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ACTIVE DAMAGE DIAGNOSIS OF BOLTED JOINTS USING SUPPORT VECTOR MACHINES

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SUMMARY

An active diagnosis method using support vector machines is presented. The support vector machine is a recently developed pattern recognition method that has some similarities with the neural network. It has a strong pattern recognition capability with relatively easy implementation processes. By introducing the support vector machines, a flexible and accurate damage diagnosis procedure is formulated. The procedure proposed here can be extended to an automatic diagnosis with strong learning capability. The multi-dimensional feature vectors that represent the features of damages are generated by active sensing technologies based on ultrasonic wave propagation. Piezoelectric transducers were used for generating ultrasonic Lamb waves in a plate and for sensing the traveling ultrasonic waves. A network of piezoelectric elements attached to neighbors of a bolted joint is utilized to obtain the inputs and outputs combinations in the time domain. The recorded time histories are converted to multi-dimensional feature vectors to teach support vector machines. Simplified bolted joints were fabricated using aluminum plates and bolts. The excitation frequency of the ultrasonic wave is 50KHz. Another pattern recognition method, the correlation analysis, is also applied to the same feature vectors. The better accuracy of the proposed method is successfully presented compared with the correlation analysis. It is also shown that the application of wavelet transform exhibits a drastic improvement of recognition accuracy.

INTRODUCTION

Structural health monitoring systems may increase the reliability of structures and reduce the maintenance costs drastically if the performance of the systems is satisfactory. Among others, piezoelectric transducers (PZT) are very promising as they can be used for actuators and sensors. Arbitrary vibration signals especially in the ultrasonic range can be transmitted and detected by the same PZT. In addition, as they can be integrated into a structural member, it is ideal for making a structure smart. However, conventional diagnosis technologies using ultrasonic waves heavily rely on the experienced engineers to conduct good damage diagnosis. Therefore, it is our purpose to propose an automatic diagnosis method using PZTs. We will show that introducing the support vector machine (SVM) and wavelet transform can achieve excellent discernment performance. The proposed method can identify the number of bolts and their exact locations using simple feature vectors generated from impulse responses.

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ACTIVE DAMAGE DIAGNOSIS

Flow chart and components of proposed method

The flow chart of the proposed method is shown in Fig. 1. It consists of three components, smart sensing, signal processing, and pattern recognition as shown in Fig. 2. Each component is briefly explained.

Smart sensing

PZT elements are used both for actuators and sensors. Each element is adhered to specimens using conductive glue. As we use aluminum plates for experiment, the specimen itself is used as the electrical ground. One of PZTs will be excited by the impulse signal to be measures by other PZTs.

Signal processing

The effectiveness of applying wavelet transform to the recorded data has been reported by Sung [1] and Jeong [2]. The wavelet transform is used to extract the data that are well correlated to excitation signals. From the transformed data, feature vectors are generated. In this paper, average amplitudes over prescribed durations are used.

Pattern recognition

The support vector machine (SVM)and correlation analysis are used. The latter is just for comparison.

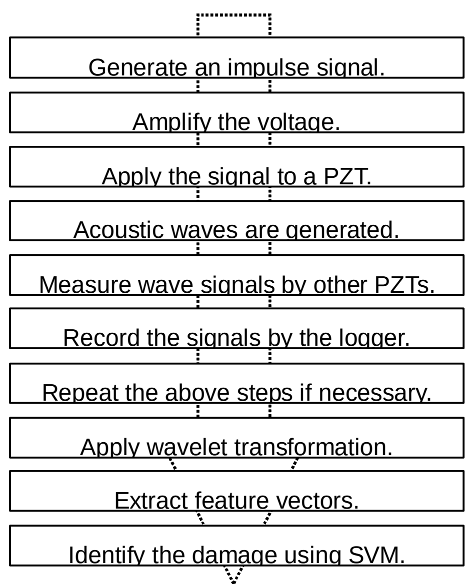

Figure 1. Flow chart of proposed method.

