Lamb파와SVM을이용한강구조물의건전성감시기법
HealthMonitoringofSteelPlates UsingLambWavesandSupportVectorMachines

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ABSTRACT

This paper presents a non-destructive evaluation (NDE) technique for detecting damages on a jointed steel plate on the basis of the time of flight and wavelet coefficient, obtained from wavelet transforms of Lamb wave signals. Support vector machines (SVMs), which is a tool for pattern classification problems, was applied to the damage estimation. Two kinds of damages were artificially introduced by loosening bolts located in the path of the Lamb waves and those out of the path. The damage cases were used for the establishment of the optimal decision boundaries which divide each damage class's region from the intact class. In this study, the applicability of the SVMs was investigated for the damages in and out of the Lamb wave path. It has been found that the present methods are very efficient in detecting the damages simulated by loose bolts on the jointed steel plate.

1.Introduction

Conventional non-destructive evaluation (NDE) techniques such as ultrasonic testing and X-radiography can provide significant details about the nature of damage. However, those techniques usually require direct access to the structure and involve bulky equipments. Moreover, the techniques usually require disruptions of the operation of the structures/equipments, which is not attractive for on-line structural health monitoring. To overcome those limitations, two PZT-based damage detection strategies have been

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considered: (a) impedance-based method and (b) Lamb wave-based method. For the impedance-based method, a successful application to a steel member has been reported by Park et al. (2004) [1]. The Lamb wave-based approach using a through-transmission method has been utilized by identifying the changes in the transmission velocity and energy of the elastic waves associated with damages [2]. In this study, a robust wavelet transform technique is explored for detecting changes in the dispersive Lamb waves before and after damages on a steel member. More specifically, the time of flight (TOF) and wavelet coefficient (WC) are used for identifying the local damages. In the cases of damages located in the path of Lamb wave (damages in path, DIP), it is observed that the TOF is delayed further and the WC gets reduced more, as damage becomes severer. However, it has been found that damages out of the Lamb wave path (damages out of path, DOP) do not cause significant changes. In order to overcome this limitation and enhance the damage detection capability, probabilistic decision making techniques are employed, where optimal decision boundaries may be determined to divide the damage regions from the undamaged region.

In the present study, support vector machines (SVMs) is employed to estimate structural damages in a steel member simulated by loose bolts. The goal of this study is to develop a comprehensive methodology for on-line monitoring of damages in steel members in civil structures. The results of experiments and signal processing/pattern recognition are presented to substantiate the feasibility of the proposed methodology for on-line health monitoring of structural component.

2.BasicsofLambWaves

Lamb waves refer to elastic perturbations propagating in a solid plate (or layer) with free boundaries, for which displacements occur both in parallel and perpendicular to the direction of wave propagation. (Viktorov, 1967) [3]. This type of wave phenomenon was first described in theory by Horace Lamb in 1917. There are two groups of waves, symmetric and anti-symmetric, that satisfy the wave equation and boundary conditions and propagate independently of each other. A graphical representation of those two groups of waves can be seen in Figure 1. The waves may propagate over distances of several meters along a plate-like structure depending on the material and geometry of the structure. If a set of transmitting and receiving transducers are placed on a structure, the received signal contains information about the integrity along the wave path between two transducers. Therefore, the present method may be used to monitor a path rather than a point, and considerable savings in testing time may be obtained.

Since Lamb waves induce stresses throughout the plate thickness, the entire thickness of the plate can be interrogated. Unfortunately, however, Lamb wave testing gets complicated by the dispersive nature of the Lamb waves. Figure 2 shows the dispersion curves obtained theoretically for the Lamb waves propagating in a steel plate. The diagram shows that many wave components with different group velocities exist at the high frequency range. Therefore, if a structure is excited by a broadband pulse, many wave components with different frequencies will travel at different speeds and the pulse shape will change as it propagates along the plate. So, attempts have been made to limit the bandwidth of the excitation to a low frequency range over which there exist only two fundamental modes (A_0 or S_0). An investigation on the dominance of the fundamental Lamb modes over the proper frequency range for the steel members was reported [4]. In the present study, the only A_0 mode is intentionally utilized and investigated. A propagating wave is reflected and/or partially transmitted, when it encounters a defect or boundary. Then the measured A_0 mode may be compared with the calculated dispersion curves for the intact case, and damage detection can be carried out based on both the attenuation and the time delay of the wave component.

