DEVELOPMENT OF AN INTELLIGENT ULTRASONIC EVALUATION SYSTEM WITH A MULTI-AXIS PORTABLE SCANNER

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Abstract

Flaw classification and sizing are very essential issues in quantitative ultrasonic nondestructive evaluation of various materials and structures including weldments. For performing of these tasks in an automated fashion, we are developing an intelligent ultrasonic evaluation system with a multi-axis portable scanner which can do consistent and efficient acquisition and processing of ultrasonic flaw signals. Here we present our efforts to develop of this intelligent system including design of the portable scanner, acquisition and processing of ultrasonic flaw signals, display of pseudo 3-D image of flaws, and classification and sizing of flaws in weldments.

Key Words : Ultrasonic Flaw Characterization, Intelligent Ultrasonic Evaluation System(IUES), Multi-axis Portable Scanner

INTRODUCTION

All kinds of engineering materials and structures, especially weldments, have flaws, some of which can cause catastropic failures. In modern high performance engineering applications, the structural integrity are quite often evaluated using fracture mechanics. This evaluation in turn requires information on the flaw geometry (location, type, shape, size and orientation). The ultrasonic nondestructive evaluation (NDE) method is one of the widely used techniques that can provide information on the flaw geometry. The ultrasonic flaw characterization in the ultrasonic NDE usually involves three steps; flaw detection (identification of flaw signals in ultrasonic responses), flaw classification (determination of the flaw type) and flaw sizing (prediction of the flaw shape, orientation and size parameters). In conventional ultrasonic NDE, this flaw characterization is usually done by a human operator based on his/her own experiences. So the result is highly operator dependent and often do not work well in practice. Thus, an automated system will be desired for the reliable flaw characterization. In this paper, we present our efforts to develop a new intelligent ultrasonic evaluation system (IUES) with a multi-axis portable scanner which can perform flaw characterization automatically when a human operator moves the portable scanner over the flawed area[1].

INTELLIGENT ULTRASONIC EVALUATION SYSTEM

As shown in Fig.1, the IUES is composed of three parts; 1) a multi-axis portable scanner, 2) an ultrasonic pulser/receiver (or a portable ultrasonic flaw detector), and 3) a control computer. When an operator moves manually the ultrasonic transducer around the flaw, the position of the transducer is monitored by rotary encoders which are mounted on each axis of the portable scanner and the information of this position is sent to the control computer (usually PC) through counter boards and a digital I/O board installed in the computer. At the same time, the ultrasonic signal from the flaw is captured by the ultrasonic receiver, and then is sent to the computer through an A/D board installed in the computer. Then based on these data, the geometric information on the flaw can be determined by a software named "Intelligent ultrasonic flaw analyzer (IUFA) " which is developed in this work. The IUFA can 1) display A-Scan waveforms of ultrasonic flaw signals on the screen, and 2) extract the various features from the waveforms for flaw classification and sizing, and 3) perform flaw classification using various classifier including neural network classifiers[2,3] and 4) finally perform flaw sizing[4].