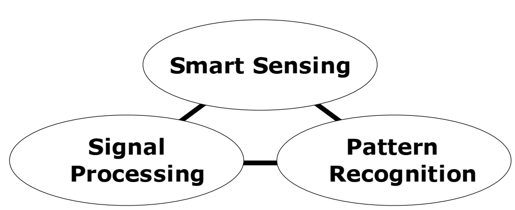

Figure 2. Three components of proposed method.

Support Vector Machine

The Support Vector Machine (SVM) is a mechanical learning system that uses a hypothesis space of linear functions in a high dimensional feature space (see Vapnik[3] and Christianini [4]). The simplest model is called Linear SVM (LSVM), and it works for data that are linearly separable in the original feature space only. In the early 1990s, nonlinear classification in the same procedure as LSVM became possible by introducing nonlinear functions called Kernel functions without being conscious of actual mapping space. This extended technique of nonlinear feature spaces is called Nonlinear SVM (NSVM) shown in Fig.3. Assume the training sample S consisting of vectors $\mathbf{x}_i \in R^n$ with $i = 1,\ldots,N$, and each vector x_i belongs to either of two classes thus is given a label $y_i \in \{-1,1\}$. The pair of $(\mathbf{w}, b)$ defines a separating hyper-plane of equation as follows:

$$S = ((\mathbf{x}_1, y_1),\ldots,(\mathbf{x}_N, y_N)) \tag{1}$$

$$(\mathbf{w} \cdot \mathbf{x}) + b = 0 \tag{2}$$

However, Eq.(2) can possibly separate any part of the feature space, therefore one needs to establish an optimal separating hyper-plane (OSH) that divides S leaving all the points of the same class on the same side, while maximizing the margin which is the distance of the closest point of S. The closest vector $\mathbf{x}_i$ is called support vector and the OSH $(\mathbf{w}', b')$ can be determined by solving an optimization problem. The resulting SVM is called Hard Margin SVM. In order to relax the situation, Hard Margin SVM is generalized by introducing non-negative slack variables $\xi = (\xi_1, \xi_2, \ldots, \xi_N)$ as follows:

$$\begin{aligned} &\text{minimize} \quad \text{margin } d(\mathbf{w}') = -\frac{1}{2}(\mathbf{w}' \cdot \mathbf{w}') + C\sum \xi_i, \\ &\text{subject to} \quad y_i((\mathbf{w}' \cdot \mathbf{x}_i) + b') \geq 1 - \xi_i, \quad i = 1,2,\ldots,N, \ \xi \geq 0. \end{aligned} \tag{3}$$

The purpose of the last term of the $C\sum \xi_i$, where the sum of $i = 1,\ldots,N$ is to keep under control the number of misclassified vectors. The parameter C can be regarded as a regularization parameter. The OSH tends to maximize the minimum distance of $1/\mathbf{w}$ with small C, and minimize the number of misclassified vectors with large C. To solve the case of nonlinear decision surfaces, the OSH is carried out by nonlinearly transforming a set of original feature vectors $\mathbf{x}_i$ into a high-dimensional feature space by mapping $\mathbf{\Phi} : \mathbf{x}_i \mapsto \mathbf{z}_i$ and then performing the linear separation. However, it requires an enormous computation of inner products $(\mathbf{\Phi}(\mathbf{x}) \cdot \mathbf{\Phi}(\mathbf{x}_i))$ in the high-dimensional feature space. Therefore, using a Kernel function which satisfies the Mercer's theorem given in Eq.(4) is required to significantly reduce the calculations to solve the nonlinear problems. In this study, we used the Gaussian kernel given in Eq.(5) as the kernel function.

$$(\mathbf{\Phi}(\mathbf{x}) \cdot \mathbf{\Phi}(\mathbf{x}_i)) = K(\mathbf{x}, \mathbf{x}_i) \tag{4}$$

$$K(\mathbf{x}, \mathbf{x}_i) = \frac{\exp(-\|\mathbf{x} - \mathbf{x_i}\|)^2}{\sigma} \tag{5}$$

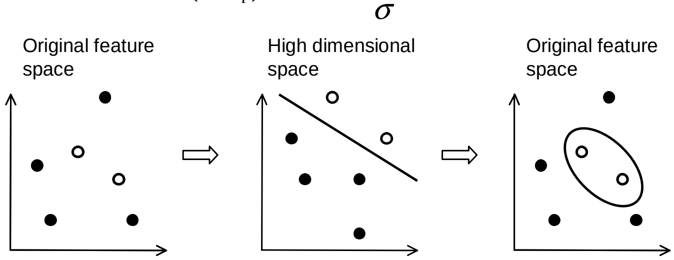

Figure 3. Nonlinear SVM.

