Pattern Classification of Decomposed Wavelet Information using ART2 Networks for echoes Analysis

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ABSTRACT

The Ultrasonic Pulse-Echo technique has been successfully used in a non-destructive testing of materials. To perform Ultrasonic Non-destructive Evaluation (NDE), an ultrasonic pulsed wave is transmitted into the materials using a transmitting/receiving transducer or arrays of transducers,that produces an image of ultrasonic reflectivity. The information inherent in ultrasonic signals or image are the echoes coming from flaws, grains, and boundaries of the tested material. The main goal of this evaluation is to determine the existence of defect, its size and its position; for that matter, an innovative methodology is proposed based on pattern recognition and wavelet analysis for flaws detection and localization.
The pattern recognition technique used in this work is the neural network named ART2 (Adaptive Resonance Theory) trained by the information given by the time-scale information of the signals via the wavelet transform. A thorough analysis between the neural network training and the type wavelets used for the training has been developed, showing that the Symlet 6 wavelet is the optimum for our problem.

KEYWORDS: Pattern recognition, ART2 Networks, Wavelets coefficients, NDT, Defect Location.

1. INTRODUCTION

The use of the Ultrasonic Non-destructive Evaluation presents a suitable scanning procedure for different materials. This technique consists of a pulse receiver system integrated in a single transducer. The receiving transducer is excited by scattered waves; a transient change appears across the transducer faces and generates an electrical pulse in the receiver section (Lester, et al., 1998). This transducer is moved along a known linear path producing an ultrasonic image composed by a set of signals named B-scan display (Lester, et al., 1998). At each path-position, the pulse is transmitted and its echoes detected, containing information about distance between the transducer and a particular flaw or physical boundary of the tested material and the inherent grain.

The useful information obtained from this technique is the time taken by the wave to travel from the transmitter to any discontinuity and/or material surface and back to the receiver. However, a further process is needed to locate and characterize flaws within the material.

The automated detection and/or classification system of flaws in a material has not been thoroughly investigated. Advanced signal analysis provides a new tool for processing transient signals, such as the Time-Frequency Analysis including the Wavelet Transform (WT) (Frazier, 1999; Demirli, et al., 2001a,b). WT is an attractive signal processing technique for evaluation and characterization of material.
Also, a pattern recognition technique using neural network and wavelet analysis has been developed to detect and characterize flaws within a material (Abbate et al., 1997; Angrisani et al., 2001; Ciftcioglu, 1999).

In order to determine pattern behaviour of temporal distance, the use of neural network is pursued. Different strategies have been proposed up to this stage. For instance, Vachtsevanos et al., (2001) propose a wavelet neural network based on the Radial Basis Function Neural Network and basic cost rap wavelet decomposition in order to extract different features related to flaw presence.

Fang et al., (2001) propose the use of a more efficient orthogonal neural network based on the behavior of the scaling function and the corresponding mother wavelet named as orthogonal wavelet neural network. Cifcioglu (1999) shows an analysis from neural networks to wavelet networks by means of a neural network as a multivariate function approximation. Yu et al., (1996) build the wavelet decomposition by using a B-Spline as the scaling function.

Alternatively, Tan et al., (2000) present a dynamic neural network with the hidden layer that consists of wavelets for non-linear system identification. In here, the use of auto-regressive connection is introduced into wavelet based neural network. Techniques related to the Non-destructive Evaluation have been presented by (Demirli et al., 2001a; Demirli et al., 2001b).

From the point of view of Neural Networks, Whiteley et al., (1996) have presented an interesting survey to ART2 network. A similar approach to that pursued in this proposal it is presented by Angrisani et al., (2001) where the combination of the wavelet transform and artificial neural networks is revised. Capabilities such as analysis of non-stationary signals and classification abilities are combined in a modular procedure.