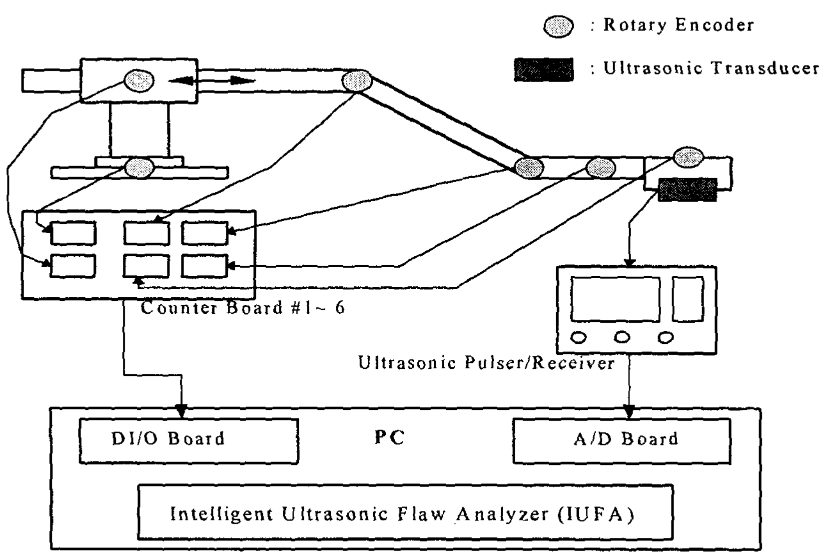


Fig. 1. Schematic diagram of the intelligent ultrasonic evaluation system

MULTI-AXIS PORTABLE SCANNER

Fig. 2 shows the multi-axis portable scanner body developed in this work. This portable scanner has 6 axes; 5 rotating axes and 1 sliding axis. The first 3 axes allow the portable scanner to move to an arbitrary point in the 3 dimensional space. And the next two axes allow the perfect tangential contact between the interrogating transducer and the surface of the test specimen with any complex curvature. Then the last 6th axis allows the rotating scanning motion of the transducer around the flaw. This scanner is very suitable for examining machine parts and structures of various shapes. Figs. 3a,b imply the excellent workability of this portable scanner, showing the capability of testing a curved sample (Fig. 3a) and a fillet welded joint from the frange and the web (Fig. 3b).

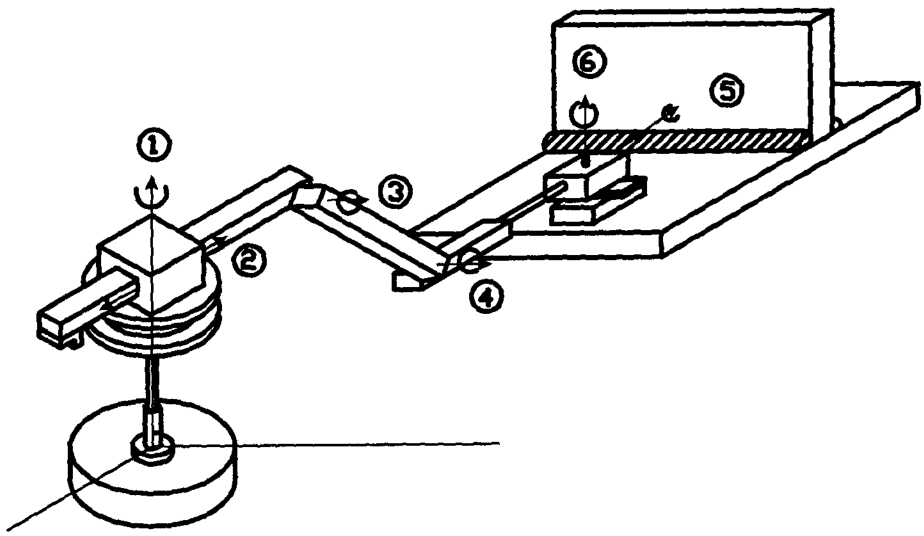
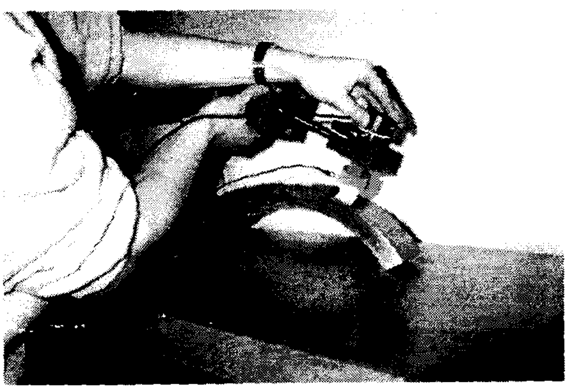
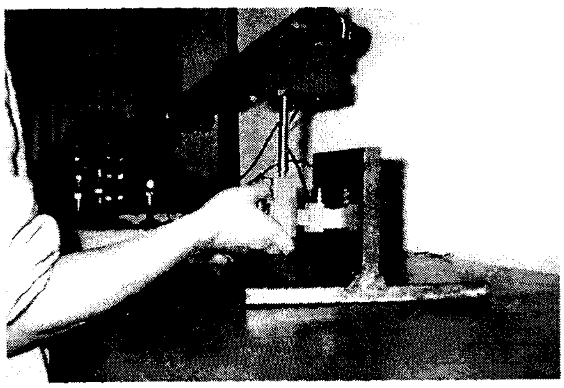