Correlation analysis

The correlation coefficients between two vectors, *A* and *B*, are defined by

$$r_{i,k} = \frac{\sum_{j=1}^{12}(A_{i,j} - \overline{A_i})(B_{k,j} - \overline{B_k})}{\sqrt{\sum_{j=1}^{12}(A_{i,j} - \overline{A_i})^2 \sum_{j-1}^{12}(B_{k,j} - \overline{B_k})^2}} \tag{6}$$

where $A_{i,j}$ is the j th value of the i th feature vector, and $B_{k,j}$, the j th value of the k th feature vector. By selecting a class that gives the largest correlation coefficient, we can use this analysis as a pattern recognition tool. The analysis is done for comparing with SVM.

EXPERIMENTS USING SPECIMEN WITH BOLTED JOINTS

An experimental specimen of bolted joints is shown in Figs. 4 and 5. The bolted joints were made with 2 aluminum plates $(200\times300\times3\text{mm})$ jointed with 2 short aluminum plates $(200\times40\times2\text{mm})$. Ten 5mm diameter steel bolts with washers and nuts were used. Total length of the bolted joints part was 40mm. The PZT has a diameter of 10mm, and a thickness of 0.2mm. Four PZTs were bonded at a distance of 20mm from the bolted joints by using conductive adhesive. For a signal generation, a two-peak narrow-band, modulated sinusoidal burst waveform was selected for the actuator signal to simulate a transient wave. The command voltage signal used here is shown in Fig. 6.

The excitation frequency was 50kHz to generate the PZT 1 as an actuator, and propagating wave was acquired by PZT 2-4 as the sensors. The signal generation, PZT selection, signal filtering, A/D signal conversion and data acquisition were done using the SMART Suitcase (Mark [5]). The photo of the acquisition system is shown in Fig. 7. The excitation frequency was decided based on the efficiency of the wave transmission and the wave length ratio with the damage dimension. Damage was introduced by extracting the bolts from the joints. At first, the robust state of bolted joints was measured. Then, total of 44 different patterns of missing bolts were performed after that. Those are 10 different patterns of 1 bolt missing, 13 patterns of 2 bolts missing, 6 patterns of 4 bolts missing, 5 patterns of 5 bolts missing, 5 patterns of 6 bolts missing and 5 patterns of 8 bolts missing. All these were measured for twice in order to collect the training data and the verification data in pattern recognition.

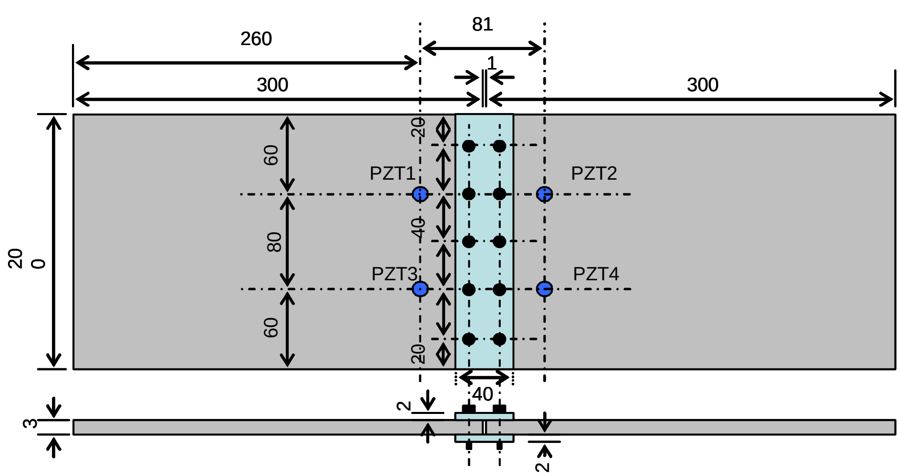

Figure 4. Aluminum specimen with bolted joints.