The proposed methodology is able to discriminate and localize echoes coming from a defect. This digital process technique consists of using the time-scale information of the signals thrown by Wavelet Transform to train the ART2 neural network. Preliminary results of this technique have been published in Solis et al., (2002) and Solis et al., (2001) where no thorough analysis of the type of wavelet was done and no results were given about on-line training stage in case of an unknown scenario.

An alternative for flaws characterization is reviewed in Moisen et al., (2004). It is a systematic approach for defect characterization for a specific geometry of flaw giving an accurate response.

In this paper, the use of multi-resolution nature as well as the localized feature of wavelet networks have been developed to capture global and local characteristics of the system. The main reason of using wavelets is to decompose important information related to energy of the signal. For instance, the wavelet decomposition procedure provides a matrix related to every spectral component of the processed signal. The resultant matrix is integrated by the number of selected levels available to be evaluated by a neural network. This decomposition allows a more straightforward classification in terms of neural network due to certain key characteristics from those evaluated signals. These can be compared with each other rather than common classification where non-valuable and valuable characteristics are mixed in one pattern.

In this paper, a classical ART2 (Adaptive Resonance Theory class two) neural network is implemented in order to reproduce the signal using a fixed number of decomposition levels of a Wavelet Transform. The pattern recognition procedure reproduces as many patterns as the learning factor permits. The associated weight matrix *W* shows those recognized patterns. From this matrix, the maximum response vector in terms of amplitude is chosen. It represents the best decomposition factor from Wavelet Transform. Once a vector of *W* matrix is taken as maximum response, this representation is named as result. The length of the *W* matrix is related to the number of patterns recognized during the evaluated time window. The graphical form of this vector represents the pulse echo without any disturbance.

Following this brief description, this paper is divided in five remind sections. The second section gives a review of the ART2 network approach; the third section presents a revision of the Wavelet Transform; the fourth section presents the current approach based upon avelet decomposition and ART2 networks;

preliminary results are presented in the fifth section; and, finally, concluding remarks are presented in the sixth section.

2. RELATED THEORY

a) ART2 Networks

The Adaptive Resonance Theory (ART) network was originally proposed by Carpenter et al., (1987). This network performs as a pattern classification non-supervised network.

The objective of this technique is to define certain groups (from actual data) around specific data points named as cluster centres. When a new group appears**,** its centre is identified in order to be defined as cluster. This new centre works as the identifier of this group. The output of the neural network system shows the presence of this new cluster as a new combination of values (zero and one).

The ART2 network has been implemented following the approach presented by Frank et al., (1998). This scheme is shown in Fig. 1. The idea is to identify already classified patterns and categorize new scenarios based upon the classification of new patterns. The use of temporal distances gives the opportunity to determine flaws within material structure by just a graphical review as it is shown in section five. The use of a new group of patterns does not overcome the identification of physical meaning from a new classified pattern. This work should still be performed off-line by the expert. This network is divided in two stages, bottom-up and top-down.

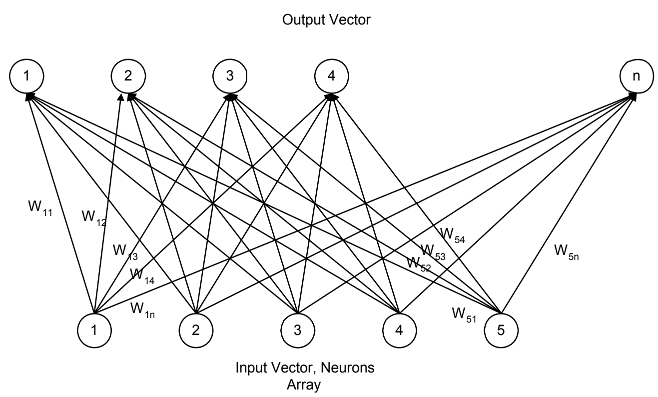

Figure 1. Typical ART2 Network

The current input vector is stated as A vector. This is normalized using the Euclidian media shown in eqn. 1.

$$I = \frac{A}{\|A\|} = \frac{A}{\sqrt{\sum_{i=1}^{m} a_i^2}} \quad a_i \geq 0 \quad \forall i \quad \|A\| \rangle 0 \tag{1}$$

where *m* is the number of elements from the non-normalized input vector *A*. The new generated vector *I* is used to perform another vector named as *t* based upon eqn. 2.

$$t_j = \sum_{i=1}^{m} w_{ij} i_i \tag{2}$$

Where w_{ij} is an element of the weight matrix. This matrix is generated by a previous pattern classification. Initially, the weight matrix is initialized with a nominal value of 0.3 in every component.