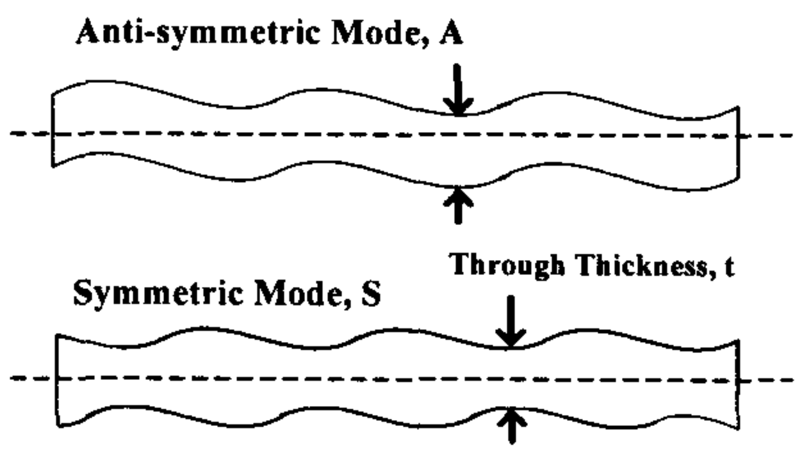


Figure 1. A Mode and S Mode of Lamb Waves

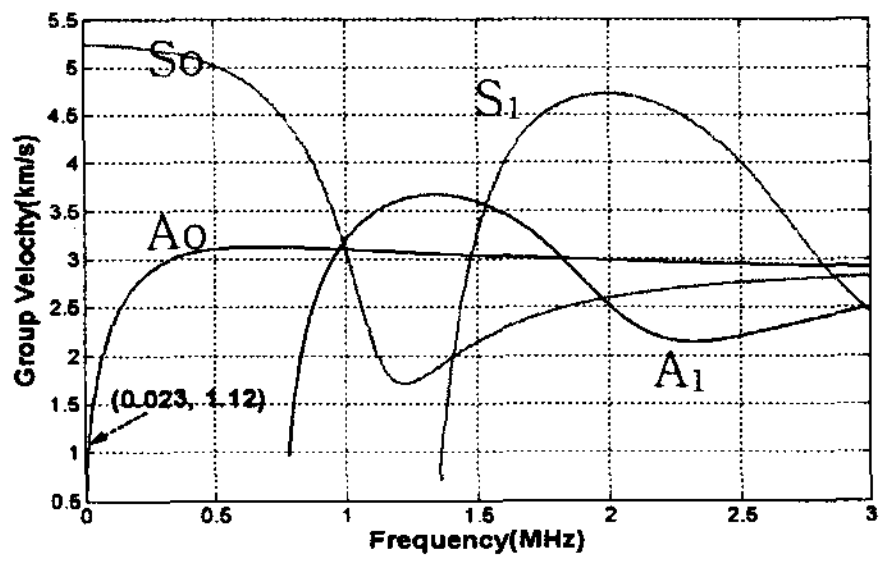


Figure 2. Lamb Wave Dispersion Curves for A Steel Plate (Thickness: 2mm)

3. Pattern Recognition for Online Health Monitoring

3.1 Basics of Pattern Recognition for Structural Damage Detection

The number of sensors required for monitoring a component very much depends on the geometry of the component to be monitored. Monitoring damage in a simple plate may require only a small number of sensors. In a complex structure with thickness changes, holes and notches, however a larger number of sensors may be needed, which may require a multi-sensor architecture with optimum sensor/actuator location, actuator input, sensor output, feature selection and reliable automated signal processing techniques. In excess, such a multi-sensor architecture needs to have a built-in redundancy so that the damage monitoring system may remain operational though one or more sensors may fail. The respective overall chain of processing is summarized in Figure 3.

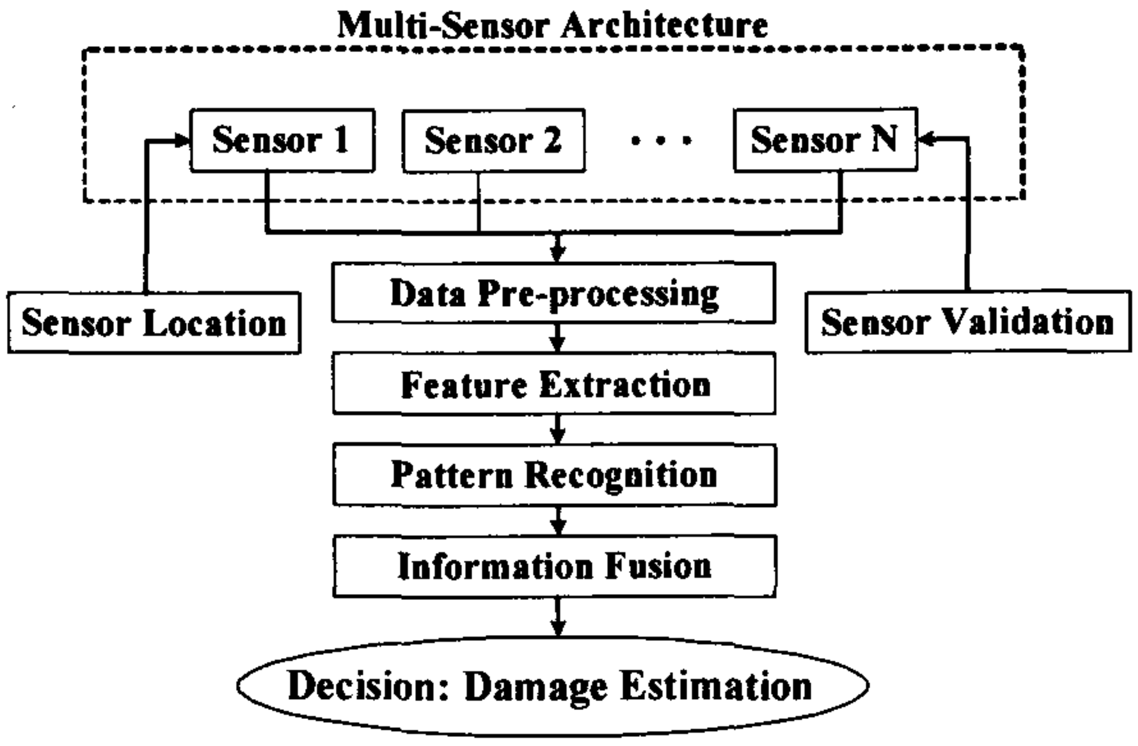


Figure 3. Pattern Recognition for Structural Damage Detection

Data pre-processing forms an important element of the pattern recognition procedures for structural damage detection. It often includes smoothing/de-noising procedures, normalization, trend analysis and reduction of outliers. The level of noise in the data may be reduced by local or global averaging. An alternative approach may be offered by smoothing and de-noising procedures. There exist a number of low-pass filters which can be used to smooth the data. This includes optimal smoothing procedures such as: the Wiener filter based on the Fourier analysis, and Savitzky-Golay, least-squares and digital smoothing polynomial filters. Recently, de-noising procedures based on the orthogonal wavelet transform have been developed [5]. Thresholds or attenuation can be applied to the wavelet coefficients to remove the noise from the data. The other pre-processing procedures are more or less related to removal of unwanted features from the data. Normalization identifies relationships between measurements and features. Trends show unwanted temporal relationships in the data. Outliers are feature patterns which are statistically far from the normal selection of patterns used for training. They can lead to poor generalization of the learning process. Outliers can be eliminated using standard statistical analysis.

