Songklanakarin J. Sci. Technol.
35 (2), 217-225, Mar. - Apr. 2013

SJST SONGKLANAKARIN JOURNAL OF SCIENCE AND TECHNOLOGY
http://www.sjst.psu.ac.th

Original Article

Test system for defect detection in cementitious material with artificial neural network

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Received 20 March 2012; Accepted 31 January 2013

Abstract

This paper introduces a newly developed test system for defect detection, classification of number of defects and identification of defect materials in cement-based products. With the system, the pattern of ultrasonic waves for each case of specimen can be obtained from direct and indirect measurements. The machine learning algorithm called artificial neural network classifier with back-propagation model is employed for classification and verification of the wave patterns obtained from different specimens. By applying the system, the presence or absence of a defect in mortar can be identified. Moreover, the system is applied to identify the number and materials of defects inside the mortar. The methodology is explained and the classification results are discussed. The effectiveness of the developed test system is evaluated. Comparison of the classification results between different input features with different number of training sets is demonstrated. The results show that this technique based on pattern recognition has a potential for practical inspection of concrete structures.

Keywords: ultrasonic waves, ultrasonic pulse velocity, defect detection, neural network, pattern recognition

1. Introduction

In general, concrete structures degrade due to aging and attacks from the environment. Damage of deteriorated structures may occur in many different forms, such as the defects inside the structures. Information about defects, such as the number of defects and types of defects in terms of materials (defect materials) are very important for structural evaluation of the defective structures. This information, however, cannot be obtained by visual inspection (Bungey *et al.*, 1996). The inspection and evaluation can be done without creating any additional damage to structure by non-destructive tests (NDT). There are various NDT techniques for structure inspection such as ultrasonic test, radar test, impact echo method, holography, or X-rays. Some techniques are relatively expensive and environmental-sensitive (Tong, *et al.*, 2006). One of the most extensively employed NDTs for defect detection is the well-known “ultrasonic pulse velocity (UPV) test” which applies ultrasonic waves.

Ultrasonic waves are acoustic waves that have frequencies above 20,000 Hz, which exceeds the limit of human hearing capacity and can be focused into narrow and straight beams (Schickert, *et al.*, 2002). Ultrasonic waves require a medium to propagate. If the ultrasonic waves travel from one medium to another different medium, with different acoustic impedances, they will partially refract if the angle of incidence is not 90 degrees because of the change in propagation velocity, and the rest of the energy will be reflected. For an interface between concrete and air, the ultrasonic waves are almost completely reflected.

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Ultrasonic waves are generally used to inspect structures by an apparatus called the UPV apparatus. The UPV apparatus only measures the travel time that ultrasonic waves need to travel through the medium from a transmitter to a receiver, therefore, only the approximate positions of defects occurred in the structure can be known. In other words, the apparatus cannot give some useful information of received ultrasonic waves such as waveform, nominal frequency, etc. As a result, the interpretation must be done with limited information.

According to the limitations of the UPV apparatus, the developed test system is introduced to inspect concrete structures with higher capability. In the developed test system, the information of ultrasonic wave pattern that travels through different specimens can be obtained so more details of defect can be analyzed. The characteristic of ultrasonic waves can also be classified with a machine learning algorithm.

In many studies, machine learning algorithms are applied in order to automate the system for structure inspection and evaluation. A test system for fault detection in long and not accessible pipelines has been designed based on the guided ultrasonic waves along the pipes while applying the traditional feed-forward artificial neural network models (Cau *et al.*, 2005). There was also another approach to estimate crack size and crack location in a steel plate using ultrasonic signals and artificial neural networks (ANNs) (Sahoo *et al.*, 2008). ANNs have also been applied, based on other NDT techniques, i.e. impact acoustic method, to evaluate the tile-wall bonding integrity (Tong *et al.*, 2006). Moreover, other machine leaning algorithms can be applied with the NDT technique, e.g., the use of a support vector machine classifier to estimate the exposed temperature for fire-damaged concrete (Chen *et al.*, 2008).

Having low computational complexity, flexibility, and being adaptive learning, artificial neural network is a machine learning algorithm that has been extensively used. An artificial neuron network also has greater fault tolerance than a traditional network. A computational neuron can produce a linear or a non-linear answer which allows the network to efficiently acquire knowledge through learning. Therefore, an artificial neural network is considered for use to automate the system by applying the ultrasonic pulse velocity test for this study of structure inspection.