Fig. 2. Multi-axis portable scanner body



a) A curved sample



b) A fillet welded joint

Fig. 3. Examination of test specimen using the multi-axis portable scanner

INTELLIGENT ULTRASONIC FLAW ANALYZER

The IUFA is an intelligent software package which is currently under developed in this work for flaw characterization (detection, classification and sizing). Fig. 4 represents schematically the flaw analysis procedure in the IUFA. The IUFA receives two types of data; 1)the transducer position data from the DI/O board, and 2) the ultrasonic flaw signal from the A/D converting board. Using these data the IUFA performs flaw characterization processes including waveform display, ultrasonic flaw signal processing, image display, feature extraction, flaw classification and flaw sizing. This package adopts various state-of-arts artificial intelligence tools and very convenient graphic user interface tools for user-friendly operation.

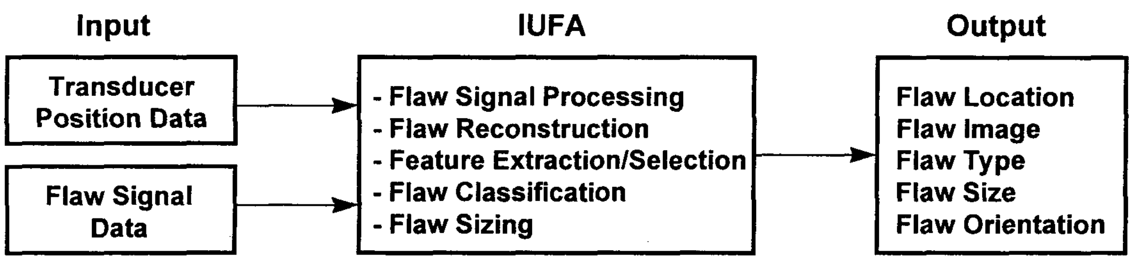


Fig. 4. Schematic diagram of the flaw analysis procedure in the IUFA

Ultrasonic Flaw Signal Display and Processing The IUFA can display the A-scan ultrasonic flaw signals on the screen of a computer, as shown in Fig. 5, so that an operator can confirm that the flaw signal is acquired correctly. Then the IUFA can perform the various signal processing such as noise elimination and thresholding for further analysis. The IUFA can also determine the flaw location using the position of the interrogating transducer and the time-of-flight data of ultrasonic flaw signal.

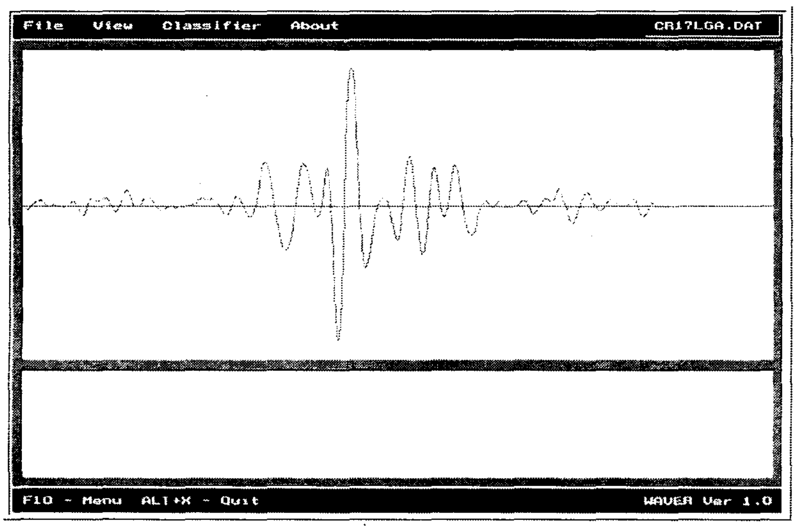


Fig. 5. Display and processing of ultrasonic flaw signal

Flaw Image Display Then the IUFA can display the pseudo 3-D image of flaws on the screen. This image reconstruction, which is currently under developed, is possible from the fact that the IUES monitors the position of the flaw at the every interrogating point.

Feature Extraction The IUFA extract the ultrasonic features from the A-scan waveform for flaw clssification and sizing. Table 1 shows examples of ultrasonic features which are currently available in the IUFA. Feature extraction from the pseudo 3-D image of flaws will be extended in the very near feature.

