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An Automatic Classification Tool for Non-destructive Testing for use in Structural Maintenance

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Abstract: *New non-destructive testing methods based on ultrasonic waves involve analysing a large amount of time series of data to classify the structural state of the system being evaluated. In North America, thousands of civil infrastructures have to be replaced to maintain the networks in good working order. Detecting faulty structures from good ones is a time consuming, error prone, and costly activity. Although, modern acoustic signal based tools are now available for such work, analysing the data automatically using computational tools is an ongoing research. We have designed a decision support system with classification ability for non-destructive testing of materials for defect classification and characterisation. The classification is performed using artificial intelligence (back propagation neural network and adaptive neuro-fuzzy inference system) and statistical techniques (k-nearest neighbor and linear discriminate analysis). The research involves identifying appropriate features for defect characterisation as there are a large number of possibilities. From the classification results, we found that k-NN gave the highest accuracy of 94% in identification of a defect and 81% in determining the size of the defect. The classification results establish the applicability of simplified methods such as k-NN in defect characterisation.*

Keywords: *Non-destructive testing, feature extraction, clustering, classification, neural networks, data mining*

1. Introduction

Rapid application of nondestructive testing (NDT) to detect faults in existing structures and systems has potential to save costs. Infrastructure renewal is a major economic and engineering activity all around the world as most of the systems built in the early 1950's are ready for major renewals. However, in order to be cost effective it is necessary to know what parts of the system need to be renewed or replaced and what parts can stay on for some more years where NDT plays a useful role. NDT was applied to detect faults with learning machines (Benitez et al., 2009), for an early work that uses statistical techniques for clustering (Fukunaga,1990, Dickstein, 1992), and for acoustic signal processing for degradation detection (Fais and Casula, 2010). In these works, the main steps are feature extraction, clustering, and classification. Features define various characteristics of each slice of the time signal, clustering is used to divide the samples into identifiable groups, and classification is used to predict the group of new samples. NDT as a research area is old but what is newly available are developments in features, clustering and classification methods.

In this paper some of these new developments are presented with a comprehensive test case from structural engineering. We have used two artificial intelligence (BPNN, ANFIS) and two statistical techniques (k-NN, LDA) for identifying and classifying defects in a non-destructive manner. Numerical models simulating a half space medium and propagation of surface waves for NDT were constructed using commercial finite element software. Defects of different sizes were introduced into the models and appropriate features from time and frequency domain were extracted. A number of samples was generated by changing the input loading conditions to maintain enough variance in the dataset. A comparison between the performance of various AI and statistical techniques for defect identification and classification are discussed in this work. The following section gives a brief description of the model set-up and features extraction. The third section gives an overview of the classification techniques employed in this work which is followed by the discussion of results and conclusion in the last two sections.

2. Signal and Feature descriptions

Ultrasonic testing is one of the commonly used NDT techniques for the detection, localisation and measurement of defects present in structural materials (Schickert, 2002). The testing is based on the transmission of ultrasonic signals to detect defects or to characterise the materials. The reflected signals from the defects are received by the ultrasonic transducers and are recorded for further processing. Among the ultrasonic waves, the use of surface waves (Rayleigh waves) seems to be more promising as they fulfill many NDT requirements (Graff, 1991).

The objective of the present study is to develop a classification scheme for defect characterisation using ultrasonics in a homogeneous medium. Numerical models to simulate the propagation of Rayleigh waves are developed using a commercial finite element code (LS-DYNA, Hallquist., 1991-1998). The numerical models, after thorough calibration, are more useful than lab testing because of their high accuracy, speed and variety of cases that can be generated (Benitez et al., 2009). The two dimensional numerical model is 250 × 250 mm in dimension with material properties chosen to represent typical values of a sound concrete structure. The geometrical and temporal parameters of the model (overall size, temporal and spatial discretisation parameters, boundary conditions, maximum dynamic time, and frequency content of the sources) are chosen to satisfy consistency, convergence and stability criteria (Zerwer et al., 2002, Vallamsundar et al., 2007).