From the t_j element, a new matrix is performed stated as *T*. This matrix represents the interaction between the already known weight matrix and the input vector. The minimum element from the current *t* vector becomes the winner for this input vector. Having defined this interaction, the bottom-up stage is completed.

The minimum value of the current *t* vector is compared against the vigilance parameter in order to determine if this current minimum value is close enough to the vigilance parameter. If this is so, the related winning W_j vector is declared as the representative pattern of this input vector. Afterwards, the winning W_j vector is modified by eqn. 3.

$$W_J^{(new)} = \eta I + (1-\eta) W_J^{old} \quad (3)$$

where η is defined as the learning parameter.

Alternatively, if comparison of the current minimum t_j element with vigilance parameter ρ is not enough, a new pattern has been identified and, therefore, declared. Then a new W_j vector is concatenated to the weight matrix. This new vector is the current input vector *I*.

The proposed algorithm

The proposed pattern recognition algorithm based on ART2 and wavelet is divided into two main blocks: *i*) learning, and *ii*) classification stages.

i) Learning stage (See Fig. 2): the ART2A network is trained using several input vectors that contain time-scale information about the detected phenomenon. The input signal is feature extracted via the Wavelet Transform, producing a matrix with time-scale information. Each vector of this matrix is processed and classified by the ART2A network, producing different patterns. The number of patterns depends on the vigilance parameter and their quality depends on the learning parameter value.

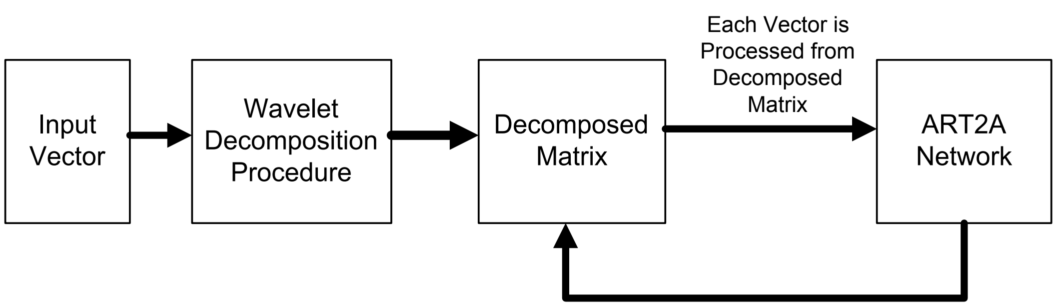

Figure 2. Schematic Procedure of Learning Stage from Proposed Algorithm

ii) Classification stage.- once a set of patterns is computed and stored, a signal without the wavelet information can be classified. If the signal does not match any known pattern, the ART2A is able to go back to the learning stage to generate a new pattern on-line. Fig. 3 shows the implementation of the second stage (named as Classification Stage) considering this eventual incorporation of the learning stage. The impact of this second stage is in terms of the computing cost, since non-wavelet decomposition procedure is performed.