Although, there are various systems that have been designed for application in construction work such as a system that employs NDT techniques (e.g. traditional UPV test, radar test, acoustic emission test, impact echo test), the limitation of these systems is that the result must be interpreted by experienced personal. Judgment is highly dependent on the personal opinion and cannot be easily standardized. The interpretation of an NDT test result also takes considerable time. Aiming to solve these problems, the objectives of this study are to develop a new test system that uses ultrasonic wave patterns and the artificial neural network classifier for detecting defects, classifying the number of defects, and identifying the defect materials. The comparison of the classification results from using different input features with a different number of training sets is demonstrated. The study was conducted under conditions that the location, size, and shape of the defects are predetermined. This study is beneficial and has a potential for practical inspection of concrete structures. A brief description of ANN classifier, the methodology, and the classification results will be discussed in the following sections.

2. Theoretical Basis of ANN

The developed test system is composed of a machine learning algorithm named artificial neural network (ANN) classifier. The patterns of normalized ultrasonic signals were classified and verified by the ANN classifier.

The artificial neural network is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process (Aleksander *et al.*, 1995).

This study employs the back-propagation model, as illustrated in Figure 1, which is a feed-forward multi-layered ANN that allow signals to travel only one way, from input to output. The feed-forward ANN tends to be a straight forward network that relates inputs with outputs. The circles represent neurons. The neurons are arranged in a number of layers (called multi-layered neurons), generally three layers. They are input, middle (hidden) and output layers, respectively (Masnata *et al.*, 1996; Ni Hong-Guang *et al.*, 2000). In this study, the network is trained with many input and hidden nodes. The number of output nodes depends on the data classes i.e. one node was used for binary classification (defect detection) and four nodes were used for four-class classification (classification of number of defect and classification of defect materials).

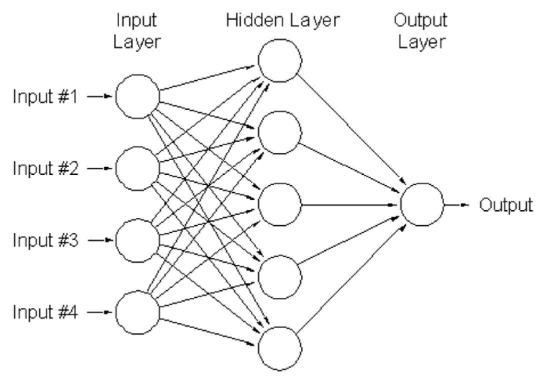


Figure 1. Back-propagated ANN model with several inputs and one output.

3. Experimental Program

In the experimental program, the developed test system with the ANN classifier was applied for detecting defects, classifying the number of defects, and identifying the defect materials in mortar. For the classification of number of defects and identification of defect materials, four types of specimens were used in each test. Direct and indirect measurements were both used to collect the data from each specimen.

3.1 Original test system

The system configuration of the original testing system (commercial UPV system; MATEST C373N) is illustrated in Figure 2. In this system, an ultrasonic pulse velocity with a mean frequency of 55 kHz was used to measure travel time of the medium. Only the travel time of ultrasonic waves from the transmitter to the receiver is obtained. Although the travel time can be used to determine the possible position of the defect, more useful information about defects, e.g. waveform, cannot be obtained. According to the limitations of original test system, the developed test system was then introduced to overcome this problem.

3.2 Developed test system

The system configuration of the developed test system is shown in Figure 3. In this system, an oscilloscope and a computer were added to the UPV apparatus. A Tektronix TDS2012B Oscilloscope was used to measure and record the ultrasonic wave patterns which travel through the medium. 'NI LabVIEW Signal Express Tektronix Edition (Version 2.5.1)' software was used to collect the time arrays and corresponding amplitude arrays. Both time and amplitudes were collected as raw data in two columns. Therefore, the ultrasonic responses in different patterns can be obtained and used to analyze further information about defects in specimens. The developed test system was applied with the artificial neural network classifier to classify the patterns of ultrasonic signals. The ANN with back-propagated model was used in the network training.

3.3 Specimen preparations

In this study, mortar samples with size 150×150×150 mm were tested. Ordinary Portland Cement Type I, water, and sand were combined to produce mortar specimens in the proportion of 539, 269, and 1,482 kg/m^3. The data of ultrasonic responses were collected when the aging of specimen is 28 days while the combinations of specimens were stable.

3.3.1 Defect detection

For defect detection, there were two characters of the cube mortar specimens prepared for two classes of defect detection:

Class I (non-defective class): mortar specimen without a defect, see Figure 4(a), and

Class II (defective class): mortar specimen with the two cylindrical air voids in a diagonal position. Both air voids had the diameter of 25 mm, see Figure 4(b).

3.3.2 Classification of the number of defects

In this part, the developed test system was applied to classify the number of defects in the mortar into four classes as follows:

Class I (non-defective class): a mortar specimen without a defect, Figure 5(a),

Class II (one-defect class): a mortar specimen with one cylindrical air void, Figure 5(b),

Class III (two-defect class): a mortar specimen with two diagonally-positioned cylindrical air voids, Figure 5(c), and

Class IV (three-defect class): a mortar specimen with three cylindrical air voids, Figure 5(d).