Table 1. Ultrasonic Feature Extracted by IUFA

Time Domain Features	• Number of signal groups • Pulse duration of the first group signal • Pulse duration of the second group signal • Pulse duration of the third group signal • Energy of th first group signal • Energy of th second group signal • Energy of th third group signal • Interval between the first and the second groups • Interval between the second and the third groups • Antisymmetry of signal
Frequency Domain Features	• Number of maxima of the magnitude spectrum • Number of minima of the magnitude spectrum • Number of deep minima of the magnitude spectrum • Number of shallow minima of the magnitude spectrum

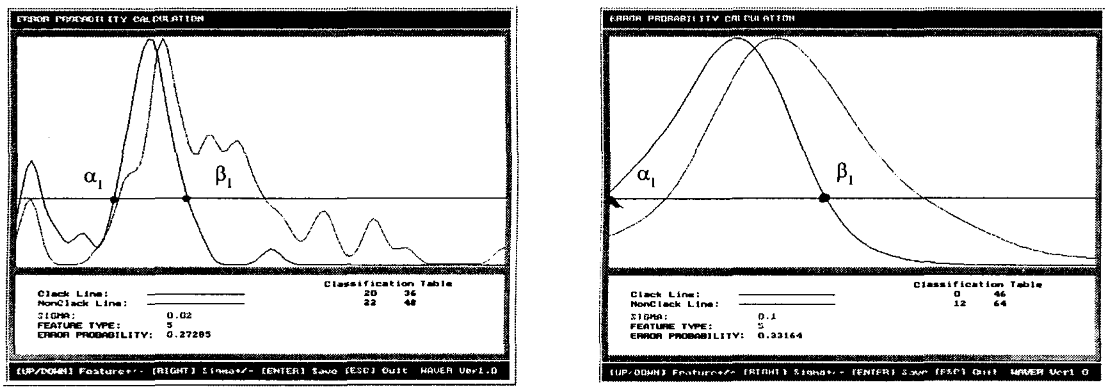
Flaw Classification Based on features extracted from the feature extraction stage, the IUFA can determine the flaw types using various intelligent flaw classifiers such as 1) rule-based classification tables, 2) rule-based enhanced classification tables, 3) probabilistic neural networks.

1. Estimation of Probability Density Functions of Features The rule-based classifiers requires class-conditional probability density functions (PDFs) of features which can be estimated from training samples. In Parzen window approach, the class-conditional PDF of a specific feature X in class A can be estimated by Eq. (1).

$$p(X|A) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{\sqrt{2\pi\sigma}}\exp\left[\frac{-1}{2}\frac{(X-X_i)^2}{\sigma^2}\right] \quad (1)$$

where A denotes a specific class "A", σ is a smoothing parameter which is defined by users, X_i (i=1,2,3,.....,n) are features of n training samples.

Figs. 6 a, b show examples of Fig. 6 shows an example of the estimated class-conditional PDFs and the descriptor entries α and β (which represent the lower and upper bounds in the distribution of a specific feature). If the descriptor entries for every feature and every class are determined from the training samples, then the rule-based classifiers can be applied to the test samples very easily. One thing that can be noted from Figs. 6a, b is that the descriptor entries α and β vary with the choice of a smoothing parameter. For a large σ wider distribution of the feature is obtained, but for a small σ narrower distribution is expected.



a) σ=0.02 b) σ=0.1

Fig. 6. Class-conditional probability density functions for a feature estimated from training samples

2. Rule-Based Classification Table Classifiers The basic idea of the classification rule of this classifier is as follows. If all features of any specific test sample (x) lie perfectly between the descriptor entries of a certain class (A), then classify x to class A. More formally, the classification rule can be written as follows ;

$$\text{IF } ((\alpha_1 \le X_1 \le \beta_1) \text{ AND } (\alpha_2 \le X_2 \le \beta_2) \text{ AND}$$
$$\vdots$$
$$\text{AND } (\alpha_n \le X_n \le \beta_n))$$
$$\text{THEN Classify x to Class A}$$

where $X_1, \ldots, X_n$: ultrasonic features

$\alpha_1 \cdots \alpha_n$ and $\beta_1 \cdots \beta_n$: descriptor entries for features

This classifier is currently available in the IUFA.