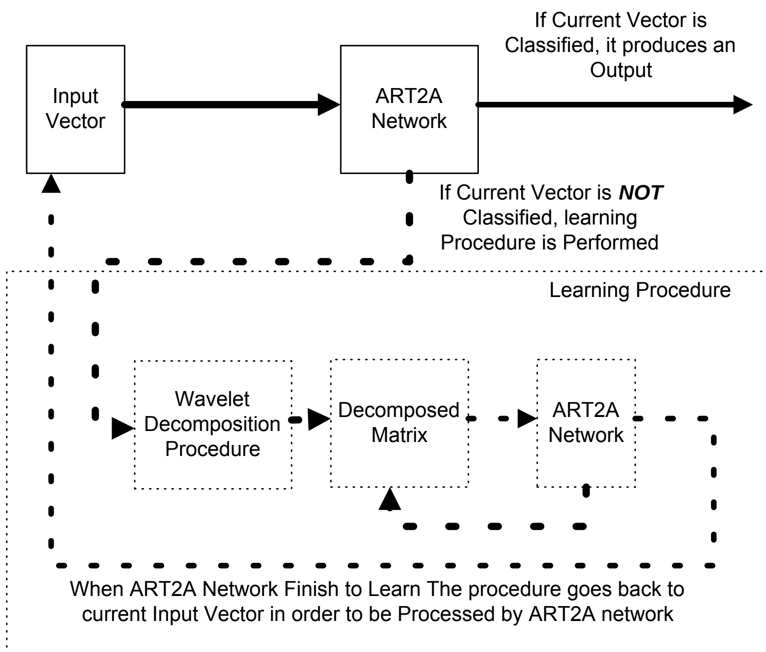

Fig. 3 Schematic Procedure of Classification Stage from Proposed Algorithm

2.2 Selection of the wavelet decomposition level

The feature extraction of a signal is computed by processing time-scale information by wavelet transformed to the echo-signals. The decomposition response depends on the mother wavelet used and the decomposition level needed to show the signal spectral characteristics without loosing time information. A thorough study, out of the limits of this paper, is needed to find or to design the optimal mother wavelet for this acoustical phenomena, therefore, an iterative method was used where the neural network is trained with different defined wavelets explained in section 4. The decomposition levels of a received ultrasonic signal of 500 points using the continuous wavelet transform was 10 levels since after this level no relevant information is given by the process (see Fig. 4, shadowed region).

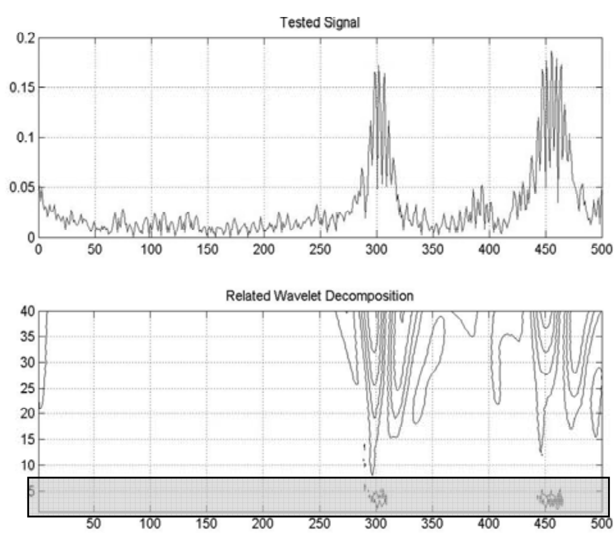

Figure 4. Tested Received Ultrasonic Signal of 500 points and the Related Wavelet Decomposition

2.3 Current Approach

Schematic diagrams of the methodology and experimental setup for material evaluation are shown in Figs. 5 and 6. The digital strategy core is the time-scale information of the input vectors given by the Wavelet Transform, therefore, an exhaustive search of the optimal wavelet for the training stage has been computed. The main processing block consists of the envelope detected (via Hilbert Transform) and normalized as defined by eq. (1) the received ultrasonic signals. Then a selected number of normalized echo signals are decomposed in its time-scale information to conform the input matrix of the ART2A network. Each row of the latter matrix is used to train the network. The resulting patterns contain information about the tested material, such as flaws or defects. The training stage depends on the vigilance and learning parameters; since no relation between the physical phenomenon and these parameters is known, the optimal parameters values must be computed by an iterative process varying values ρ and η from 0.1 to 0.99 at 0.05 steps.

