A Time Frequency Distribution and ART2 Network approach in Non Destructive Evaluation

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Abstract: Nowadays the use of pattern recognition for signal processing presents a novel approach in order to determine the position and number of flaws within a tested material. The aim of this work is to propouse a pattern recognition technique in order to determine different types of flaws based upon pulse echoes using ultrasonic measurements. This approach is performed by the processing of an ultrasonic measurement using time frequency distribution technique and ART2 Network. This approach is focused to understand how pattern recognition can be pursued into fault diagnosis.

1. Introduction

The use of ultrasonic Non-Destructive Evaluation presents a suitable scanning procedure for different materials. This technique consists of a pulse echo 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 linear scan path where the temporal distance of a particular flaw, the bottom part of the material as well as the inherent grain thickness are monitored. This sort of strategy is known as B-scan display.
The goal of this paper is to detect flaws using ART2A networks and time frequency distribution approaches. This information cached by the transducer when it performs the receiver task during B-scan.
In order to process this information the use of pattern recognition for signal processing presents a novel approach to determine temporal distance based upon echoes analysis, without using classical signal processing techniques. The use of model building instead of data acquisition is a significant step, which involves characterization and abstraction of the process (Legendre et al., 2001).
Having defined the aim of this work in order to detect flaws within a material based upon pulse echoes using ultrasonic measurements, this approach is performed by processing the ultrasonic measurement using time-frequency distribution and ART2A neural network (Lester et al., 1998 and Kirby, 2001). In particular, time-frequency distribution such as Wigner-Ville (Martin et al., 1985; García-Nocetti et al., 2001) presents a feasible approach.
Moreover, this study classifies the response of different levels of this type of time-frequency distribution under the evaluation of a sample of aluminium material. This is based upon the speed of sound elapsed in a time difference between two reflections within the same propagation medium. Those echoes may represent the type of grain, the thickness of the material and different sort of flaws within the material.
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 upon the use of Radial Basis Function Neural Network and basic cost rap wavelet decomposition in order to extract different features related to Flaw presence.
Fang et al., (2000) propose the use of a more efficient orthogonal-neural network based on the behaviour of scaling function and the corresponding mother wavelet. The name of this technique is orthogonal wavelet neural network. Moreover, Ciftcioglu (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) built the wavelet decomposition by using a B-Spline as the scaling function. Alternatively, Tang 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.

Angrisani et al., (2001) and Solis et al., (2001) present a combination of wavelet transform and artificial neural networks that combine analysis of non-stationary signals and classification abilities. Related techniques to nondestructive evaluation have been presented by Demirli et al., (2001a) and Demirli et al., (2001b).

Fault classification and localization presents an advantage over fault detection and isolation in order to determine abnormal scenarios on-line, although, fault localization, lacks of fault isolation in terms of a formal declaration. In fact, this fault classification and localization enhances the availability of the system to localize abnormal behaviour rather than enhances the safety of the system. Different approaches have been followed by the use of neural networks, Principal Component Analysis (PCA) (Moya et al., 2001), and statistical approaches.

The approach followed in this paper is based upon pattern recognition on-line using cluster classification techniques (Baraldi et al., 1999) which is enhanced by the of Time Frequency Distribution (TFD) as pre processing module of pulse echo signal. The pattern vector shows, which TFD level presents the echo pulse without disturbances. Therefore, the associated weight vector represents the response of this decomposition.

Following this brief description, this paper is divided in five sections. Second section presents the Time-Frequency Distribution Wigner-Ville using in this work. Third section describes the ART2 network approach. Fourth section, presents current approach based upon Wigner-Ville TFD and ART2 networks. Preliminary results are presented in fifth section. Finally concluding remarks are presented in sixth section.

2. Time Frequency Distribution

There are several types of time frequency distributions based upon Cohen proposal (Cohen, 1989) such as Choi-Williams, Bessel , Wigner-Ville or Born Jordan. In this work Wigner-Ville TFD is used to estimate the mean frequency quasi-instantaneous of current echo-pulse signal. This TFD is used because its computational simplicity (García-Nocetti et al., 2001).