Features are any parameters extracted from the measurements through signal processing in order to enhance the damage detection. The choice of features involves a trade-off between the computational feasibility associated with low-level features and extensive pre-processing required for high-level features. Feature extraction includes either signature or advanced signature analysis. Signature analysis employs simple feature extraction methods, based on data reduction procedures, which lead to scalar representations. This includes for example statistical spectral moments, physical parameters of the analyzed system or modal based criteria. Advanced signature analysis uses sets of features in the form of vectors or pattern representations such as: spectra, envelope function or amplitude of the wavelet transform. A number of advanced signature analysis procedures have been developed in the past few years. This includes time-frequency and time-scale methods. Feature selection is a process of choosing input for pattern recognition in order to reduce a number of features for training and therefore to reduce dimensionality of feature space. In this study, for the efficient feature selection, the wavelet transform isutilized as a way of obtaining the both TOF (time of flight) and WC (wavelet coefficient) on the time-frequency plane.

A set of features given by continuous, discrete or discrete-binary variables which are formed in vector or matrix representation is called a pattern. Patterns represent different conditions of an analyzed structure. Therefore damage detection can be regarded as a problem of pattern recognition. Classical methods of pattern recognition use statistical and syntactic approaches. Statistical pattern recognition assigns features to different classes using statistical density functions. Syntactic pattern recognition classifies data according to its structural description. In recent years neural networks have been established as a powerful tool for pattern recognition. A number of different network architectures for pattern recognition include: feed-forward, recurrent and cellular networks. The architecture and process of training a neural network depends on which level of damage identification is required. An unsupervised scheme (Kohonen networks) offers a possibility of novelty detection. Methods of novelty detection based on neural networks and outlier analysis use a description of normality using features representing undamaged conditions and then test for abnormality or novelty. A supervised learning scheme (Multi-Layer Perceptron, Radial Basis Functions) is required for location and severity of damage [6-7]. In the present study, as an example of damage estimation by supervised learning scheme, support vector machines (SVMs) is applied to the detection of damages on a jointed steel specimen.

3.2WaveletTransformforFeatureExtraction

The Fourier transform decomposes a signal into its various frequency components. As it uses the sinusoidal basis functions that are localized in frequency only, it loses the transient feature of signals. Therefore, it is necessary to implement the time-frequency analysis for diagnostics of transient signals induced by the impulse loading. In time-frequency analysis, the short-time Fourier transform calculates the local spectral density using windowing techniques to analyze a small section of the signal at a time. However, it has a higher resolution in the frequency domain but a lower resolution in the time domain. Moreover, it is impossible to simultaneously achieve high resolution in time and frequency. In order to overcome the limitations of harmonic analysis, it has been considered to use alternative families of orthogonal basis functions called wavelets. The continuous wavelet transform (CWT) decomposes a signal into time and frequency domain by the dilatation of a wavelet $\psi(t)$ given in the following equation, where continuous variables a and b are the scale and translation parameters, respectively [8].

$$Wf(b,a) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{a}}\psi^*(\frac{t-b}{a})dt \tag{1}$$

where the asterisk (*) denotes the complex conjugate. In the present study, "Gabor wavelet" is employed as a way of the wavelet transform for the efficient feature extraction.

3.3SupportVectorMachine(SVM)-basedDamageEstimation

The Support Vector Machine (SVM) is a mechanical learning system that uses a hypothesis space of linear functions in a high dimensional feature space (Vapnik et al., 1995) [9]. 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 Figure 4. Assume the training sample S consisting of vectors $\mathbf{x}_i \in R^n$ with $i=1,...,N$, 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:

$$S = ((\mathbf{x}_1, y_1),...,(\mathbf{x}_N, y_N)) \tag{2}$$

$$(\mathbf{w}\cdot\mathbf{x}) + b = 0 \tag{3}$$

where $\mathbf{w}$ and b are arbitrary constants.

However, Equation (3) 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 relaxthe situation, Hard Margin SVM is generalized by introducing non-negative slack variables $\xi = (\xi_1, \xi_2, \ldots, \xi_N)$ as follows:

$$\text{Minimize} \quad \text{Margin } d(\mathbf{w}') = -\frac{1}{2}(\mathbf{w}' \cdot \mathbf{w}') + C\sum \xi_i,$$
$$\text{Subject to} \quad y_i((\mathbf{w}' \cdot \mathbf{x}_i) + b') \geq 1 - \xi_i, \quad i = 1, 2, \ldots, N, \ \xi \geq 0. \tag{4}$$

The purpose of the extra term of the $C\Sigma\xi_i$, 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. A Kernel function that satisfies the Mercer's theorem given in Equation (5) significantly reduces this process. In this study, a radial basis function machine with convolution function given in Equation (6) was used as the kernel function [10].