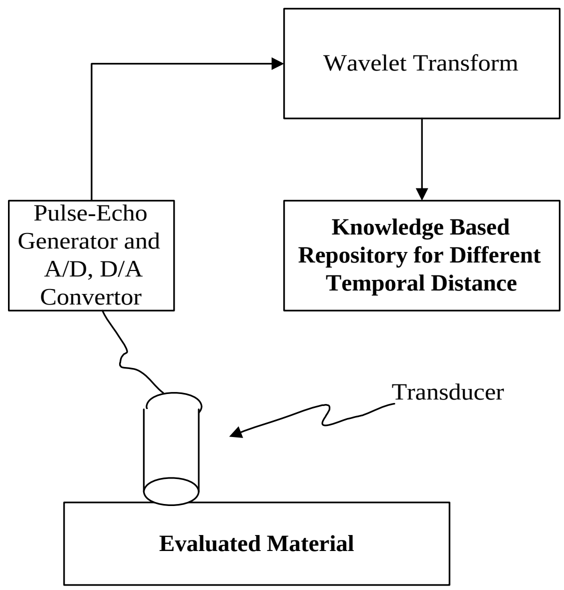

Figure 5. Proposed Approach

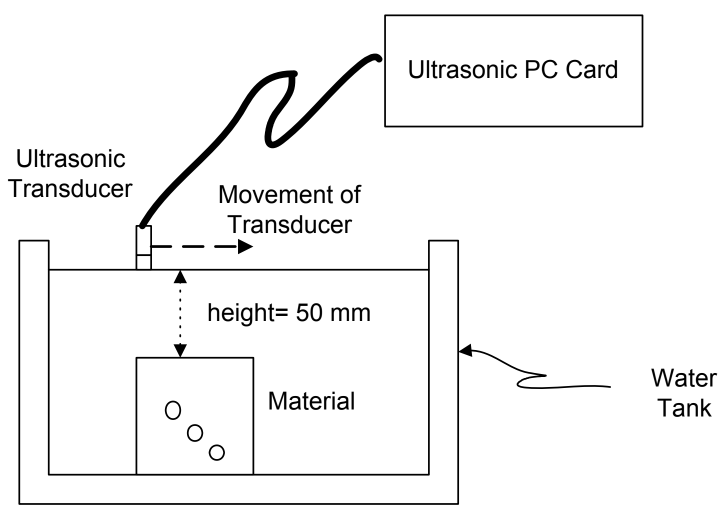

Figure 6. Schematic Diagram of the Experimental Setup Experiment

3. MATERIAL AND EXPERIMENTAL FRAMEWORK

A block of aluminum of 7x7x4 cm^3 with three man-made circular holes (see Fig. 7) is scanned with an ultrasonic transducer of 2.25 MHz (Krautkramer) attached to a robot arm capable of moving 10 □m motor steps (Hydrophone Scanning System, Specialty Engineering Associates, SEA). At each motor step, an ultrasonic pulse is transmitted (Pulse eco card MATEC SR9000) through the medium and received information back from the propagation medium, producing a signal which is captured and stored by an oscilloscope TDS-340 Tecktronics and then sent to a PC and processed by MATLAB. This experimental process is done until the tested material is fully scanned producing a B-scan image (see Fig. 8).