The Wigner-Ville time frequency distribution in a discrete form is expressed as eqn. 1.

$$DWVD(n,k)= = 2\sum_{\tau=-N+1}^{N-1} W(\tau)W^*(-\tau)e^{-j\frac{2\pi k\tau}{N}}x(n+\tau)x^*(n-\tau) \quad (1)$$

where the index $-N+1 \le n \le N-1$ represents the discrete time; the index $0 \le k \le N-1$ represents frequency vector; vector $W(n)$ with the related index $-N+1 \le n \le N-1$ is a sampled time window (Hanning) and vector $x(n)$ with index $-N+1 \le n \le N-1$ is the analytical signal of the measured signal.

3. ART2 Neural Network

Adaptive Resonance Theory (ART) network was originally proposed by Carpenter et al., (1996), This network works as 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 appear its centre is identified in order to be defined as cluster. This new centre works as identifier of this group. The output of fuzzy 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 material patterns and categorize new temporal distances based upon the classification of new patterns. The use of new group of patterns does not overcome the identification of the physical meaning of the new classified pattern. This work still should be performed off-line by the expert. This network is divided in two stages, bottom-up and top-down.

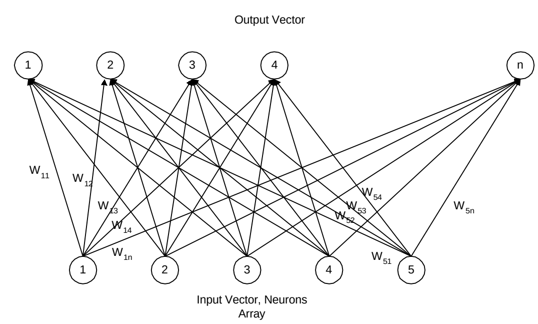

Fig. 1 Typical ART2 Network

The current input of the network is stated as A vector. This is normalized using the Euclidian media shown in eqn. 2.

$$I = \frac{A}{\|A\|} = \frac{A}{\sqrt{\sum_{i=1}^{m} a_i^2}} \quad a_i \ge 0 \quad \forall i \quad \|A\| \rangle 0 \qquad (2)$$

where m is the number of elements from non normalized input vector A. The new generated vector I is used to performs another vector named as t based upon eqn. 3.

$$t_j = \sum_{i=1}^{m} w_{ij} i_i \qquad (3)$$

Where w_{ij} is an element of weight matrix. This matrix is generated by previous pattern classification.

From t_j element, a new matrix is performed stated as *T*. This matrix represent the interaction between the already known weight matrix and the input vector. The minimum element from current *t* vector becomes the winner for this input vector. Having defined this interaction, the stage bottom-up is completed. The minimum value of current *t* vector is compared against to vigilance parameter named as ρ in order to determine if this current minimum value is closed enough to vigilance parameter. If this it so, the related winning W_j vector is declared as representative pattern of this input vector. Afterwards, winning W_j vector is modified following eqn. 4.

$$W_J^{(new)} = \eta I + (1-\eta) W_J^{old} \tag{4}$$

Where η is defined as learning parameter.

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

4. Current Approach

The approach proposed in this work will be described be means of a case study that concerns with the evaluation of an aluminium sample material. The schematic diagram in order to evaluate materials is shown in Fig. 2. Fig. 3 shows the block diagram of the set up experiment. The proposed strategy has been developed under MATLAB using time frequency distribution and ART2 network using this approach MATLAB processes the pulse-echo signal. The result of this process is a matrix whose elements are the energy associated to a specific time and frequency pair. This matrix is processed by a ART2 network in order to classify a finite number of patterns.