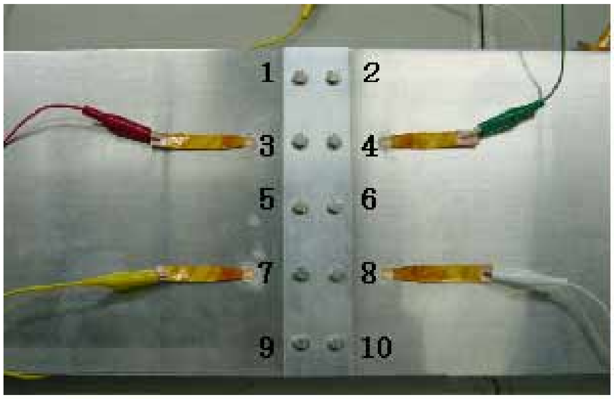

Figure 5. Bolted joints and PZT.

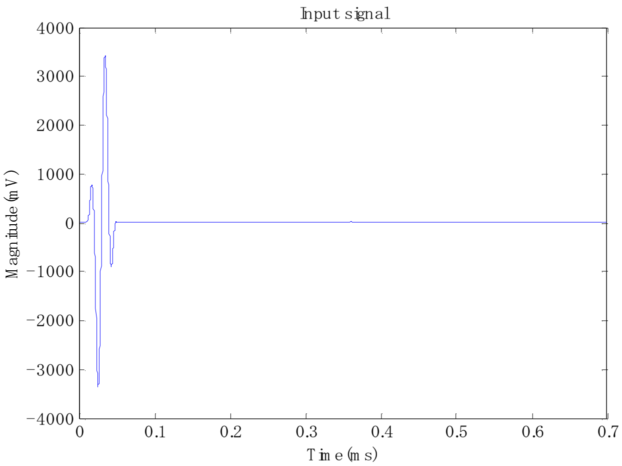

Figure 6. Command signal used for generating impulse.

Figure 7. Data acquisition system.

Feature vectors

For the damage detection using pattern recognition methods, creation of the feature vectors is needed. In this study, we divided waveforms of the time domain into four 0.1ms intervals, then calculated the sum of the second power average of the amplitude for each interval (Fig.8). Therefore, four values can be acquired from one sensor, and a total of 12 values can be obtained from all sensors as shown in Table 1 for a typical experimental data. This procedure was applied to one robust and all 44 damage patterns, which were used as the feature vectors for pattern recognition in this study.

Table 1. Typical feature vector.

Time interval	Sensor No.	Data No.	Second Power
	PZT#2	1	1.547
0.05 – 0.15ms	PZT#3	2	5.935
	PZT#4	3	0.987
	PZT#2	4	0.865
0.15 – 0.25ms	PZT#3	5	1.651
	PZT#4	6	0.523
	PZT#2	7	1.128
0.25 – 0.35ms	PZT#3	8	3.347
	PZT#4	9	0.979
	PZT#2	10	1.656
0.35 – 0.45ms	PZT#3	11	3.888
	PZT#4	12	1.227