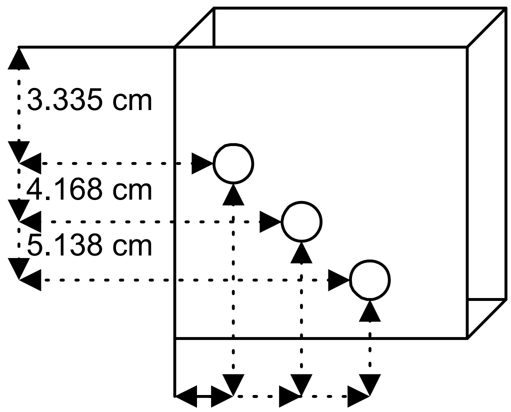

Figure 7. Position of Flaws

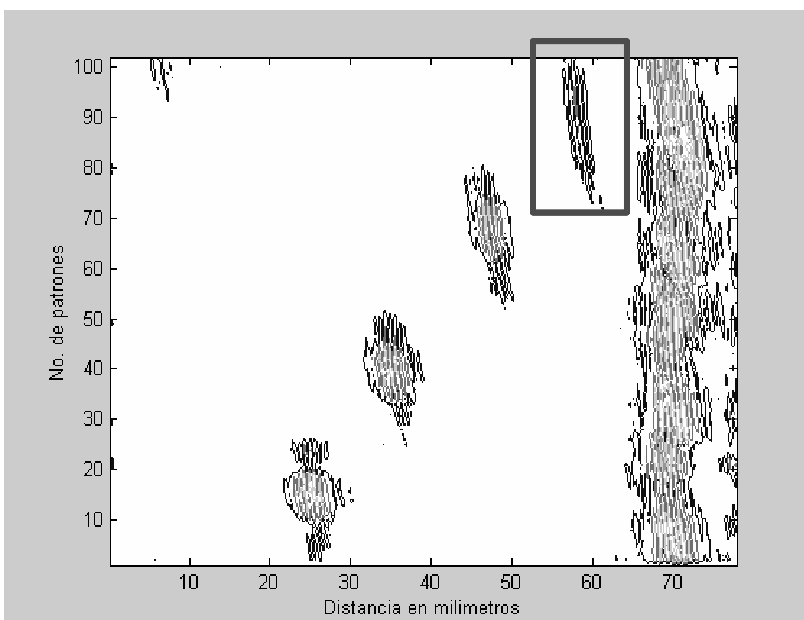

Figure 8. Evaluated Material with non-presented Flaw

A lateral view of the B-scan image where three flaws and the bottom echo are presented can be analytically constructed as shown in Fig. This is then used as a reference pattern to find the optimal wavelet as well as the vigilance and learning parameters values.

4. PRELIMINARY RESULTS

The stored B-scan image is a matrix where each of its columns is an ultrasonic echo-signal that corresponds to a specific acquisition point. The motor step used in the experimental work is 0.635 mm, covering a total of 80 mm. The 10% of this matrix is then used to train the network to compute a pattern database with different scenarios (Fig. 9).