A general sketch of the 2-D axi-symmetric models is used. Figure 1 shows a homogeneous medium, which is used for calibration purposes; whereas Figure 2 shows a homogeneous media with the presence of a void, where ‘a’ and ‘b’ show the void dimensions and ‘h’ represents the embedment depth of the void. The numerical model developed is calibrated by adjusting the model parameters so that the measured surface responses are matched with the theoretical responses computed by Lamb (1904) for the case of a point-load on the surface of a semi-infinite half space.

To simulate the ultrasonic test in the presence of defects, models are developed by inserting voids with three different sizes in the calibrated model. Dimensions of the voids are chosen based on the effective depth of penetration of Rayleigh waves (Doyle, 1995) which is approximately equal to their wavelength.

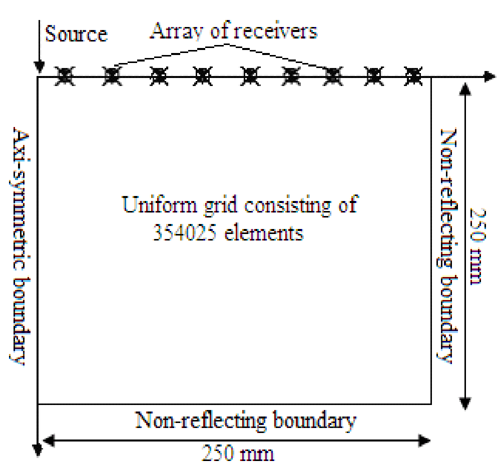

Figure 1. Schematic geometry of the numerical basic models

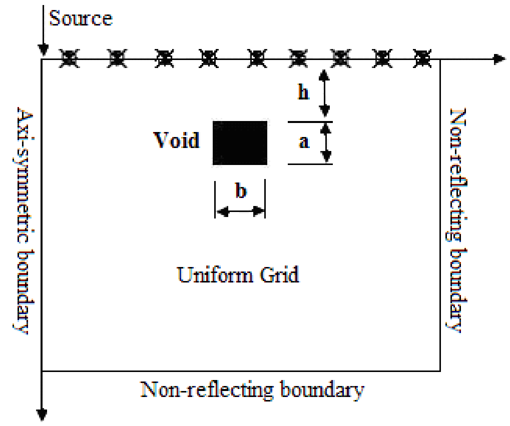

Figure 2. Schematic geometry of the model with a void

The dimensions and location of the voids are listed in Table 1. Surface displacements at 75 different locations are recorded and analysed in time and frequency domains.

Table 1. Dimensions and location of voids

Type of Void	Height (a) in mm	Width (b) in mm
Small	6.3	37.8
Medium	12.6	75.6
Large	25.2	151.2

Figures 4 and 5 show the vertical displacement responses recorded at different distances from the source for the case of no void and a small void, respectively. The oscillations seen at the end of the responses are produced by spatial discretisation and the use of zero material damping (Vallamsundar et al., 2007). From the figures, it can be seen that the pattern of the responses obtained from the no void and the void case is different due to the presence of reflections from the void.