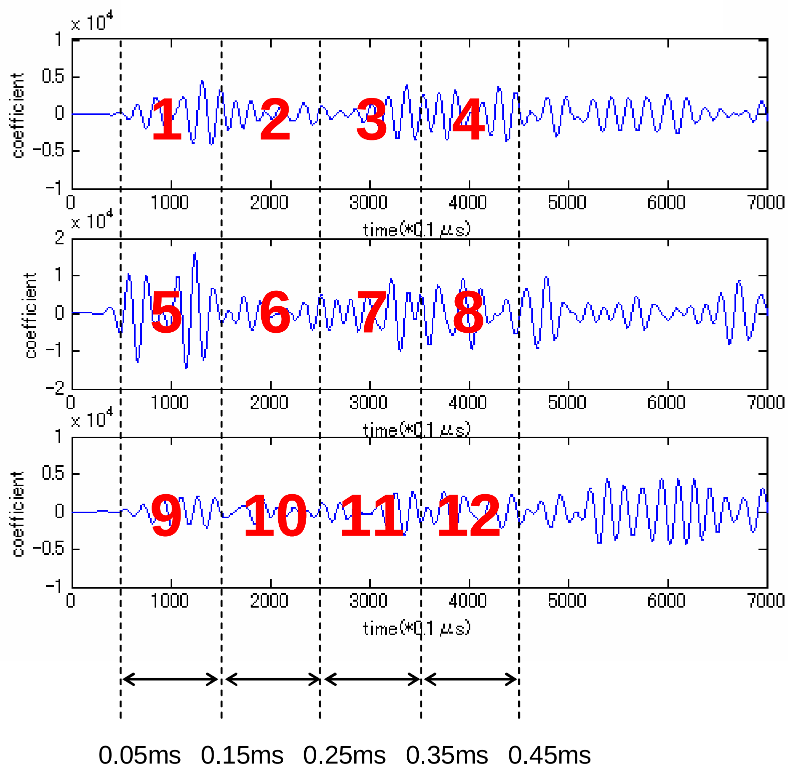

Figure 8. Extraction of feature vector.

Damage diagnosis using correlation analysis

The location of the missing bolts was estimated by using the calculated feature vectors. In this method, 45 different kinds of damage patterns were utilized as the standard data. Then the data of extracting arbitrary positions of bolts was compared with the standard data and from the largest correlation coefficient, one can estimate the location of the missing bolts in a simple manner. The results of damage detection using correlation coefficients are shown in Table 2 $(i = 0 \sim 10)$. The meaning of "after applying WT" is the case where the feature vector was created using the waveform extracted from 50kHz domain only, from the sensor signal. For the results in all damage patterns $(i = 0 \sim 44)$, 31 out of 45 were correct for before applying WT, and 38 out of 45 were correct for after applying WT. Although there were some unforced errors, the damage detection using the correlation coefficients and applying wavelet transform to extract the waveform of a certain specific frequency for creation of the feature vector, the location of missing bolts could be identified at a certain level of accuracy.

Table 2. Diagnosis results using correlation coefficients.

		Before applying WT		After applying WT	
i	**Extracted bolt number**	**Correct**	**Incorrect**	**Correct**	**Incorrect**
0	none	0.999		0.999	
1	1		0.982		0.986
2	2		0.982		0.983
3	3	0.979		0.978	
4	4	0.989		0.989	
5	5		0.990	0.992	
6	6	0.997		0.998	
7	7	0.994		0.994	
8	8	0.993		0.994	
9	9	0.998		0.998	
10	10		0.965		0.972

Damage diagnosis using 45 SVMs

The 45 different kinds of damage classes were recognized by the SVM. As the feature vectors were complicated enough, application of the LSVM is not possible. Therefore, the Gaussian kernel was applied as the kernel function to build optimal NSVM by following: (1) it is based on the classification, which divides each class and the other into two classes. (2) Slack variables are introduced as Soft Margin SVM. Consequently, 45 NSVMs were built in total, and the parameters of each NSVM, σ as in Eq.(5), and C as in Eq.(3) were determined to minimize the misclassified data. If the *l-o-o* (leave-one-out bounds) represents the probability of the data that does not exist in a margin, the boundary of classes that has a 100% correctness and l-o-o close to 100% were determined to raise the accuracy of discernment results.

The verification of SVM was performed with the same sets of data acquired for second measurement $(k = 0 \sim 44)$. As an example, the outputs of first 10 damage patterns using built SVMs are shown in Table 3. The data number of positive output indicates the location of the damage recognized by the SVM, and SVM with training data shows good results within the verification data. The influence of WT to SVM is shown in Table 4. For the results in all damage patterns $(i = 0 \sim 44)$, 33 out of 45 were correct for before applying WT, and 45 out of 45 were correct for after applying WT. Therefore, the effect of WT appeared in SVM as well as correlation coefficient. Moreover, SVM could identify the damage with very strong discernment capability.

