# AUTOMATIC SELECTION OF RELEVANT DATA DURING ULTRASONIC INSPECTION

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**ABSTRACT**
In recent years, research concerning the automatic interpretation of data from non destructive testing (NDT) is being focused with an aim of assessing embedded flaws quickly and accurately in a cost effective fashion. This is because data yielded by NDT techniques or procedures are usually in the form of signals or images which often do not present direct information of the condition of the structure.
Signal processing has provided powerful techniques to extract from ultrasonic signals the desired information on material characterization, sizing and defect detection. The imagery available can add additional and significant dimension in NDT information and for exploiting information.
The task of this work is to minimize the volume of data to process replacing ultrasonic images type TOFD by sparse matrix, as there is no reason to store and operate on a huge number of zeros. A combination of two types of neural networks, a perceptron and a Self Organizing Map of Kohonen is used to distinguish between a noise signal from a defect signal in one hand, and to select the sparse matrix elements which correspond to the locations of the defects in the other hand. This new approach to data storage will provide an advantage for the implementations on embedded systems.
Keywords: workstation design, work measurement, ergonomics, decision support system.

Keywords- Automatic tesing; Materials; Ultrasonics; Neural Networks.

## 1. INTRODUCTION
The use of non destructive testing (NDT) allows the analysis of internal properties of structures without causing damage to the material. Various methods have been developed to detect defects in structure and to evaluate eventually their locations, sizes and characteristics. Some of these methods are based on analysis of the transmission of different signals such as ultrasonics, acoustic emission, thermography, x-radiography, eddy current (Cartz 1995). In the last decade,
ultrasonic techniques have shown to be very promising for non destructive testing (Blitz 1996) and they are becoming an effective alternative to radio-graphic tests. X-ray widely used to detect and sizing discontinuities, presents the disadvantage to produce ionising radiation and needs to develop a film, which takes some times to provide the results.

Operators are often required to acquire and interpret large volumes of complex inspection data. So, automated signal analysis systems are finding increasing applications in a variety of industries where the diagnostics is difficult. Ultrasonic data can be displayed as images and can add additional and significant dimension in NDT information and thus for exploiting in applications. Many advanced image processing algorithms have provided powerful techniques to extract from ultrasonic images the desired information on sizing and defect detection (Chen 2004; .Merazi, 2006; Jasiuniene 2007). But all these methods require considerable amount of computation, making them difficult for real-time operation.
Many mechanized inspection techniques, sensors, and systems for automating defect detection and location have been developed (Cchatzakos 2007, Martin 2007, Berke 2000; Moles 2005; Shuxiang 2004). However, the location and sizing of a defect is an almost entirely manual process: An operator will mark on the scan, using a mouse, where the component echoes lie, and thus where defect lies. The apparatus will then perform the correction and give an indication of the defect size according to what has been indicated by the operator.

Hardwares have been developed and integrated tools of image processing are implemented in order to completely automate the control. Most of these algorithms are computationally intensive, so it is desirable to implement them in high performance reconfigurable systems. Recently, Field Programmable Gate Array (FPGA) technology becomes a viable target for the implementation of algorithms for image processing. (Satoh 2009; Johnston 2004; Nelson 2000).
E. Ashari developed a method for NDT image binarization by thresholding, implemented in FPGA (Ashari 2004). K.Appiah uses a single ship of FPGA in