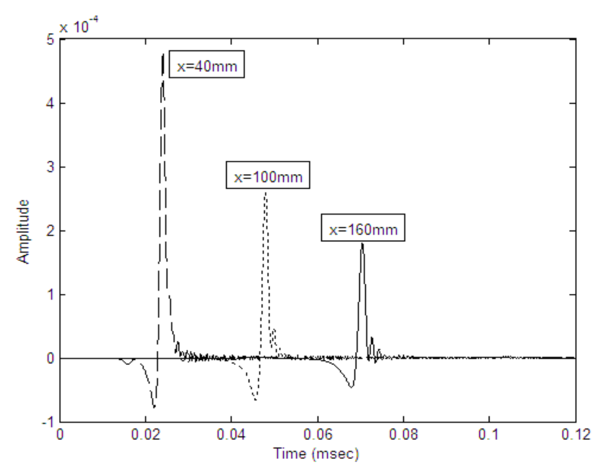

Figure 4. Typical responses recorded: Vertical displacements with no void

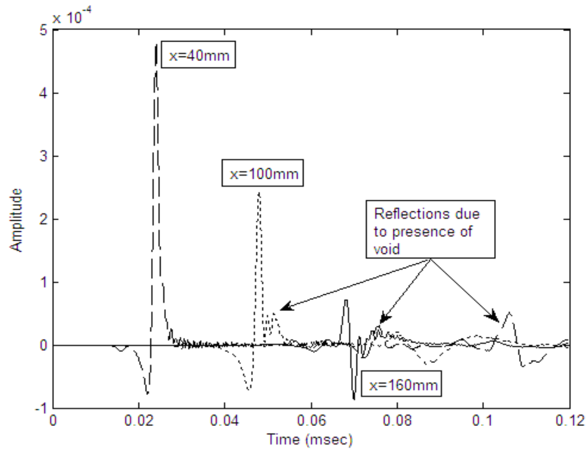

Figure 5. Typical responses recorded: Vertical displacements with a small void

Numerical investigations with the medium and large size void confirm that the dimensions of the void play an important role in the pattern of the responses obtained and these differences are useful in the detection and classification process.

Sufficient number of samples is generated for each of the void case by changing the type of the loading condition. Four different ultrasonic sources are used: Lamb, Ricker, impact and sinusoidal which are some of the commonly used sources to study the surface wave-void interaction (Roësset et al., 1994; Nasseri-Moghaddam et al., 2005). A block diagram showing the process of sample data set generation is presented in Figure 6.

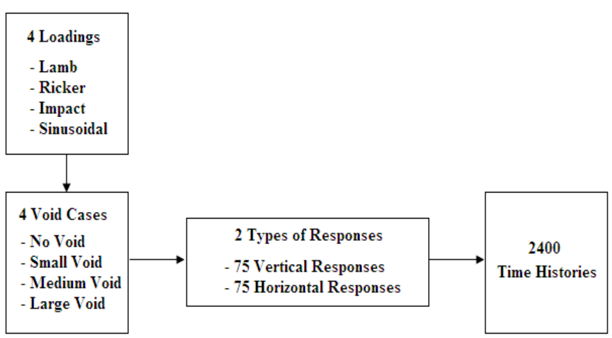

Figure 6. Process of Data Set Generation

2.1 Feature Extraction

A vital step in the design of any signal classification system is the selection of a "good" set of features that are capable of characterising the signals in the feature space. Features are extracted from the surface displacements by applying suitable transformations. The basic domain from which the features are extracted is listed in Table 2.

In Table 3, the features extracted from the various domains are presented. For example, the first set of six features in Table 2 are extracted from time traces of the signals which correspond to the max, min amplitudes, and the four statistical moments, as mentioned in the top six rows of Table 3. The feature space consisting of a total of 37 features extracted from 2,400 samples is subjected to further preprocessing by applying scaling and normalisation. The choice of features needs to fulfill a basic criterion which is preserving all and only the important information contained in the data.

Table 2. Domain of feature vectors

Feature Type	Numbers of Features
Time Traces (T)	6
Derivatives from time traces (DT)	3
Fourier Transformation (FT)	9
Log Discrete Fourier Transforms (LDFT)	6
Wavelet Coefficients (WC)	9
Cepstrum Coefficients (CC)	4

Finding the best features was a difficult task and we came up with the best features based on a trial-and-error process. It is to be noted that this is the first time in the literature that a number of such features have been reported for NDT work. The features that have already been used are the FT based features (Benitez et al., 2009). The development of new and efficient features is a current research area.

3. Classification Methods

Defect characterisation in any application requires partition of the space that contains vector representations (features) of the classes into clusters. Each cluster ideally must contain samples from a single and unique class only. This characterisation can be achieved by either artificial intelligent or statistical techniques or a combination, called fusion.

The basic requirement of any defect characterisation system is to possess a detailed knowledge about the characteristic features of the classes; the next stage is selecting a classification method which involves choosing from one of the two learning paradigms: supervised learning and unsupervised learning.

The supervised approach is a machine learning technique for learning a function from training data; which is used when the original classes are known. Unsupervised classification or clustering is needed when the original class is unknown. Clustering technique is used to cluster the data into two or more clusters such that the prediction accuracy is reasonable which depends on the kind of problem solved and the consequences of false prediction. In this work, the classes are known (no void or void) of the three type of voids mentioned in Table 1. The following supervised classification techniques are adopted in this work.