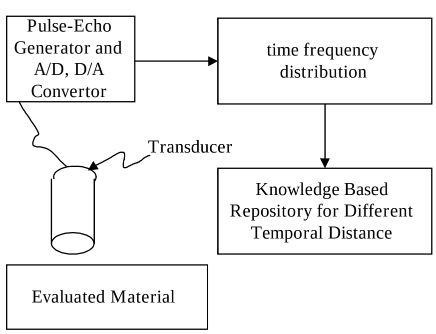

Fig. 2 TFD-ART2A Approach

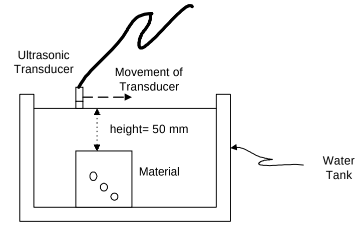

Fig. 3 Schematic Diagram of Setup Experiment

These patterns form the ART2 network representation as shown in Figs. 4. Based upon this pattern matrix different features of the same material can be evaluated without using the TFD technique. The evaluation of the sample material is performed in one of the axis, which is named as face one. During this evaluation if there is a flaw without a related pattern, this is processed using time frequency distribution such as Wiegner-Ville in order to generate a decomposed matrix.

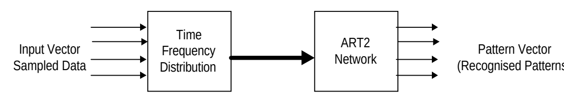

Fig. 4 Information Data Flow within Current Approach

Afterwards, a new pattern is declared by the ART2 network as soon as this is processed using the decomposed matrix. The information presented as input of this approach is the normalized sample of the signal obtained from pulse echo generator (Fig. 2). The flow chart shown in Fig. 6 depicts two stages. First, the training procedure based upon time frequency distribution and neural network processes. Second stage named as classification procedure without using time frequency distribution process.

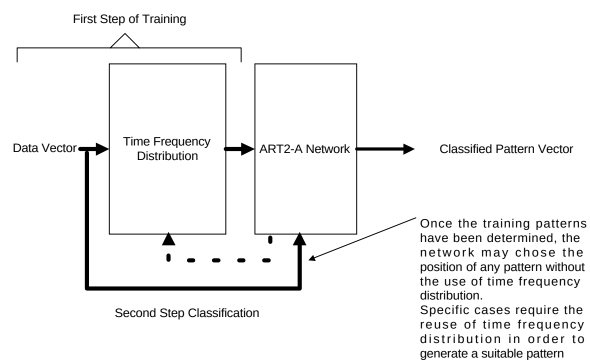

Fig. 6 Training and Classification Processes

Following training and classification strategies, it is possible to determine which temporal distance (out of the knowledge database) is the most suitable and represents the evaluated section of the material without using time frequency distribution process. As the reader may realize, the temporal distance is represented by the patterns database.

Having defined this approach, it is used to B-Scan an aluminium material in order to make a pattern database of different characteristics with several flaws and borders of the material named as scenarios. Each sample is captured, discretized by the oscilloscope and passed to MATLAB environment in order to be processed. Each sample depends on each step from the linear movement of the transducer. Each step has a distance of 0.635 mm. The sampled material is a volume of 7x7x4 cm as shown in Fig. 7.

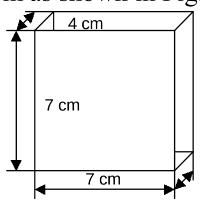

Fig. 7 Sampled Material

This material is composed of 90% aluminium and it has (Fig. 8.a) three determined flaws of 2cm deep with a diameter of 0.5 cm (flaw1, flaw 2 and flaw 3). Positions of these flaws are shown in Fig. 8.b.

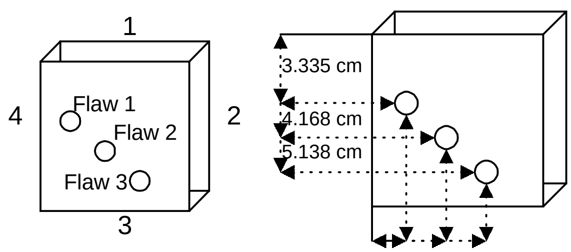

Fig. 8.a Fig. 8.b

Fig. 8 Sampled Material with Flaws

5. Preliminary Results

Next group of Figs., show how this approach has been implemented firstly by the process of Wigner-Ville TFD and secondly by the ART2A algorithm in order to generate a B-scan pattern database.