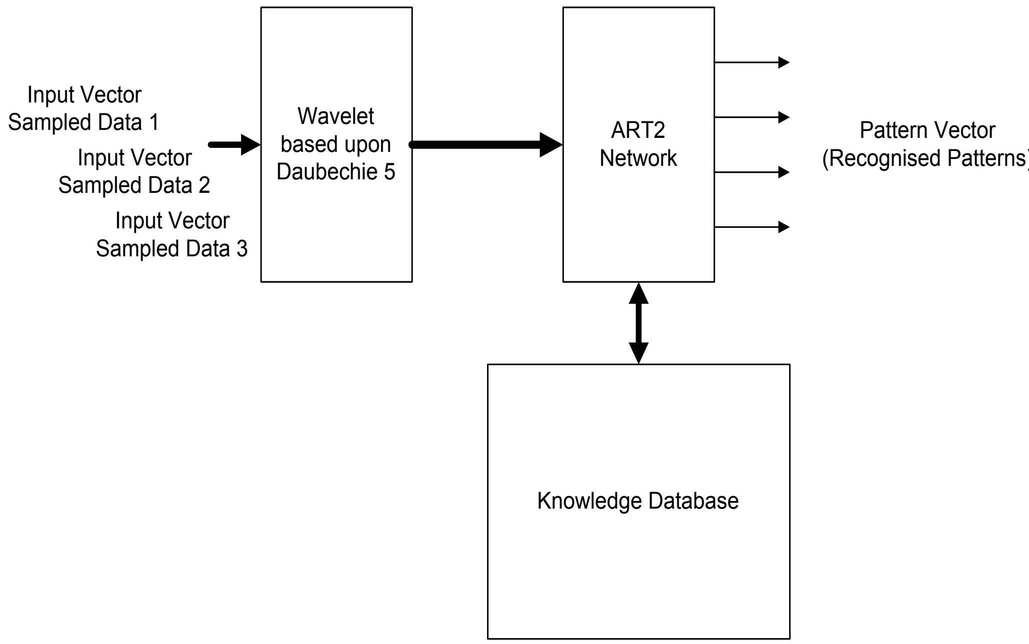

Figure 9. Integration of Knowledge Database

The first step is to normalize the training set. Each column is wavelet transformed producing a decomposition matrix with time-scale information. This decomposed matrix is then used to train the ART2A producing a pattern database. The number of patterns within this resulting matrix depends on the chosen values of vigilance and learning parameters. This iterative process is done until the selected set is fully processed.

The second stage is in charge of classifying a current echo-signal; if no similar pattern is declared, a neural network training procedure is performed to update the database.

The process explained in the last paragraph has been applied using different mother wavelets (section 2.3), defined in the MATLAB wavelet toolbox and several values of the vigilance and learning parameters. The resulting pattern database for each wavelet as well as for each vigilance and learning parameters values were computed and stored. The total number of generated databases is 4335 that corresponds to 15 different mother wavelets, 17 values for each vigilance and learning parameters (ρ and η).

In order to find the adequate mother wavelet and the related neural network parameters, a heuristic error is calculated as follows: each database is represented by its lateral view which is calculated from the maximum value of column (Fig. 10). The square difference between the lateral view vector and the reference pattern is calculated (Fig. 10) and named as error.

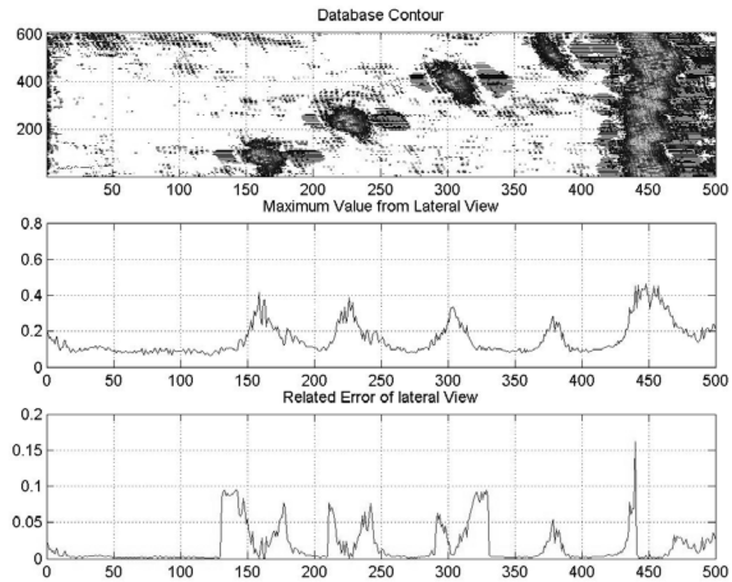

Figure 10. Related Evaluation Performed between one database and a Tested Signal

Thereafter, the area under the curve of this error is computed to give a heuristic scalar value. Finally, the minimum error is selected giving the adequate mother wavelet and the network parameters. Each lateral view is composed by the maximum value of each row from the selected database. From this evaluation the minimum error is found from comparison of every error. This value corresponds to tupple 2057 which is Symlet wavelet with and the related winning database is shown Fig. 11 where ρ= 0.1 and η=0.9.