3. Enhanced Rule-Based Classification Table Classifiers Rule-based classification table classifiers often do not work since even a single outlying feature can make the decision hard. To overcome this difficulty the IUFA adopts a new rule-based classifier called "enhanced classification tables." In this classifier the test sample x is classified to the class A where the largest number of features of x lie between the descriptor entries of A. More formally, the classification rule of this classifier can be written as follows;

$W_j = 0$ (j = 1, · · · , M , M is the number of classes)

IF ($\alpha_1 \le X_1 \le \beta_1$) THEN $W_j = W_j + 1$

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IF ($\alpha_n \le X_n \le \beta_n$) THEN $W_j = W_j + 1$

IF Class J has Max(W_j) THEN Classify x to Class J.

where $X_1, \ldots, X_n$: ultrasonic features

$\alpha_1 \cdots \alpha_n$ and $\beta_1 \cdots \beta_n$: descriptor entries for features

This classifier is currently available in the IUFA.

4. Probabilistic Neural Network Classifiers The basic architecture of the probabilistic neural network[6] is shown in Fig. 7. The network contains four layers whose structures consist of 1) an input layer, where the features to be used by the network are presented, 2) a set of pattern units where each of these units accepts a weighted sum of the inputs and applies a gaussian activation function to that sum at its output, and 3) a set of third layer units (which are connected to each pattern unit of the appropriate class) that sum the output of the attached pattern units, weights that sum by a user-defined "cost factor" and presents the resulting output to the fourth and final output layer.

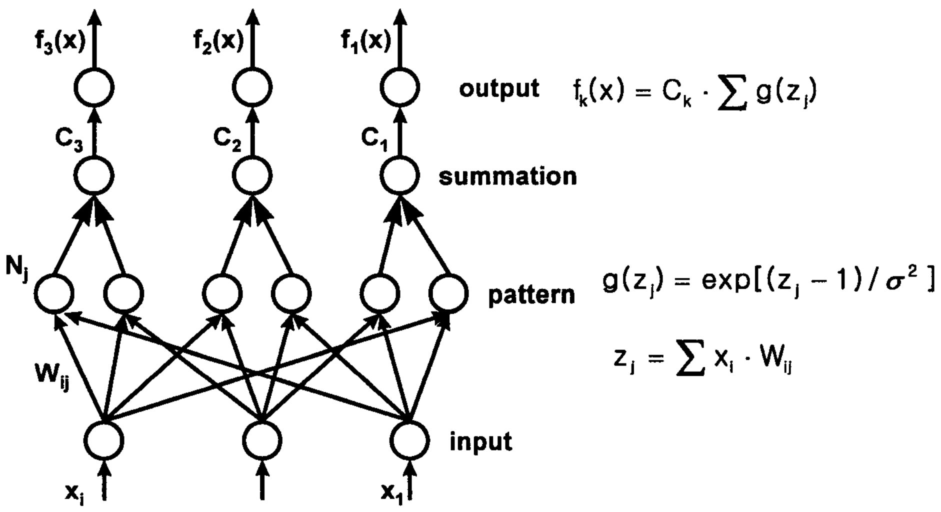


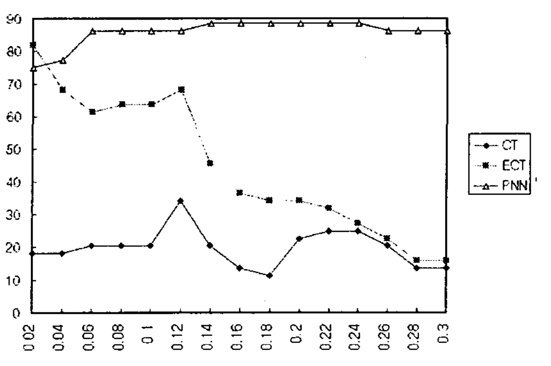
Fig. 7. Architecture of the probabilistic neural network

In the probabilistic neural network, the training method is a very simple three stage process :