In order to determine the temporal distance of the flaws in the sampled material, the following experimental setup has been used:

- Osciloscope MATEC 25msamples/second. Time base of 20micro seconds.
- MATEC card has a 22.5db gain no damp.
- Krautkrammer transducer with a central frequency of 3.5 Mhz.
- Lab Scanner (water tank) trademark MATEC.

In order evaluate this material without using time frequency distribution approach, it is necessary to normalize the each sample from a range of values between 0 and 1. Furthermore, the length of this vector consists of 1000 points. Where just 499 points are used in order to be processed by Wigner-Ville TFD.

Moreover, neural network learning and vigilance parameters are set to 0.85 and 0.3 respectively. Each sampled signal is 499 points length. Having established basic values for this experiment several results are presented.

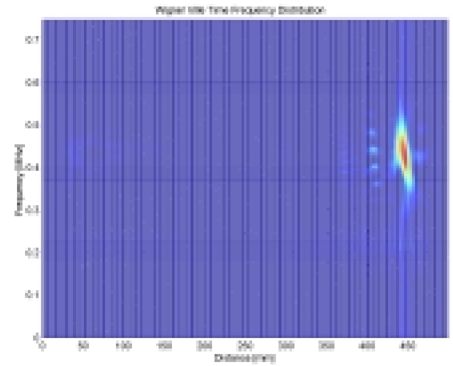

Fig. 10 Echo-Pulse Signal Processed by using TFD without Flaw

Fig. 10. shows the result of an echo-pulse signal been processed by Wigner-Ville TFD. In this case, a matrix of 499x350 elements has been formed. Y axis represents those frequencies selected during the performing of time frequency distribution. This graphic shows the bottom part of the element at the main frequency of the chosen transducer. X axis is the temporal distance that this echo-signal shows. In this case, the bottom of the element is depicted. It is essential to mention that this distribution is centred with respect to main frequency from transducer. This whole matrix is processed by the neural network in order to generate a number of representative patterns.

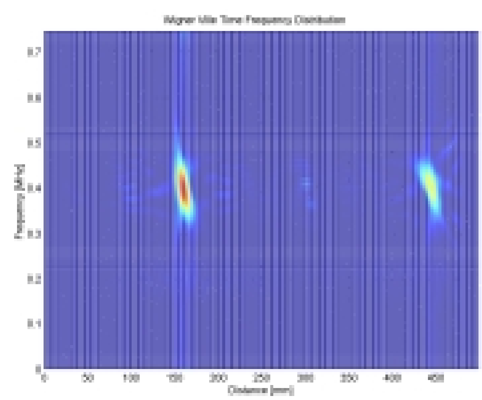

Fig. 11. Echo-Pulse Signal Processed by using TFD with First Flaw

Thereafter, Fig. 11 shows the result of another echo-pulse signal where first flaw is shown as well as Fig. 10, main frequency presents the location of this flaw. In this case the temporal distance shown between first flaw and the bottom of the sampled material as the real temporal distance. For the case of Figs. 12 and 13 present similar information with respect to flaw 2 and flaw 3 respectively. However, both present a small "spot" of a sort of flaw between the bottom and current flaw. This "spot" is due to inherent crossing terms within Wigner-Ville TFD.

