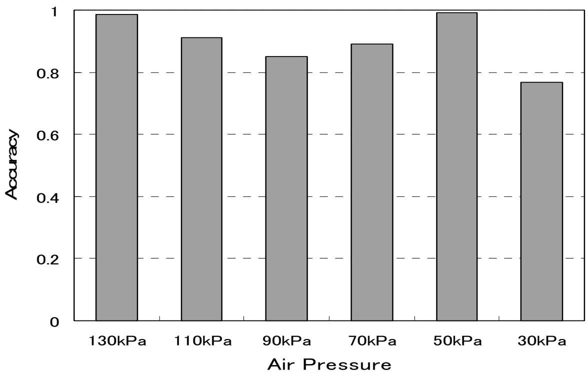

Fig. 8. The recognition accuracy using SVM with polynomial kernel

4.4 Detecting the Loosened Bolts

Then we evaluate the structural health diagnosis of the vehicle structure by detecting the loosened bolts joint a tire-wheel to a hub from the vibration response. Figure 9 shows the bolts and table 2 shows the experimental conditions.

Fig. 9. The bolts joint a tire-wheel to a hab

Table 2. Experimental conditions

Speed	20km/h
Road surface	Asphalt
Sampling frequency	1kHz
State of the bolts	Normal One bolt is loosened Two bolts are loosened Three bolts are loosened

Figure 11 shows the time domain response in the driving test and the DWT-processed waveform of the vibration response when three bolts are loosened. Cyclical fluctuations appear in the DWT-processed waveform.

Then we created discrimination units for each states of the bolts and diagnosed. The discrimination unit was created from 60 items of randomly selected learning data. There were 30 positive data items and 30 negative items. Table 3 shows the results.

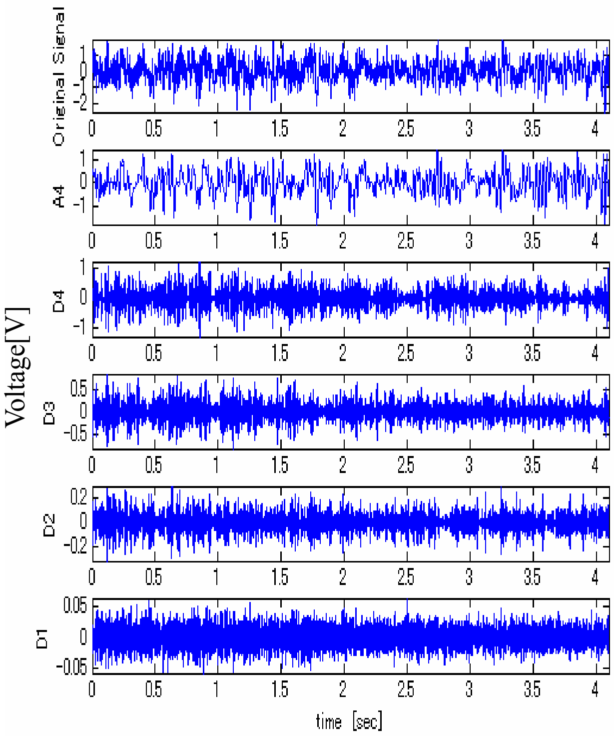

Fig.10. The waveform of the vibration response (normal state)

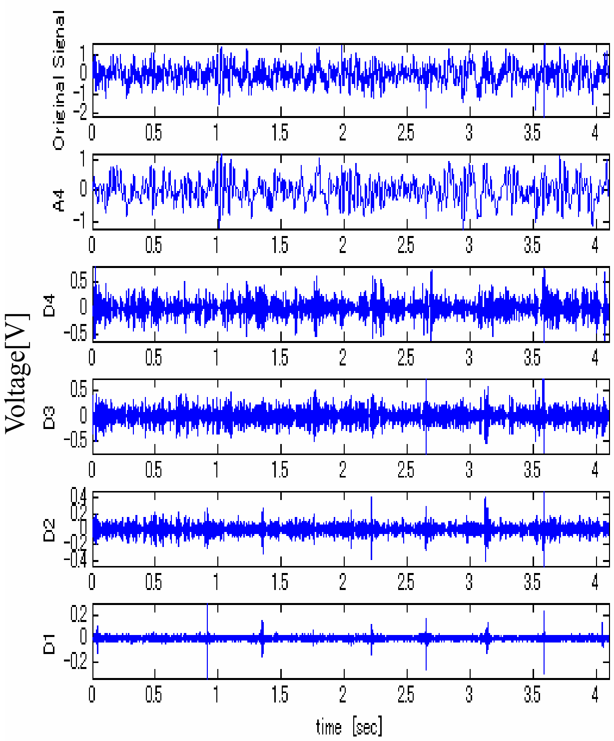

Fig.11. The waveform of the vibration response (three bolts are loosened)

Table 3. The recognition accuracy

		Learned discrimination unit			
		Normal	1bolt	2 bolts	3 bolts
Test pattern of the response vibration	Normal	1	0.58	1	1
	1 bolt	0.63	1	1	1
	2 bolts	1	1	1	1
	3 bolts	1	1	1	1

More than two bolts are loosened, the looseness of the joint can be diagnosed.

5 Conclusions

In this study, we use a PVDF sensor to monitor the vibration response transmitted through a vehicle chassis while it was running. A PVDF sensor is sensitive to fluctuations of the vibration response. We investigated a method for extracting feature vectors for SVM from vibration response waveforms after wavelet transformation to establish a technique for diagnosing the structural health of a vehicle by using SVM. The tire air pressure could be detected from the vibration response. Also the loosend bolts join a wheel to a hub could be detected from the response vibration.

References

[1] V. N. Vapnik, Statistical Learning Theory, John Wiley & Sons, 1998.

[2] The Japan Society of Mechanical Engineers ed., Structural Health Monitoring, The Japan Society of Mechanical Engineers, 2005.