$$(\mathbf{\Phi}(\mathbf{x}) \cdot \mathbf{\Phi}(\mathbf{x}_i)) = K(\mathbf{x}, \mathbf{x}_i) \tag{5}$$

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

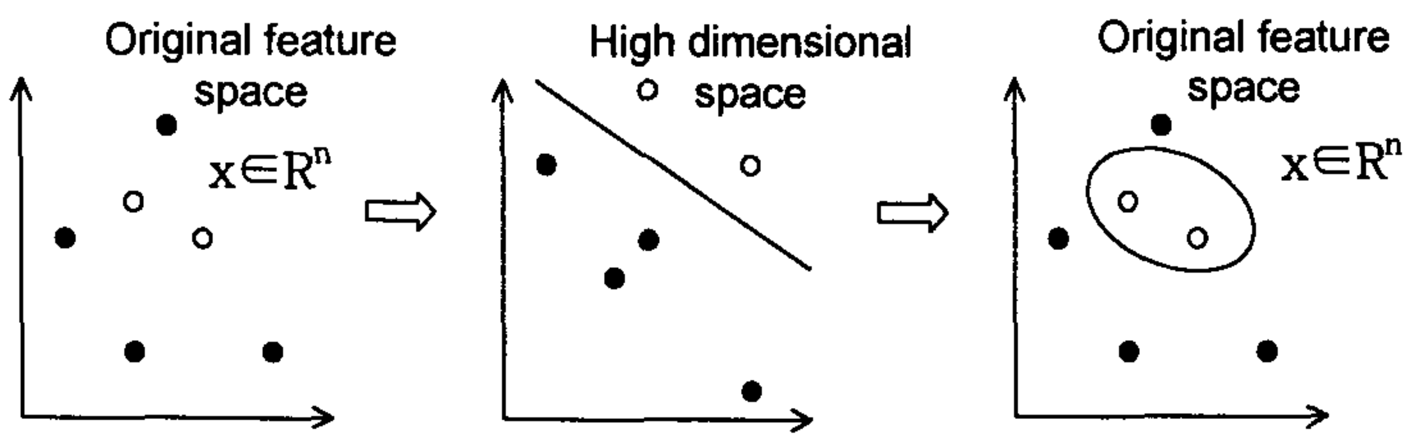


Figure 4. Non-linear SVM

4.ExperimentalStudyfortheVerificationofProposedMethods

The experiments in this study have 2 objectives: (1) to extract the efficient feature vectors from wavelet transform of Lamb wave signals, and (2) to improve the damage detection performance by using the SVMs trained by a set of the feature vectors. An experimental setup and its overall configuration are shown in Figures 5 and 6. The specimen (700x100x2mm) was made of 2 steel plates (400x100x2mm) jointed. Eight steel bolts with 10mm in diameter with washers and nuts were used. Two PZTs were placed at locations 100mm apart from the ends. The distance between two PZTs is 475mm. The dimension of each PZT patch is 35x25x0.2mm. An impulse waveform was applied to PZT 1 serving as a transmitter, and the propagating wave signal was measured at PZT 2 serving as a sensor. The exciting frequency by the PZT patch was found as 23.4 kHz, so that A_0 mode of the Lamb waves may be easily separated from the S_0 mode component as in Figure2. It is noted that the most Lamb waves tend to propagate along with the path (area between two red dotted lines) which depends on the width of the PZT patch as in Figure 6. Therefore, it can be expected that damages out of the Lamb wave path (damages out of path, DOP) do not cause significant changes in the Lamb wave signal compared with the case of damages in the Lamb wave path (damages in path, DIP). Damages were introduced by removing several bolts from the joints. At first, the test was carried out on the intact state of the bolted joints, and then experiments were performed on 8 different damage cases as described in Table 1.