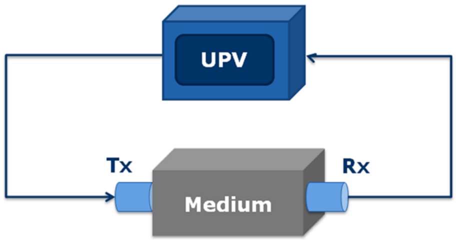


Figure 2. System configuration of original test system.

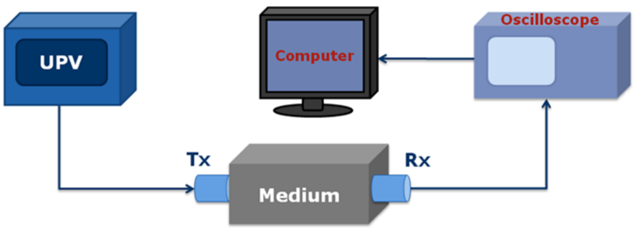
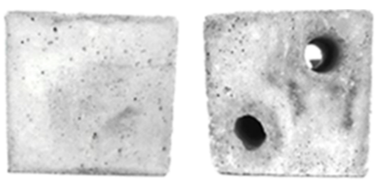


Figure 3. System configuration of developed test system.



(a) (b)

Figure 4. Samples for defect detection: (a) Non-defective specimen, and (b) Defective specimen.

3.3.3 Identification of defect materials

In this part, the developed test system was also applied to identify the material of defects in the mortar into four classes as follows:

Class I (non-defective class): a mortar specimen without a defect, Figure 6(a),

Class II (air void defect class): a mortar specimen with one cylindrical air void, Figure 6(b),

Class III (steel defect class): a mortar specimen with one cylindrical steel rod, Figure 6(c), and

Class IV (wood defect class): a mortar specimen with one cylindrical wood rod, Figure 6(d).

3.4 Test methods and data collections

There are three possible measurement settings in which the transducers of UPV equipment may be arranged on the medium: direct measurement, semi-direct measurement, and indirect (or surface) measurement, Figures 7(a), (b), and (c), respectively. The selection of measurement arrangement depends on different situations. Direct and indirect measurements are most commonly used in practice. Normally, for prism elements, like columns and beams, it is possible to apply direct measurement which is theoretically more preferable. For flat elements, like floor and wall, indirect measurement is normally applied since both direct and semi-direct measurement is practically impossible. Semi-direct measurement is rarely used in real applications. Therefore, direct and indirect measurements were employed to collect data in this study.

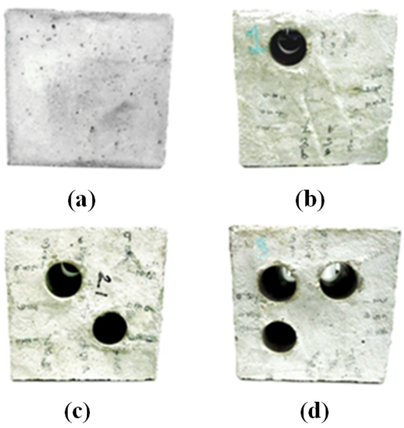


Figure 5. Samples for classification of the number of defects: (a) Non-defective specimen, (b) One defect specimen (c) Two defects specimen, and (d) Three defects specimen.

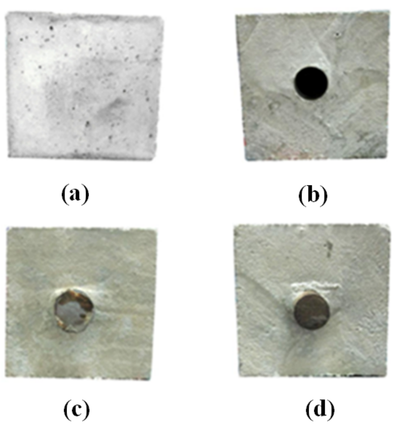


Figure 6. Samples for identification of defect materials: (a) Non-defective specimen, (b) Specimen with air void, (c) Specimen with steel rod, and (d) Specimen with wood rod.

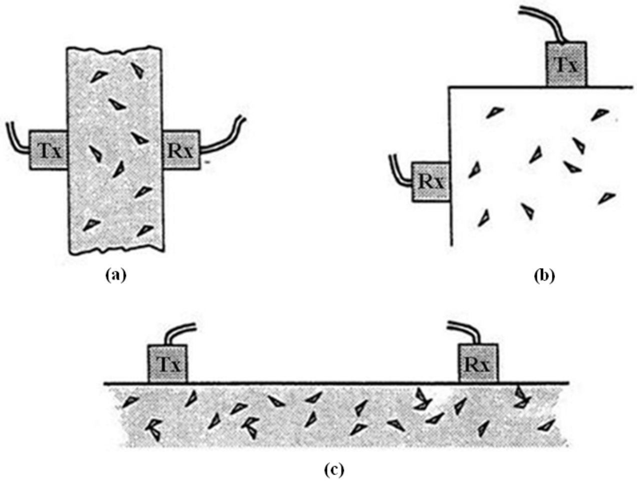


Figure 7. Ultrasonic pulse velocity measurement methods: (a) Direct measurement, (b) Semi-direct measurement, and (c) Indirect measurement.