Table 3. Outputs from SVM

	Verification data										
i \ k	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0	1.000	-1.000	-1.030	-1.000	-1.001	-1.905	-2.832	-1.000	-1.000	-2.308	-3.410
1	-0.914	0.213	-0.782	-1.646	-1.529	-1.554	-2.122	-0.926	-0.606	-1.805	-0.767
2	-1.034	-1.002	0.126	-2.904	-0.964	-2.340	-1.474	-0.994	-1.654	-0.539	-0.912
3	-0.941	-0.971	-1.293	0.542	-1.048	-2.021	-2.524	-0.960	-2.590	-0.129	-4.245
4	-1.047	-0.968	-1.217	-1.986	0.014	-1.727	-1.471	-0.862	-1.291	-1.045	-2.005
5	-0.984	-1.062	-1.470	-1.933	-2.958	0.452	-2.630	-0.965	-2.222	-1.076	-2.731
6	-1.050	-0.965	-1.043	-2.515	-1.077	-0.430	0.773	-0.971	-0.424	-0.679	-2.607
7	-0.918	-0.913	-1.495	-1.765	-0.872	-2.196	-1.467	0.234	-1.426	-2.207	-1.434
8	-1.130	-1.038	-1.334	-2.311	-0.915	-1.543	-0.465	-0.941	0.433	-0.737	-0.871
9	-1.011	-0.919	-0.890	-2.441	-1.754	-1.371	-1.503	-0.982	-1.368	0.834	-1.156
10	-1.052	-1.101	-1.266	-3.269	-0.076	-2.356	-0.015	-0.963	-0.334	-1.104	0.215

Table 4. Correctness of diagnosis using SVM.

		Before applying WT		After applying WT	
i	**Extracted bolt number**	**Correct**	**Incorrect**	**Correct**	**Incorrect**
0	none	1.000		1.000	
1	1		-0.082	0.213	
2	2		-0.199	0.126	
3	3	0.600		0.542	
4	4		-0.301	0.014	
5	5	0.482		0.452	
6	6		-0.413	0.773	
7	7	0.343		0.234	
8	8	0.205		0.433	
9	9	0.047		0.834	
10	10		-0.293	0.215	

Damage diagnosis using 7 SVMs

In this diagnosis, an SVM was built for each number of extracted bolts so that the information on the location was neglected. They are; a class of robust state, class of 1 bolt missing, 2 bolts missing, 4 bolts missing, 5 bolts missing, 6 bolts missing and 8 bolts missing. Therefore, total of 7 NSVMs were built with the training data $(i = 0 \sim 44)$. For parameters σ and C of each NSVM, we determined them by 100% correctness and l-o-o close to 100% as the same way as 45 classified damage patterns described before. In addition to that, the parameters σ and C were selected to minimize the number of Support Vectors as shown in Fig.9. From the Figure, it is recognized that an NSVM tends to minimize the number of Support Vectors with small σ and with large C.

Fig. 10 shows the results of seven classified damage detection after applying WT. In the x-axis, data number 1 denotes the class of robust state and No.2~11, No.12~24, No.25~30, No.31~35, No.36~40 and No.41~45 represent the class of 1 bolt missing, 2 bolts missing, 4 bolts missing, 5 bolts missing, 6 bolts missing and 8 bolts missing, respectively. The data number of positive output indicates the division of damage classified with the number of extracted bolts, and SVMs indeed show promising results that classified the data into 7 classes, perfectly.

Based on the above results, it can be concluded that we can arbitrarily set up the index of the damage and can define what indicates as the damage. For example, if two or more missing bolts are chosen as damage, then a designer should simply build an SVM with the data of robust state to 2 missing bolts as a class 1 which are data number 1~11 in the experiment and choose other as class 2 for index of the damage. However, to improve the proposed method for practical use, the use of simulation data for creating training data may be necessary.