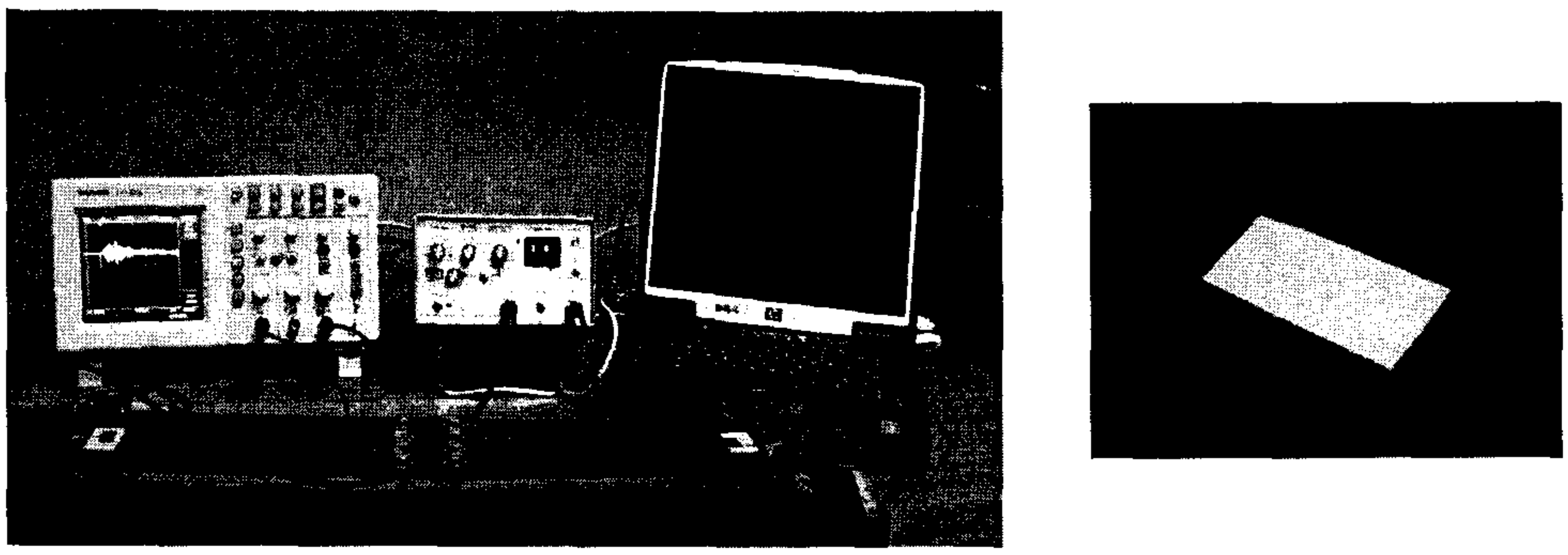
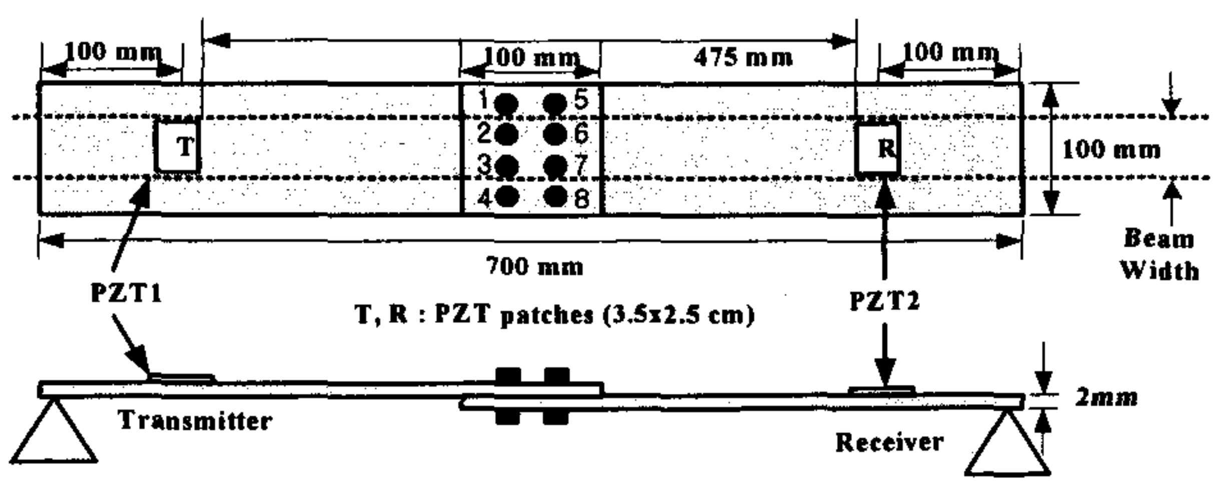


Figure 5. Experimental Setup and PZT patch



1,4,5 and 8: Damages out of Lamb wave path (DOP),

2,3,6 and 7: Damages in Lamb wave path (DIP)

Figure 6. Test Specimen Configuration

Table 1. Damage Scenario

Case 1	#1
Case 2	#2
Case 3	#1 & 4
Case 4	#2 & 3
Case 5	#1,2,3 & 4
Case 6	#1,2,3,4,5 & 8
Case 7	#1,2,3,4,5 & 6
Case 8	#1,2,3,4,5,6 & 7