To collect the data by using direct measurement, the transmitter and receiver probes were pressed and varied on the specimen on the opposite surface, i.e. top-bottom and left-right sides. For using indirect measurement, the transmitter and receiver probes were pressed and varied on the same specimen's surface, i.e. top-top, left-left, and right-right sides. The positions of transmitter and receiver probes were equally varied on the surface many times to collect data thoroughly. By collecting data, the ultrasonic wave patterns in the time domain were obtained.

4. Classification Via ANN Classifier

4.1 System framework for classification

After collecting data on each specimen using direct and indirect measurements, the ultrasonic waves in time domain with 2,500 data points sampled at 1,000 kHz were obtained from different positions. The block diagram of signal processing part in the system is shown in Figure 8. The pre-processing was performed on the obtained ultrasonic waves. Noise occurs in the earlier component of the wave before the considered wave starts. The unwanted components which occur in the earlier part of the time responses were then removed because they are not a part of the ultrasonic response. The threshold was set to select the starting point

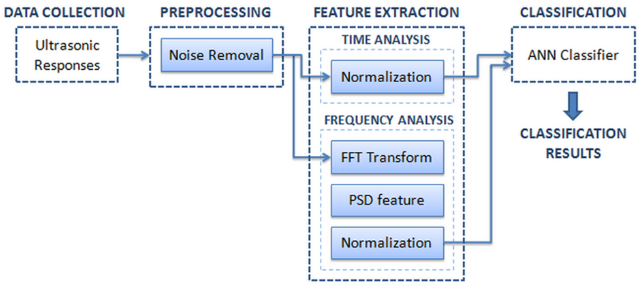


Figure 8. Block diagram of the signal processing part for classification.

of the signal and to remove the unwanted part. When the peak value is higher than three times the accumulated average value, the signal at this point was selected as the starting point. Finally, the 1,000 data points were considered as shown in Figure 9. After that, the ultrasonic responses were extracted in both time and frequency domains. In the time domain, the ultrasonic signal was normalized in order to make adjustment for the effect of pressure on the probe during the measurement. To extract the frequency domain feature, the power spectral density (PSD) of the signal was calculated from Fast Fourier Transform (FFT) with the time domain response (Rao *et al.*, 2010), and the signal was also normalized. Fast Fourier Transform is an algorithm that allows the Discrete Fourier Transform (DFT) of a sampled signal to be obtained rapidly and efficiently. The PSD describes how the power of a time series is distributed with frequency. An equivalent definition of PSD is the square modulus of the Fourier Transform of the time series, scaled by a proper constant term or size of data (N).

These collected ultrasonic waves using direct and indirect measurements were extracted in time and frequency features and individually used as the input of the ANN classifier. In other words, there are four individual input features

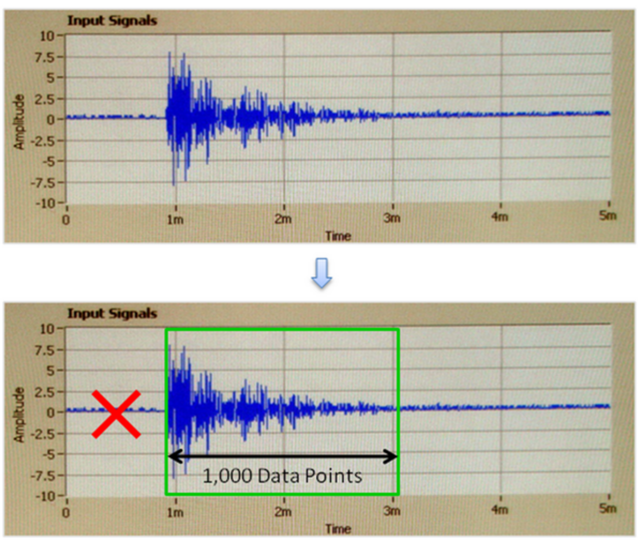


Figure 9. Preprocessing: Noise removal of obtained ultrasonic waves.

that were considered in this study: the signals that are collected by direct measurement and extracted in the time domain; the signals that are collected by direct measurement and extracted in the frequency domain feature; the signals that are collected by indirect measurement and extracted in the time domain feature; the signals that are collected by indirect measurement and extracted in the frequency domain feature. Examples of input signals of each feature are demonstrated in the following section.