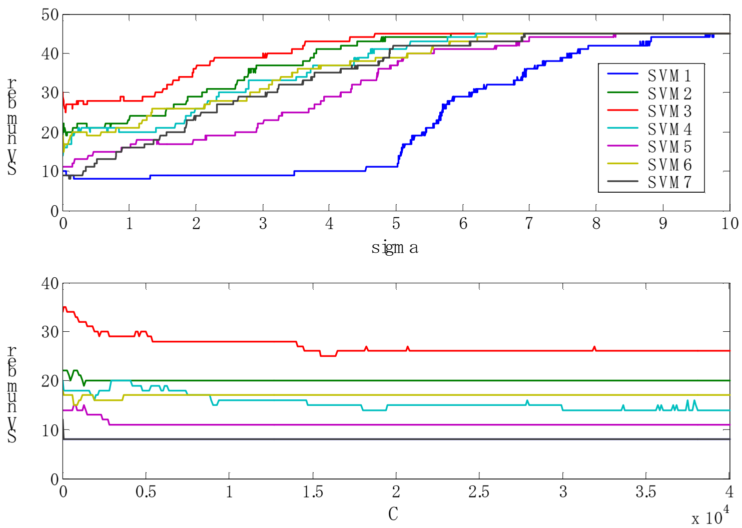

Figure 9. Number of support vectors.

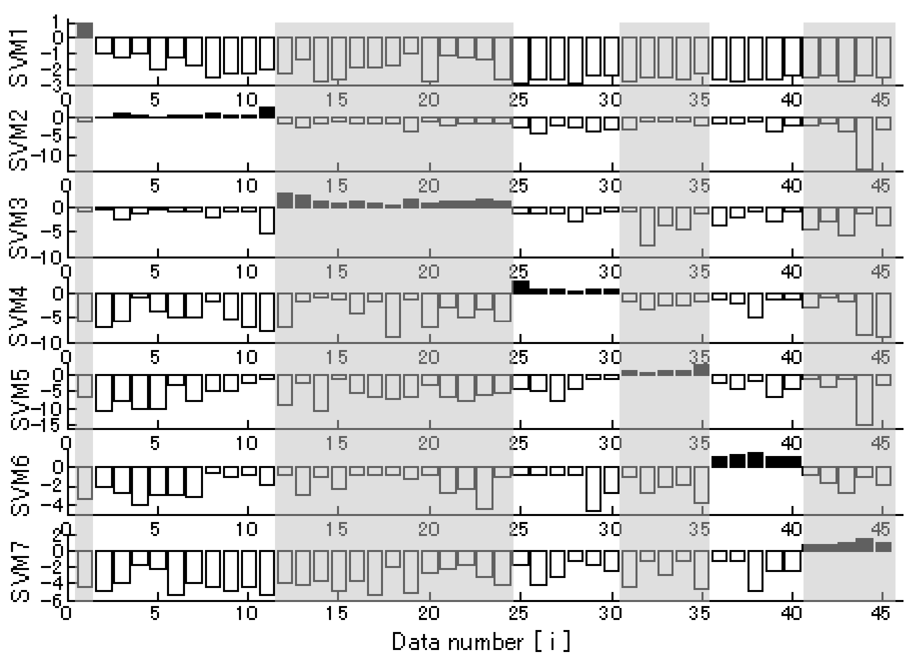

Figure 10. Outputs from 7 SVMs.

CONCLUSIONS

An active diagnosis method using support vector machine (SVM) and impulse responses was proposed. The effectiveness of the method was demonstrated by experiments using an aluminum specimen with bolted joints. The feature vectors needed for pattern recognition were created by calculation of second power average of the amplitude from the sensor signals obtained by PZTs. They were successfully used as the training as well as verification data for SVM. By applying the wavelet transform to time-frequency analysis, the accuracy of pattern recognition was drastically raised. Moreover, each SVM could identify the damage with very strong discernment capability. The accuracy was confirmed excellent and was better than the pattern recognition based on the correlation analysis.

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