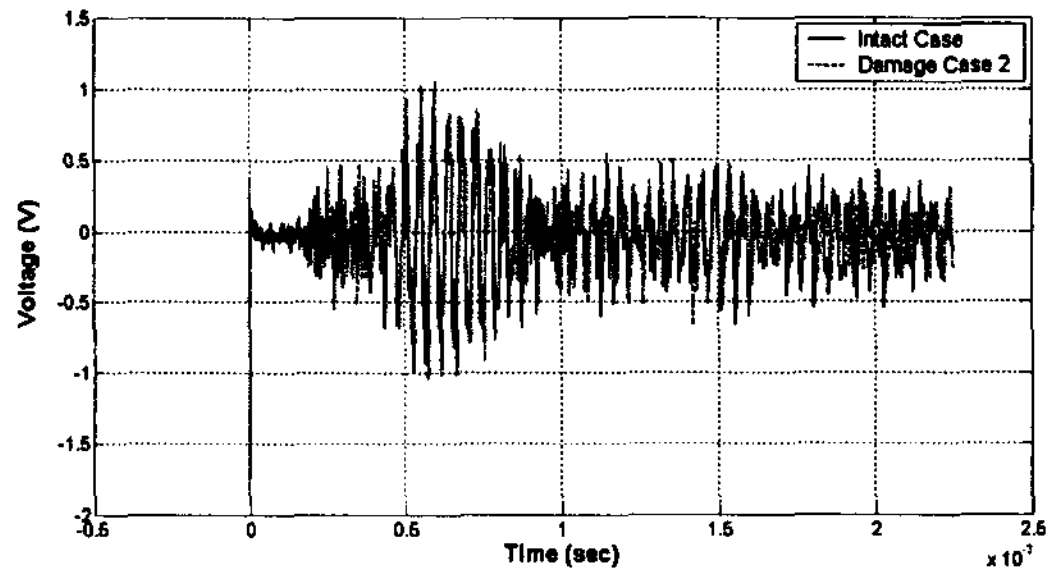
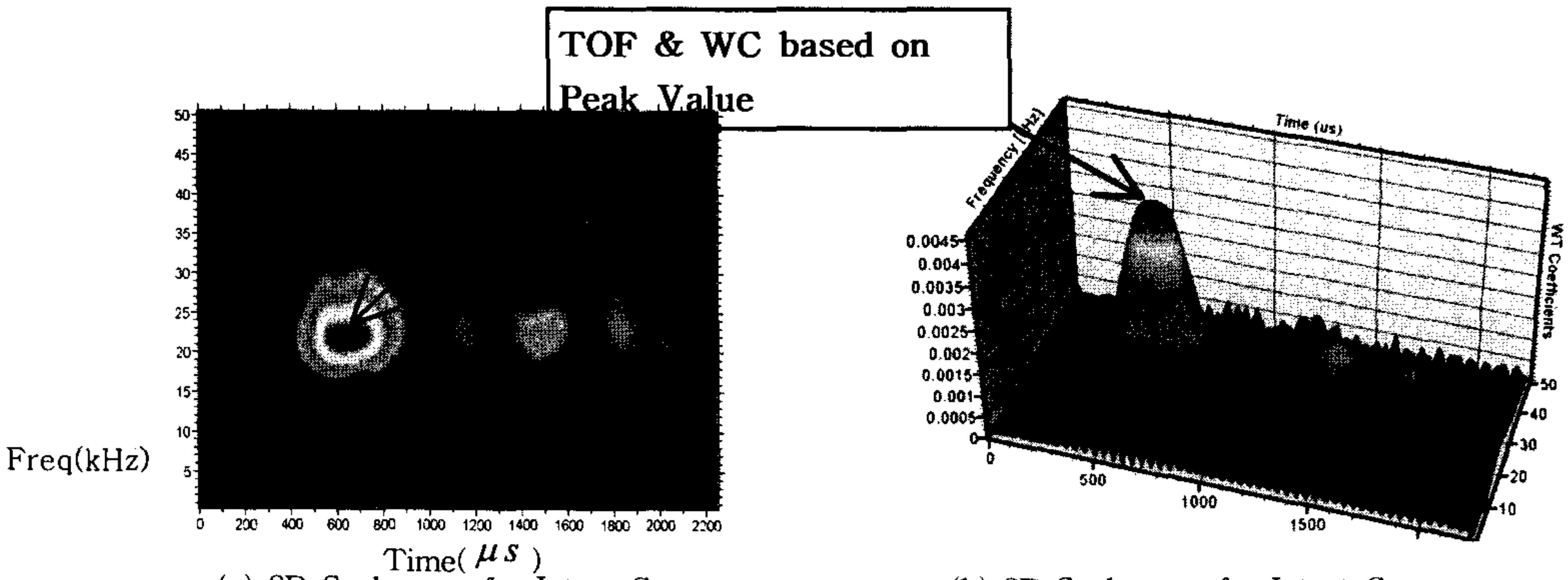
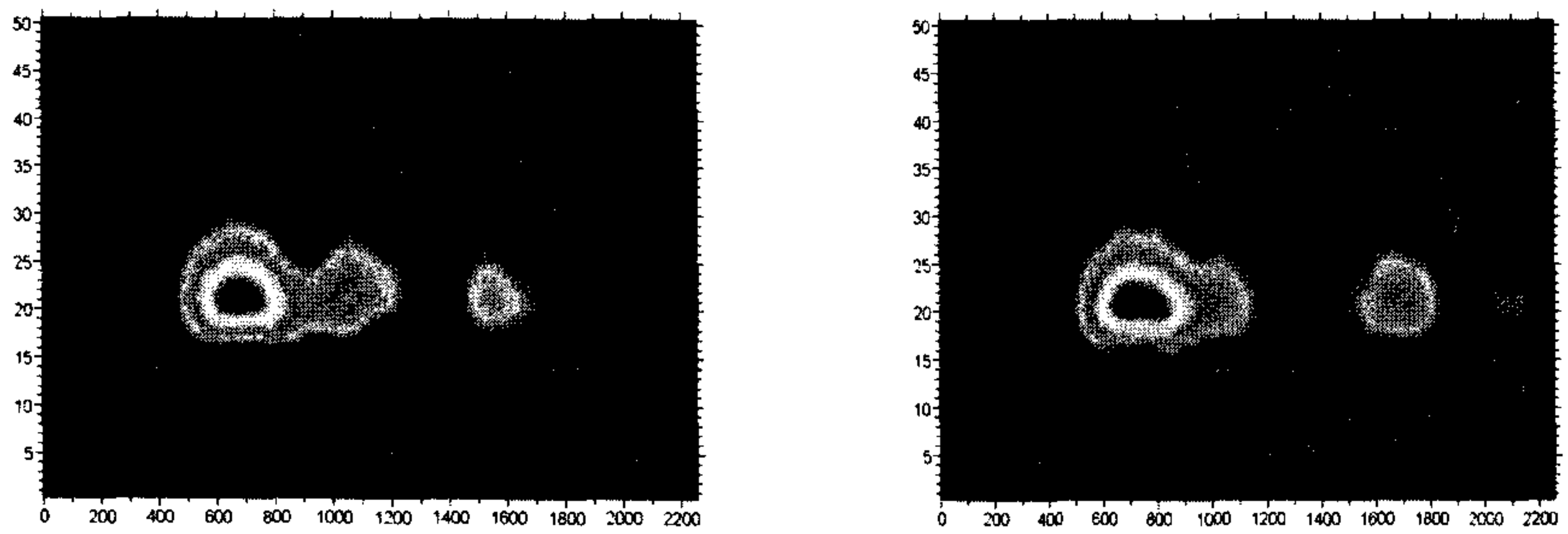