4.2 Examples of input signals

This section demonstrates the examples of input features that are obtained from the specimens for each work task describing in Section 3.3. In each task, the obtained signals that are extracted in four different methods as mentioned in Section 4.1 are shown. Since the data were collected with varying the position of transmitter and receiver probes as mentioned in Section 3.4, example signals that are shown below are selected from randomly position of the probes.

Note that the position of defects embedded in the structure in real work side are not predetermined and cannot be exactly located by visual observation, so, the positions of transmitter and receiver probes were varied to collect data in many positions during the experiment. When the positions of transducers were varied, it equates to the positions of embedded defects were also varied. Thus, this experiment focused on detecting the defects, the number of defects, and defect materials without varying the position of defects.

4.2.1 Defect detection

For the direct measurement, examples of normalized signals in the time domain and the frequency domain for case I samples (non-defective case) and case II samples (defective case) are illustrated in Figure 10(a) and 10(b), respectively.

For the indirect measurement, examples of normalized signals in the time domain and the frequency domain for case I samples and case II samples are illustrated in Figure 11(a) and 11(b), respectively.

For both time and frequency domains, there are 1,000 data points as the input features. Since the whole signal is symmetric in normalized PSD signal in the frequency domain, only 500 data points are shown in the figures.

4.2.2 Classification of the number of defects

For the direct measurement, examples of normalized signals in the time domain and the frequency domain for case I samples (non-defective case), case II samples (one defective case), case III samples (two defective case), and case IV samples (three defective case), are illustrated in Figure 12.

For the indirect measurement, examples of normalized signals in the time domain and the frequency domain for case I, case II, case III, and case IV samples, are illustrated in Figure 13.

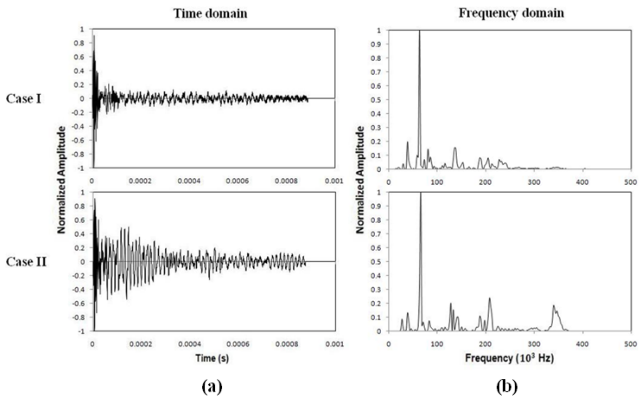


Figure 10. Normalized signals from direct measurement for defect detection: (a) Time domain signals, and (b) Frequency domain signals.

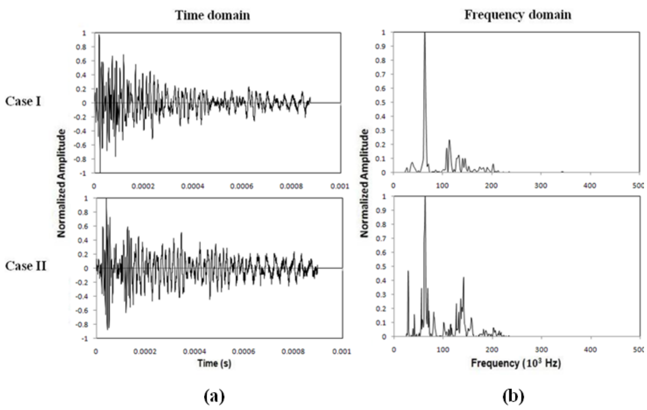


Figure 11. Normalized signals from indirect measurement for defect detection: (a) Time domain signals, and (b) Frequency domain signals.

4.2.3 Identification of defect materials

For the direct measurement, examples of normalized signals in the time domain and the frequency domain for case I (non-defective case), case II (air void defect case), case III (steel defect case), and case IV samples (wood defect case), are illustrated in Figure 14.

For the indirect measurement, examples of normalized signals in the time domain and the frequency domain for the case I, case II, case III, and case IV samples, are illustrated in Figure 15.