Table 3. Features extracted in various domains

Feature Number	Domain	Description
1	T	Max amplitude
2	T	Min amplitude
3	T	Mean value
4	T	Standard deviation
5	T	Skewness
6	T	Kurtosis
7	DT	First derivative
8	DT	Second derivative
9	DT	Third derivative
10	FT	Max spectral amp (A_{max})
11	FT	Frequency corresponding to A_{max}
12	FT	Area under spectrum
13	FT	First order moment w.r.t area
14	FT	Second order moment w.r.t area
15	FT	Mean value
16	FT	Standard deviation
17	FT	Skewness
18	FT	Kurtosis
19	LDFT	Max value
20	LDFT	Min value
21	LDFT	Mean value
22	LDFT	Standard deviation
23	LDFT	Skewness
24	LDFT	Kurtosis
25	WC (AC)	Max value
26	WC (AC)	Min value
27	WC (AC)	Mean value
28	WC (AC)	Standard deviation
29	WC (AC)	Skewness
30	WC (AC)	Kurtosis
31	WC (AC)	Coefficient of variation
32	WC (DC)	Mean value
33	WC (DC)	Standard deviation
34	CC	Mean value
35	CC	Standard deviation
36	CC	Skewness
37	CC	Kurtosis

Remarks: AC and DC denote the approximate and detailed wavelet coefficients respectively.

3.1 Artificial Intelligent Techniques (AI)

3.1.1 Backpropagation neural network (BPNN)

BPNN consists of a network of layers comprising of an input layer, output layer and a number of hidden layers. This type of neural network is trained using a process of supervised learning in which the network is presented with a series of matched input and output patterns. The connection strengths or weights of the connections are automatically adjusted to decrease the difference between the actual and desired outputs (Karray and De Silva, 2004).

3.1.2 Adaptive Neuro-fuzzy Inference System (ANFIS)

ANFIS is a combination of neural network and fuzzy system in such a way that neural network learning algorithms are used to tune parameters of the fuzzy system (Karray and De Silva, 2004). Such system makes fuzzy logic control more systematic and less relying on expert knowledge. Because ANFIS cannot manage higher-dimensions in the feature vector, we used principal components analysis (Jolliffe, 2002) to reduce all the original features to a two dimensional feature vector.

3.2 Statistical techniques

3.2.1 Linear discriminate analysis (LDA)

In LDA, the original training data is transformed into a new feature space in which class separability can be carried out more effectively. LDA maximises the ratio of between-class variance to within-class variance (Fukunuga, 1990). After transformation, the Euclidean distance is used to classify data points. In the testing phase, test vectors are transformed; the Euclidean distances between the test vector and the class means are calculated. The test vector is classified as belonging to the class that has the shortest distance.

K-nearest neighbor classifier (k-NN)

The training phase of k-NN consists of storing the feature vectors and class labels of the training samples. During the testing phase, the test sample (unknown sample) is represented as a vector in the feature space. Distances from the test sample to all stored vectors are computed using the Euclidean distance measure. Classification of the test sample is based on the maximum number of neighbors and the sample is assigned the most frequent class amongst its surrounding k-nearest neighbors (Fix and Hodges, 1951).

Sensitivity analysis was performed on the two AI methods in order to select the optimal values for the tunable parameters that give the maximum classification accuracy. The value of these parameters for BPNN and ANFIS is mentioned in Table 4.