Figure 7. Lamb Wave Signals Obtained at PZT 2



(a) 2D Scalogram for Intact Case (b) 3D Scalogram for Intact Case



(c) 2D Scalogram for Damage Case 4 (d) 2D Scalogram for Damage Case 8

Figure 8. Wavelet Transform Results

Figure 7 shows the examples of Lamb wave signals obtained at PZT 2 from Intact Case and Damage Case 2. It can be observed that the changes in arrival time and other properties due to damages are not clear to be recognized. Therefore, the wavelet transform technique was explored for detecting the changes in the dispersive Lamb waves due to damages. The wavelet transform results for the intact case and two typical damage cases are shown in Figure 8. The TOF and WC were obtained based on peak values, and their results are showed in Table 2. It was obvious that damages in the Lamb wave path (as in Bolts 2, 3, 6 and 7) caused significant changes in TOF and WC, while damages out of the Lamb wave path (as in Bolts 1, 4, 5 and 8) did not.

That is, for the former cases, TOF and WC gave good representation for identifying of localized damages. For the latter cases, however, their variations did not give consistent trend correlating with damages. To improve the damage detection performance for the latter cases, the proposed pattern recognition technique, SVMs was investigated.

Table 2. TOF and WC based on Peak Values from Wavelet Transform

Cases	TOF (μs)	WC	Number of DIP
Intact	640	0.004518	0
Case 1	640	0.004241	0
Case 2	644	0.004170	1
Case 3	642	0.004113	0
Case 4	652	0.003742	2
Case 5	650	0.003906	2
Case 6	648	0.003842	2
Case 7	700	0.003503	3
Case 8	702	0.003374	4

* Note: TOF corresponding to the group velocity of Lamb A0 mode at 23.4 kHz (Figure 2) is 424μs for an intact case of a steel plate of one piece with the same thickness (i.e.: not a bolted case)

4.1SVM-baseddamageclassification

Three damage classes were introduced considering damage locations, as described in Table 3. Totally, 120 patterns to train SVMs were prepared by forty samples with 1 bolt removed from each class. They composed a 2D feature space as shown in Figure 9. From Figure 9, it can be noted that the distinctions of each class's regions are very ambiguous. Therefore, probabilistic decision-making (the establishment of optimal decision boundaries) between three classes were strongly required.

Table 3. Three Classes Considering Damage State

Classes	Descriptions
1	Intact Case
2	Damages out of Lamb wave path (DOP)
3	Damages in Lamb wave path (DIP)

Figure 10 shows three kinds of classifying cases with different combinations of classes, and the optimal decision boundaries for each case were constructed on high dimensional feature space. To verify the capability of the SVM-based classifier, 20 test patterns prepared by ten arbitrary samples with 1 loose (not removed) bolt from Classes 2 (DOP) and 3 (DIP) were used, and the results are showed in Figure 11. It can be founded that the SVM gave very good detection performance for not only DIP (detection rate: 100%) but also DOP (detection rate: 90%).