4.3 Proposed ANN architecture and parameter setting

This study employs the three-layer back-propagation ANN as described in Section 2. The output node depends on the classes of specimen preparation in Section 3.3. There are inputs, hidden (middle), and targets (outputs) layers. There can be various nodes assigned to be inputs, hidden, and outputs. This section explains the selection of the ANN's

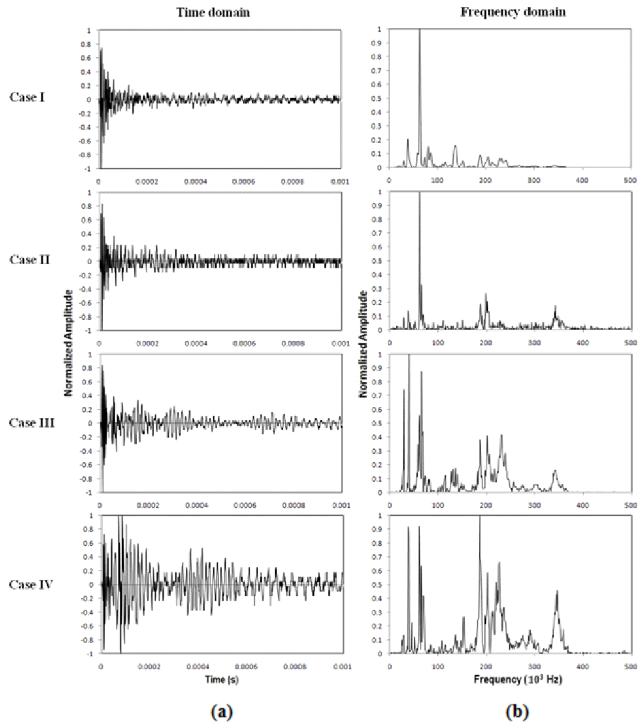


Figure 12. Normalized signals from direct measurement for classification of the number of defects: (a) Time domain signals, and (b) Frequency domain signals.

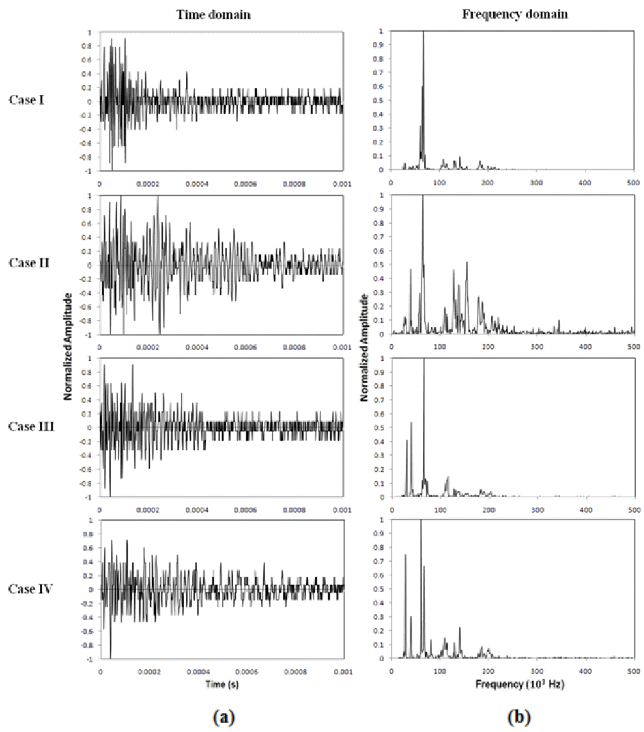


Figure 13. Normalized signals from indirect measurement for classification of the number of defects: (a) Time domain signals, and (b) Frequency domain signals.

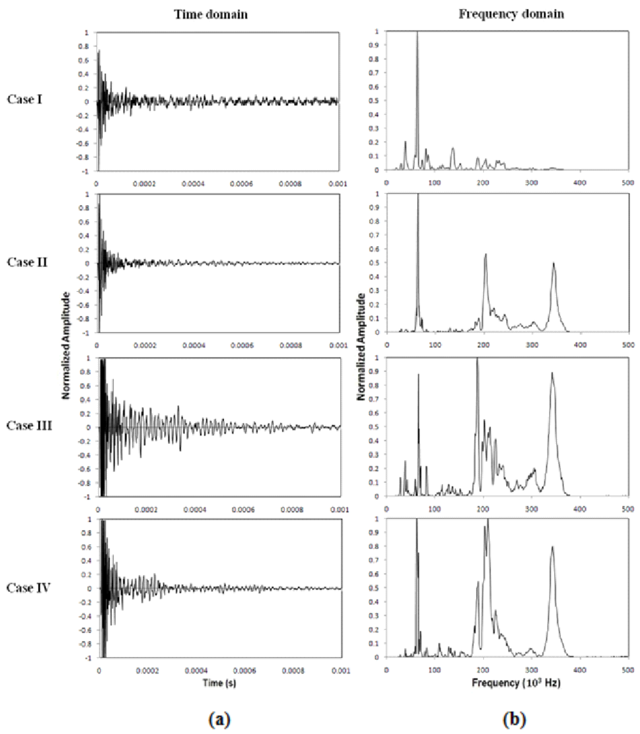


Figure 14. Normalized signals from direct measurement for identification of defect materials: (a) Time domain signals, and (b) Frequency domain signals.