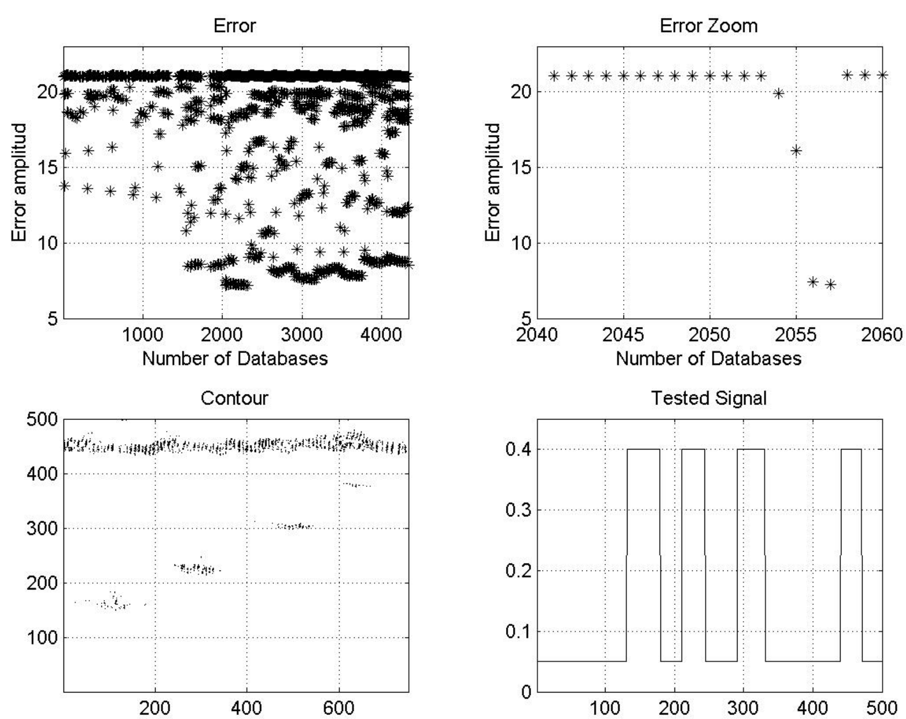

Figure 11. Winning Database and the value of the minimum Error

5. CONCLUDING REMARKS

This work has presented a novel approach in order to detect and localize flaws of a sampled material based upon echoes analysis. This approach uses a pattern classification technique to establish a knowledge database for different flaws. One of the key strategies of this work is related to the evaluation of different flaws where data normalization is required in order to produce similar patterns in terms of amplitude. Nevertheless, the temporal distance is depicted as the maximum amplitude pattern for each scenario. In fact, when an already known material is evaluated under the same geometric conditions, the selected pattern is that of maximum amplitude.

The procedure presented in here is divided in two stages. Firstly, a learning stage is performed by the use of wavelets and the ART2 network in a cascade procedure. The second stage is based upon the ART2 network on its own. For both stages, network parameters are constant. For the case of a new scenario is reported by the neural network during the second stage, the wavelet module is set to perform a proper classification.

Having defined this interaction, it is necessary to report that the vigilance parameter should be high enough for plastic purposes in order to avoid undesirable pattern recognition. The selection of this parameter is a trade off between the plasticity of the network and the noise ratio. Further work is to pursuit the evaluation of this technique for a richer variety of failure scenarios. This strategy gives the opportunity to determine the most suitable learning and vigilance parameters of the ART2 network. Otherwise, a new group of parameters would be necessary to be established for each local scenario.
From this evaluation procedure different parameters can be tuned in order to obtain a suitable response, mainly selection of wavelet as well as ρ and η values. These three have been selected as daubechies-4, ρ=0.7 and η=0.1 due to feasible results for this particular case study.

Another recommendation for the Non-Destructive Evaluation is related to other kind of pre-processing techniques such as time-frequency response of processing techniques like self-organizing maps in order to define more detailed characteristics of inspected flaws and other uncertainties such as corners. Further studies need to be carried out in terms of better pattern classification and flaw characterization.

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