order to extract background models presented in an image and to reduce inspection time (Appiah 2005) and D. J Durlington uses a reconfigurable features FPGA performing a variety of operations in hardware, the control program being executed on a microprocessor (Durlington 1997).
On ultrasonic images the zone of interest is often very small in comparison with the image dimensions. This make sense to use a special matrix type called sparse matrix, where only the non zero elements are stored. Not only this reduces the amount of data to store, but also operations of this type of matrix can take advantage of the a-priori knowledge of the positions of non-zero elements to accelerate the calculations (Pissanetzky; Duff 1987 ).
The aim of this work is to minimize the data to store and to process in order to save memory and computational time. An original approach for data acquisition and representation**,** which consists on sparse matrix construction instead of an ultrasonic image type TOFD (Time Of Flight Diffraction) is described. It is based on the TOFD technique but avoids the image formation. The sparse matrix is built by combination of a perceptron and a self organizing map algorithm of Kohonen in order to select a defined number of samples from the signals.
Section 2 and 3 in this paper describe respectively ultrasonic non destructive inspection and TOFD technique. In section 4, the two types of Neural Networks used in this work are developed, namely perceptron and Self Organizing Map of Kohonen. Experimental measurements and application of combination of the neural nets are described in section 5. Section 6 concerns the conclusion.
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## 2. ULTRASONIC INSPECTION

The basic components of an ultrasonic inspection system are a pulser/receiver, the cabling, the transducers, and the acoustic/elastic wave propagation and scattering (Figure 1).

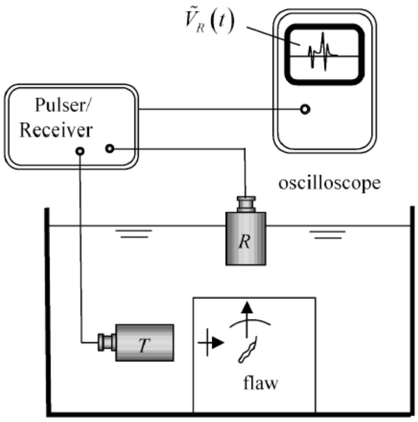


Figure 1: Signal acquisition system for ultrasonic inspection

The pulser section of the pulser/receiver generates short electrical pulses which travel through the cabling to the transmitting transducer. The transducer converts thes electrical pulses into acoustic pulse at its acoustic output port, which can be or not be in contact with the material under control. In the latter case, a liquid (couplant) is used to facilitate the transmission of ultrasonic vibrations from the transducer to the test surface. This ultrasonic beam is also transmitted into the solid component being inspected and interacts with any flaw that is present. The flaw generates scattered wave pulses travelling in many directions, and some of these pulses reach the receiving transducer which converts them into electrical pulses. These electrical pulses travel again through cabling to the receiver section of the pulser/receiver, where they are amplified and displayed as a received A-scan voltage Vr(t) as a function of the time. Figure 2 shows an example:

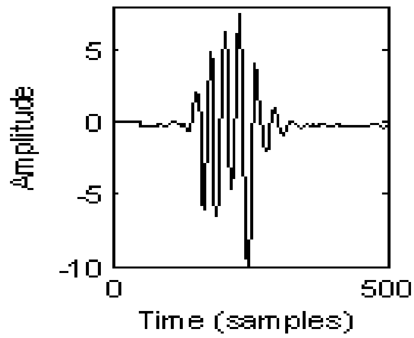


Figure 2: Example of an ultrasonic signal

## 3. THE TOFD TECHNIQUE

TOFD technique uses the travel time of a diffracted wave at the tip of a discontinuity (Silk1984). The TOFD research concludes that technique is portable, fast, reliable, accurate and inexpensive in the defect detection and sizing. Further, inspection can be semi or fully automated for the defect detection in metal structures. Two transducers, one as a transmitter and the second as a receiver are moved automatically step by step according to a straight line and the diffracted signals are recorded and displayed as images. Those images provide different texture patterns for the detected defects and automatic texture segmentation is investigated using different techniques to improve the detection and classification of defects.
In his thesis, J. Sallard demonstrates that a generator of a hole, can be assimilated to a top of a crack (Sallard 1999). So, a test block containing a hole has been used in this work to test this method (figure 3).

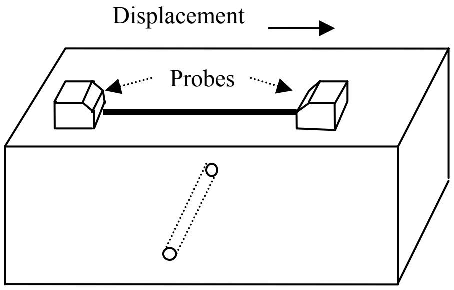


Figure 3: Test block with an artificial defect

Figure bellow shows the result obtained scanning a test block containing an artificial crack. Every row is constituted of a samples of a reached signal.