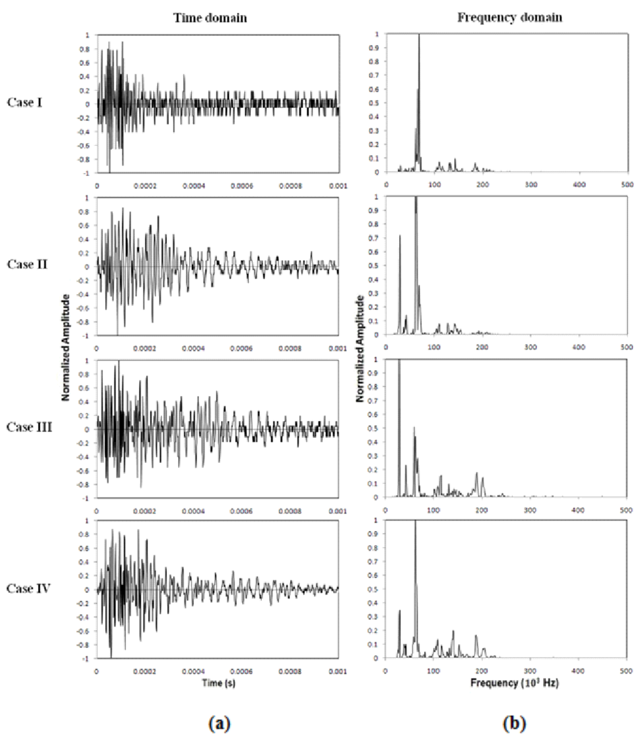


Figure 15. Normalized signals from indirect measurement for identification of defect materials: (a) Time domain signals, and (b) Frequency domain signals.

input, hidden, target, and parameter setting for the network training.

For defect detection (2 classes), there were 200 total normalized signals (samples) with 1,000 data points used as the input of the ANN while 100 samples were obtained from each case of specimen. The output from ANN can be either 0 or 1, which represents the non-defective or defective case, respectively. Fifty hidden neurons were selected.

For classification of the number of defects (4 classes), there were totally 400 samples with 1,000 data points used as the input of the ANN while 100 samples were obtained from each case of specimen. The ANN's targets were set to be either [1 0 0 0]', [0 1 0 0]', [0 0 1 0]' or [0 0 0 1]' which represents the mortar in case I through case IV, respectively. One hundred hidden neurons were used.

For identification of defect materials (4 classes), the setting of input, hidden, and target were similar to the classification of the number of defects.

Pattern recognition of the defects can be simulated and analyzed by applying the "nprtool" command which is the Neural Network Toolbox in 'MATLAB' software. The training parameter is set to be 70% of total input samples. These are presented to the network during training, and the network is adjusted according to its error. The validation parameter is 15%. This is used to measure network generalization, and to halt training when generalization stops improving. The testing parameter is 15%. This has no effect on training and provides an independent measure of network performance during and after training. Therefore, for the defect detection, 200 input samples can be assigned to be 140 training samples, 30 validation samples, and 30 test samples. For classification of the number of defects and identification of defect materials, 400 input samples consist of 280 training samples, 60 validation samples, and 60 testing samples.

In addition, the training sets were increased to be 90% of total input samples. The validation and test samples were both 5%. Therefore, for defect detection, 200 input samples can be assigned to be 180 training samples, 10 validation samples, and 10 test samples. For classification of the number of defects and identification of defect materials, 400 input samples consist of 360 training samples, 20 validation samples, and 20 testing samples. The proposed input, training and testing samples are summarized in Table 1.

To train the ANN classifier for each work task (defect detection, classification of the number of defects, identification of defect materials), different input feature types (mentioned in Section 4.1) were used as the inputs of the classifier, individually. After the network training, the classification results can be analyzed by the obtained confusion matrices.

4.4 Classification results

After the training process, the trained classifier was evaluated by test samples. The mean classification results used different number of training sets obtained from the ANN

Table 1. Input, training, and testing samples

Classification works	Input Samples	Number of training and testing samples	
		70% and 30%	90% and 10%
Defect detection(2 classes)	200	140 and 60	180 and 20
Classification of number of defects(4 classes)	400	280 and 120	360 and 40
Identification of defect materials(4 classes)	400	280 and 120	360 and 40

Table 2. Classification results obtained from ANN classifier.