4. Results

Three types of classifications are performed where, the Case 1 classification (sound or void), checks if the structure is sound or imperfect with void inside it. Case 2 classification (sound + small or medium + large) is to fine tune the classification process, where, the classifier categorises the structure as either being sound to having a small void or having a medium to large size void. Case 3 classification determines the extent of damage due to the presence of a void, which is done by determining the size of the void present in the structure. The accuracy of the classifiers is defined by the confusion matrix (Kohavi and Provost, 1998) which contains information about actual and predicted classification. The overall accuracy is based on the proportion of the total number

Table 4. Sensitivity analysis for BPNN and ANFIS

Type	BPNN			ANFIS		
	No. of epochs*	No. of hidden layers and neurons	Accuracy (%)	No. of epochs*	No. of membership functions	Accuracy (%)
Case 1	50000	2 hidden layers with 20 and 10 neurons in each layer respectively	92	50	2	47
Case 2	10000	2 hidden layers with 20 and 10 neurons in each layer respectively	78	50	2	44
Case 3	10000	3 hidden layers with 20, 10 and 5 neurons in each layer respectively	56	50	2	26

Remarks: *Epoch refers to a step in the training process of an artificial neural network

of predictions that were correct. The supervised classification techniques are trained with 75% of the total data set and tested with the rest 25%. The testing data are completely different from the training data which were randomly selected. The classification accuracies assessed through the confusion matrix obtained by the different techniques are summarised in Table 5.

The performance of k-NN for all the three classifications proved to be superior when compared with the others. The performance of BPNN and LDA is found to be satisfactory. However the classification accuracies reported by ANFIS are very low, likely because of the severe reduction in dimensionality of the feature set from 37 to 3. The low accuracies obtained for the void size classification are because this classification not only determines the presence but also the size of the void. The robustness of the best classification technique namely, the k-NN classifier is tested by training the classifier with 50% of the data set and testing with the rest of the 50% data as opposed to training with 75% and testing with the rest 25%. Comparison between the results obtained from both these data sets are presented in Table 6. The results are encouraging, as there is not much difference in the accuracies. Further, critical features are identified in order to determine those features which give the maximum classification accuracy in this test problem.

Table 7 gives the overall classification accuracy for different categories of feature vectors using K-NN. Features extracted from the time and frequency domain are found to give the best results although this cannot be assured as a universal result. The reason for the lower accuracies obtained with features extracted from wavelet coefficients are because of the single level wavelet decomposition of the response vector.

Table 5. Overall classification accuracies

Technique		Sound/ Void Accuracy (%)	Sound-Small/ Medium-Large Accuracy (%)	Void Size Accuracy (%)
Soft Computing	Backpropagation neural network	92	78	56
	Adaptive neuro-fuzzy inference system	47	44	26
Statistical	Linear Discriminate Analysis	83	75	52
	k-Nearest Neighbor Classifier	94	88	81

Table 6. Comparison between the classification accuracies (k-NN)

Type	75 % training & 25% testing Accuracy (%)	50% training & 50% testing Accuracy (%)
Case 1	94	91
Case 2	88	84
Case 3	81	73

Table 7. Classification accuracy (%) for individual categories of feature vectors (k-NN)

Type	Time Traces	Derivatives	Fourier Transforms	Log DFT	Wavelet Coefficients	Cepstrum Coefficients
Case 1	**92**	69	**93**	83	90	81
Case 2	**81**	54	**86**	73	83	74
Case 3	**71**	32	**76**	64	69	59

5. Conclusion

A diagnostic system based on supervised learning paradigm is developed for the identification and classification of voids in a homogeneous medium. From the results, it is discovered that the performance of k-NN proved superior when compared with the other techniques. An overall accuracy of 94% and 81% was obtained in identification and determination of the void sizes, respectively.

The obtained classification accuracies are encouraging showing the suitability of the proposed approach in the development of an automatic decision support system for non-destructive testing of materials for defect characterisation. Further assessment of the various classifiers performance establishes the applicability of simplified classification methods such as k-NN in defect characterisation.

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Giovanni Cascante *and his University of Waterloo research teams are working towards innovating techniques to help distinguish the good from the bad -- without manually taking the system apart. Dr. Cascante uses waves detect fracturing, corrosion, and decay in anything from concrete to wood. He has had many interests since earning his B. Sc. Degree in Structural Engineering from the University of Costa Rica, his M.Sc. in Earthquake Engineering from Central University of Venezuela, and his Ph. D in Geotechnical Engineering from the University of Waterloo. Dr. Cascante serves as an associate editor for the Geotechnical Testing Journal (ASTM) and the Journal of Environmental and Engineering Geophysics.*

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