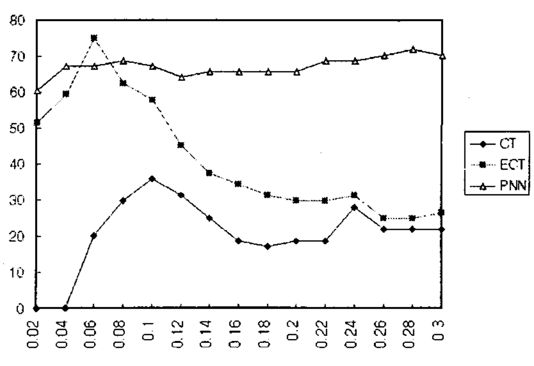
1) Given the choice of inputs, a second layer output node, N_{ij} (j=1,2···N) is chosen for each of the N training examples.
2) If we let X_{ij} (i=1,2···M, j=1,2···N) denote the M features corresponding to each training example, then the weights, W_{ij}, between the jth second layer node and the ith input feature, X_i, are obtained by simply setting $W_{ij}=X_{ij}$.
3) Finally, each second layer pattern unit is connected to the summation unit which corresponds to the class of that training example.

Once the network is trained, as described above, the only remaining parameter choices are the cost factors C_i (i=1,2,3) and the "smoothing" parameter σ. The cost factors can be simply set equal to one, in which case all output flaw classes are weighted equally. However, if the user wishes to place a stronger weight on a particular class, say cracks, the C_i can be used to adjust the decision-making process. The smoothing parameter, σ, in contrast, is used to adjust the collective importance of each of the individual patterns in the second layer pattern units. A small value of σ tends to emphasize the individual patterns while a large value of σ instead smoothes out the behavior over many patterns. The choice of σ is normally made on a trial and error basis with the optimal σ being one which both produces "good" classification results as well as a stable behavior of the network over a wide range of σ-values.

5. Performance of Classifiers To demonstrate the performance of classifiers developed in this work, ultrasonic flaw signals taken in the previous work[2] were used. This data set is composed of 239 digitized A-scan waveforms: 104 waveforms from cracks and 135 waveforms from non-cracks. Approximately half of these waveforms were used to train the classifiers, and the remaining waveforms served as a testing set to evaluate the performance of the classifiers



a) Crack



b) Non-crack

Fig 8. Correct accept rate of welding defects by three classifiers developed in this work for different choices of the smoothing parameter σ. (CT : classification table, ECT : enhanced classification, PNN : probabilistic neural networks)

Figs. 8a, b show plots of the correct accept rate (proportion of samples from a certain class classified correctly) for cracks and non-cracks, respectively, for the parameter σ varied over a range of 0.02-0.3. As shown in Figs. 8a,b, the performance of probabilistic neural networks did not vary substantially with the choice of σ in this range, but the performance of classification table classifiers and enhanced classification table classifiers did vary very much with the choice of σ.

Flaw Sizing Obtaining flaw size, shape and orientation information from ultrasonic measurements is an example of having to solve an inverse problem which conventional ultrasonic NDE have not been particularly effective in solving. The IUFA can solve this difficult problem in two ways. Firstly, the IUFA provides the fairly detailed pseudo 3-D image of a flaw from which size parameters of a flaw can be determined easily. Secondly, the IUFA adopts the equivalent flaw sizing where flaws are reconstructed in terms of "best-fit" equivalent ellipsoids (for volumetric flaw) or ellipses (for cracks) obtained from a relatively small number of ultrasonic measurements. Currently a time-of-flight equivalent (TOFE) sizing algorithm[4], is under implemented.

CONCLUSIONS

In this work we have reported our effort to develop a new intelligent ultrasonic evaluation system with a multi-axis portable scanner. In this system, a human operator moves manually the multi-axis portable scanner around the flaw, then the information on flaw geometry such as location, type, shape, size and orientation is determined automatically by the intelligent flaw analysis software package. The versatility and the intelligence of this system shown in this work demonstrates that it can be served as a robust flaw characterization tool for many practical applications. Currently, the extensive work is undertaken to enhance the performance of the IUFA software package.

ACKNOWLEDGMENTS

This study was supported by Factory Automation Research Center for Parts of Vehicles (FACPOV) in Chosun University, Kwangju, Korea. FACPOV is designated as a regional research center of Korea Science and Engineering Foundation and operated by Chosun University.

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