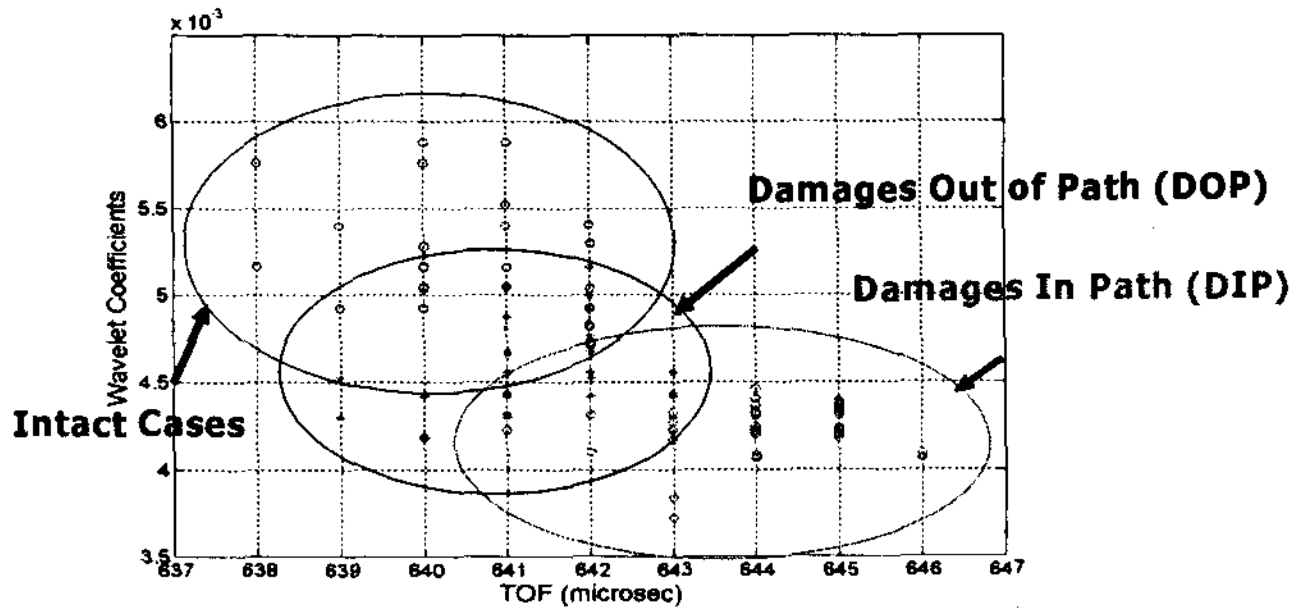
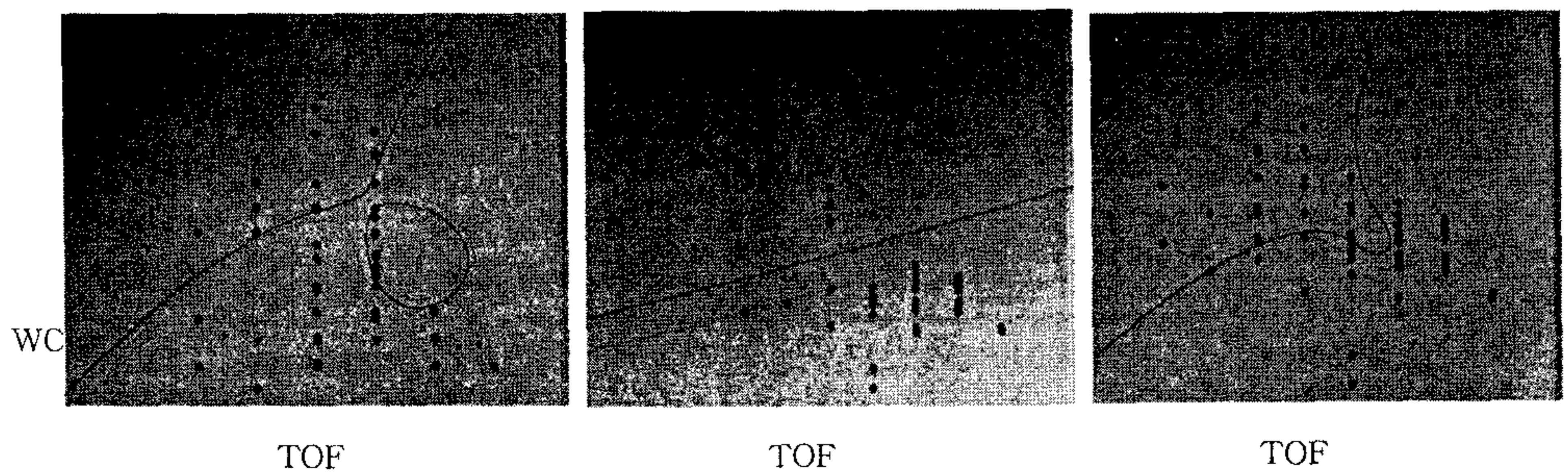
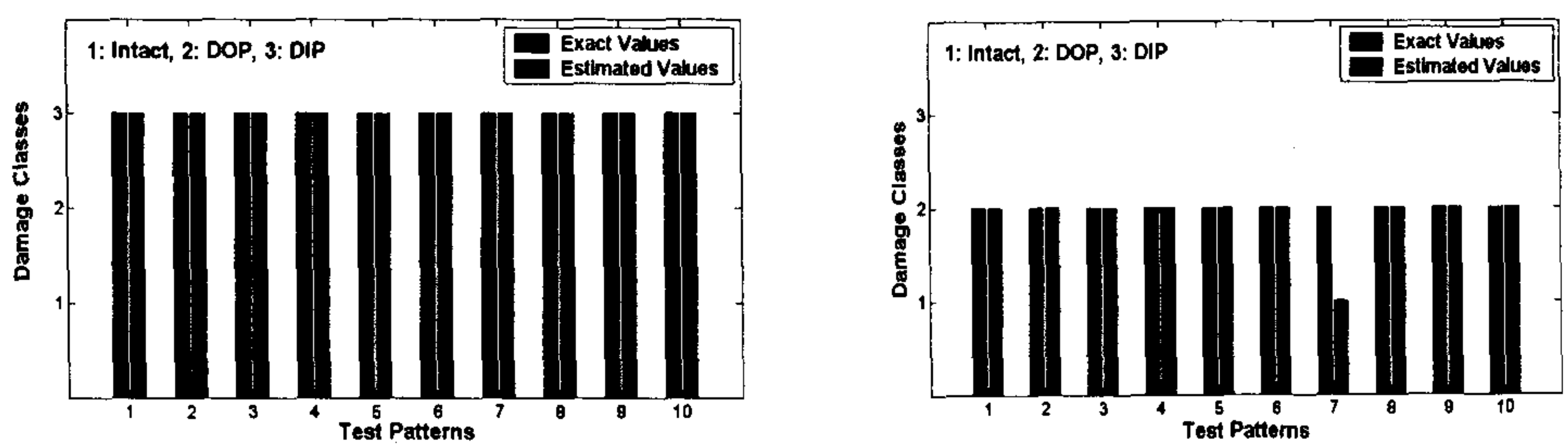


Figure 9. Preliminary Test Results for Training Patterns



(a) Classes 1 & 2 (b) Classes 1 & 3 (c) Classes 2 & 3

Figure 10. Feature Space Divided by SVMs



(a) Performance for DIP (100% Detection Rate) (b) Performance for DOP (90% Detection Rate)

Figure 11. SVM-based Damage Estimation Results

5.Conclusion

In this study, PZT-induced Lamb waves-based methods have been proposed for structural health monitoring (SHM) of steel members of plate-type. The wavelet transform and support vector machines (SVMs) are employed. It was demonstrated through a series of experiments on a steel member that the proposed methods can be viable tools for SHM based on the following: 1) PZT patches are cheap, light, conformal, but require small voltage for actuating, 2) TOF (time of flight) and WC (wavelet coefficient) of the Lamb wave signal can be effectively used as damage features, and 3) SVMs (support vector machines) can give very reasonable results for damage detection.

Acknowledgement

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