Work	Number of training samples	Average accuracy (%)			
		Direct measurement		Indirect measurement	
		Time	Frequency	Time	Frequency
Defect detection	140 samples	88.30	97.44	84.85	97.25
	180 samples	92.00	98.95	88.05	98.00
Classification of the number of defects	280 samples	82.88	91.59	49.53	86.90
	360 samples	85.24	92.00	55.15	88.33
Identification of defect materials	280 samples	86.93	93.32	50.13	78.20
	360 samples	88.10	94.05	59.00	87.25

classifier of defect detection (2 classes), classification of the number of defects (4 classes), and identification of defect materials (4 classes) in Table 2. Each value in Table 2 shows the average accuracy of 10 classifications which are obtained from the test results in confusion matrices. The data that was collected and extracted in different ways were used as the input, separately: data was collected by direct measurement and extracted in the time domain, data was collected by direct measurement and extracted in the frequency domain, data was collected by indirect measurement and extracted in the time domain, and data was collected by indirect measurement and extracted in the frequency domain.

ccording to the first row of Table 2, defect detection, the values show the average classification accuracy between 2 classes (non-defective and defective classes). When using a small number of training sets (140 samples), the 2-class classification was 88.30% when using the data which was collected by direct measurement and extracted in the time domain. The result was 97.44% when using the data which was collected by direct measurement and extracted in the frequency domain. It was 84.85% when using the data which was collected by indirect measurement and extracted in the time domain. It was 97.25% when using the data collected by indirect measurement and extracted in the frequency domain. When the number of training sets increased to 180 samples, the average accuracies were slightly increased to be 92.00%, 98.95%, 88.05%, and 98.00%, respectively.

The second row of Table 2 shows the results of classification of the number of defects. The values show the average classification accuracies between 4 classes (non-defective, one-defect, two-defect, and three-defect classes). The classification accuracies when using a small number of training sets (280 samples) from the different types of input features were 82.88%, 91.59%, 49.53%, and 86.90%, respectively. When the number of training sets increased to 360 samples, the average accuracies were also increased to 85.24%, 92.00%, 55.15%, and 88.33%, respectively.

For the last row of Table 2, identification of defect materials, the values also show the average classification accuracies between 4 classes (non-defective, air void defect, steel defect, and wood defect classes). The classification accuracies with 280 training samples, using different input features were 86.93%, 93.32%, 50.13%, and 78.20%, respectively. When the number of training sets increased to 360 samples, the average accuracies also slightly increased to 88.10%, 94.05%, 59.00%, and 87.25%, respectively.

According to the classification results, the ANN classifier can give satisfactory results to classify the different signal patterns from different specimen's characteristics. In this study, the ANN classifier can better classify with an increased number of training sets to be 90% of number of inputs. Using the input data that are collected and extracted in a different manner can give different classification results. Classification results by extracting in the frequency domain are higher than the time domain in all cases. Because of the reflection of ultrasonic waves in the structure can easily change in the frequency response, the different wave patterns in the frequency domain of the different specimens can be well classified (Oosawa *et al.*, 1996; Drinkwater *et al.*, 1997). Moreover, when the frequency domain is used, the results from using direct and indirect measurements are both satisfactory, especially using direct measurement, with different extents of accuracy for each classification case in this work; i.e., defect detection, classification of the number of defects, and identification of defect materials. The results of classification of the number of defects and identification of defect materials (multi-class classification) were slightly less than results from the defect detection (binary classification) due to the difficulty of multiple classifications.

The experiment was performed with an average stable ultrasonic frequency of 55 kHz. The frequency cannot be changed due to the limitation of the ultrasonic pulse velocity apparatus which is normally used in practice. In this study of the structure inspection with the developed test system, the classification results show that the ANN classifier can give satisfactory performance. The capability of the system will be proved and developed to apply to practice inspections.

5. Conclusions and Outlook

The new developed test system, implemented by applying the ultrasonic pulse velocity test with an artificial neural network, gives good recognition of defects and good classification of the number of defects, as well as the identification of defect materials. According to the classification results, a larger number of training sets can give better classification. Using different input features can give different classification results. Employing frequency domain signals as the ANN's input give higher accuracy and better reliability in classification. When frequency domain signals are used, using both direct and indirect measurement can give better accuracy than using time domain, especially for the data collected from direct measurement.

In future study, the system can be improved to analyze defects in more combinations, e.g., the system can firstly detect defects inside a structure and then continually identify the number of defects or defect materials for the same specimen. The system will be able to use other machine learning algorithms, such as a support vector machine classifier. This system can be developed by applying NI data acquisition with the GUI programming of LabVIEW software in order to make a portable system with real time classification (Wongsuwan *et al.,* undated).

In summary, by applying the proposed machine learning algorithm based on pattern recognition, the results show that this system has a potential for practical inspection of concrete structure in the future.

Acknowledgements

The authors thank the School of Information, Computer, and Communication Technology (ICT) of SIIT and the National Metals and Materials Technology Center (MTEC) for supporting this study. This study is also supported by the National Research University Project of Thailand Office of Higher Education Commission. We thank P. Saranrom for assistance in completing this project successfully. We also thank P. V. Neilson for correcting the manuscript.

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