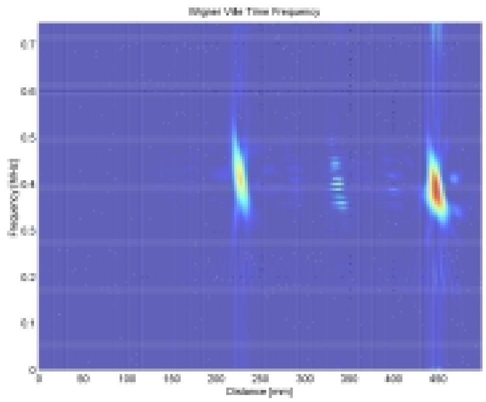

Fig. 12. Echo-Pulse Signal Processed by using TFD with Second Flaw

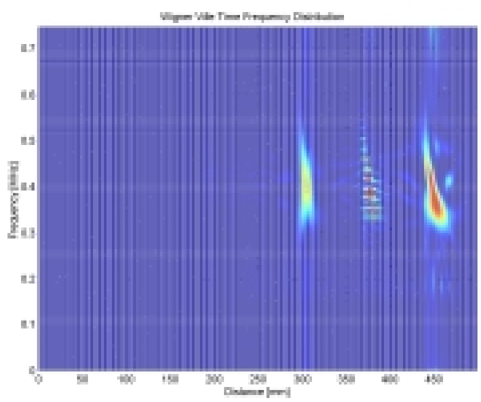

Fig. 13. Echo-Pulse Signal Processed by using TFD with Third Flaw

The ART2A network processes 10 of these matrices in order to generate a confident pattern database, which characterized the sampled material. The total number of sample pulse-echo signals obtained along the path is 100. As was mention before, ten of these signals equally separated are chosen to train the network.

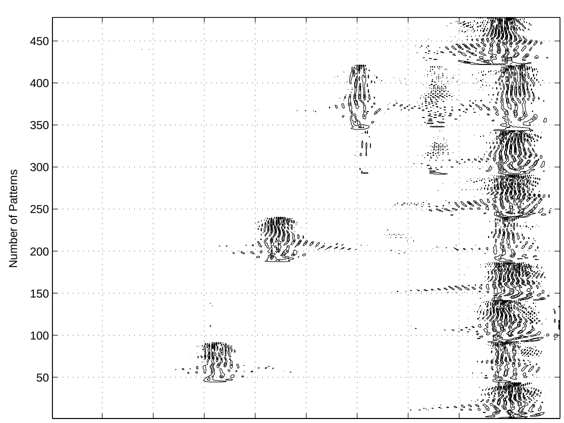

Fig. 14. Transversal view of whole sampled material based upon ART2 Network Approach

Having trained the network with those selected signals and their respective matrices, a transversal view of sampled material is constructed based upon weight matrix of ART2 network. Fig. 14 depicts this information where y-axis presents the number of patterns and x axis presents the temporal distance in terms of points.

Fig. 15 shows one signal used to test ART2A network without been processed by the TFD module. In this, one of the patterns (pattern no. 47) has been selected. The number of patterns remains constant (130).

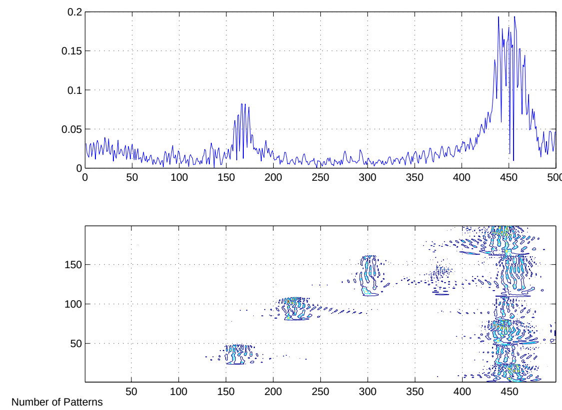

Fig. 15. Evaluated database based upon another pulse echo signal with same flaw at different Scan Position

6. Conclusions

This work has shown the use of a time frequency distribution strategy combined with a neural network for Non-Destructive Evaluation. This strategy has shown an alternative approach for classification of abnormal situations with no information from current case study. Furthermore, patterns database have been constructed based upon several selected echo-signals, which have been obtained off-line. This initial information is basic in order to obtain an accurate model of the inspected material.

This approximation enhances the capabilities of the simple use of neural network for pattern classification. It has been shown that, the combination of these two different strategies with some selected scenarios propose more information in order to on-line classification of unknown scenarios.

Further work is pursued in order to justify the use one specific Time Frequency Distribution over the rest of current algorithms. Moreover, this strategy could be address a proper dynamic non-linear system for on-line classification of unknown scenarios.

It is expected to minimize those mentioned “spots” by using other types of TFD such as Bessel or Born Jordan.

On the other hand, an aspect worth to mention is the geometry of marginal transform of TFD with respect to frequency preserves the same data geometry of that original signal without high frequency components.

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