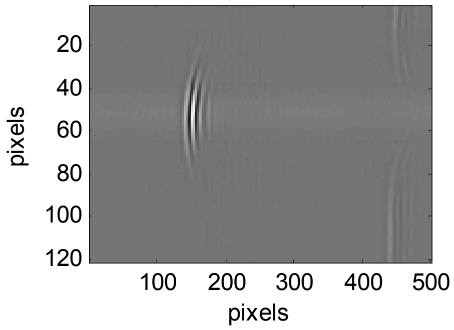


Figure 4:TOFD image showing a defect

## IV. ARTIFICIAL NEURAL NETWORKS

The Artificial Neural Networks (ANN) parallel, distributive computational structure is reminiscent of the human neural system. In an ANN structure, many simple nonlinear processing elements, called neurons, are interconnected via weighted synapses to form a network inputs. The functionality is mostly dependent on the values of the weights which can be updated over time, causing the neural network to adapt and possibly "learn". The learning process is of different types: supervised learning, unsupervised learning, self-organized learning. In a supervised approach, the network is fed with necessary input and the appropriate output for the specified inputs is given the output is achieved together with a global error function. The computed output is compared to the desired output to evaluate the performance of the neural network. The computed error function is then used to update the weights with an aim of achieving output that is close to the desired output.
In contrast to the supervised learning, unsupervised learning or self organizing learning does not require any assistance of desired outputs or an external teacher. Instead, during the training session, the neural network receives a number of different patterns and discovers significant features in these patterns and learns how to classify input data into appropriate categories.

### 4.1 The Perceptron

The Perceptron is a binary classifier that maps its input x (a real-valued vector) to an output
single binary value. If two sets are linearly separable, this classification can be used to decide whether a given vector belongs to one class or another (Rosenblatt 1962).

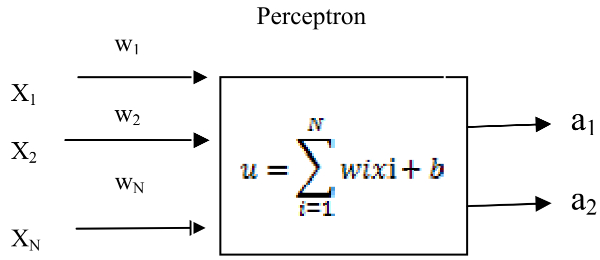


Figure 5: Functional description of a perceptron

The function of each neuron is to compute a weighted sum of all synapse inputs, add the sum to a predefined bias and pass the result through a nonlinear sigmoidal (threshold) function *f* whose output ranges between 0 and 1:

$$a = f(u) = \frac{1}{1+\exp(-u)} \quad . \qquad (1)$$

In this work, inputs ($X_1$, $X_2$,...$X_N$) correspond to the N signal samples. The outputs $a_1$ and $a_2$, are respectively the defect-signal-classe and the noise-signal-classe.

### 4.2 Kohonen Self-Organizing Maps

Kohonen Self Organizing Maps (SOM) is a widely used ANN model based on the idea of self organized or unsupervised learning (Kohonen
1988). The SOM network is a data visualization technique, which reduces the dimensions of data through a variation of neural computing networks. It is a non parametric approach that makes no assumptions about the underlying population distribution and in independent of prior information. The problem that data visualization attempts to solve is that humans simply cannot visualize high dimensional data. So, SOM goes about reducing dimensions by producing maps of usually one or two dimensions which plot the similarities of the data by grouping similar data items together. Thus, SOM's accomplish two things : they reduce dimensions, and display similarities. In this work, this property allows to select a fixed number of relevant data to store and to process. Figure 6 demonstrates basic structure of self-organizing Kohonen map:

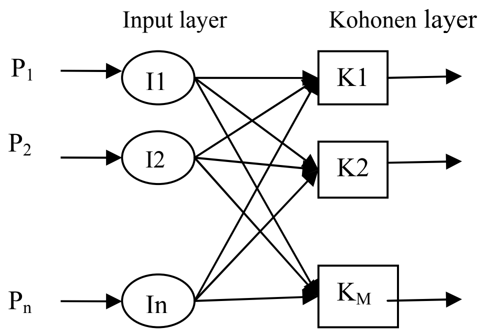


Figure 6: Self Organizing Kohonen Map network

The network has input and output layers of neurons that are fully interconnected among themselves. At each step of training phase an output layer's neuron with weights that best match with input data (usually in a minimum Euclidian distance sens) is proclaimed as the winner. The weights of this neuron and its neighborhood neurons are then adjusted to be closer to the presented input data. The algorithm is described as follows:

1- Initialize W with uniform-random values.

2- For each input vector P, compute the distance d between the vector P and the M weight vectors based on the mean square root:

$$d = (P_k - W_l)^2 \qquad l = 1, 2, 3,\ldots M \qquad (2)$$

3- Select the vector Wx such that Wx satisfies Equation (3) :

$$(P_k - W_X)^2 = \min(P_k - W_l)^2 \qquad l = 1, 2,3,\ldots M \qquad (3)$$

4- Update $W_x$ using Equation 4:

$$W_x(t+1) = W_x(t) + \alpha(X_k - W_x) \quad (0 < \alpha < 1) \qquad (4)$$

5- Go to step 2 until $W_l \approx P_l$ .

In the early learning stage, α is set about 0.8. As the learning progresses, α gradually becomes closer to 0.

**V. MEASUREMENTS AND RESULTS**

According to the principle of the TOFD technique, two transducers (2 Mhz) are moved step by step by 5 mm each time, straight a line. At each position of the probes, the reached diffracted signal is first analyzed by a perceptron in order to determine if it is a "defect signal" or "a noise signal".

In the next step, every defect signal (classe $a_1$) is processed and the sample corresponding to the maximum of the amplitude is detected. This sample corresponds to the time of flight of the reached ultrasonic signal (cross on figure bellow).

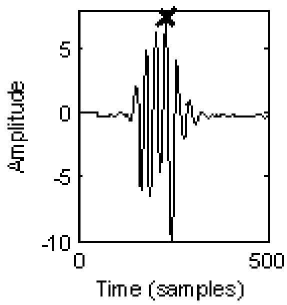


Figure 7: Example of ultrasonic reached signal. The horizontal coordinate of the maximum (indicated by the cross) corresponds to the time of flight of the reached ultrasonic wave

From every signal of defect-signal class, the coordinates $p_i$ and $p_j$ corresponding respectively to the time of flight and the position of the probe, according to the straight line of the displacement, are stored.

At the end of this processus, a set of points $P(p_i, p_j)$ are determined and their number equals the number of the signals in class $a_1$.

The Self Organization Map of Kohonen is applied with those points as inputs in order to reduce their number to a defined one depending on the desired sparse matrix dimension (30 in this work). Figure below shows the positions of the output elements resulting, obtained using the signals that form the TOFD image on figure 4.

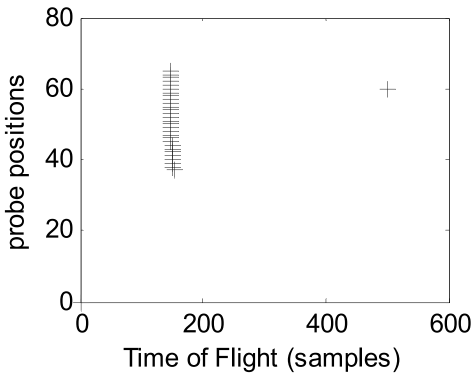


Figure 8: Sparse Matrix obtained instead of the TOFD image of figure 4.

Instead of 120x500 pixels of the TOFD image, this method selects 30 elements which are sufficient to describe the pattern presented in the image. This number is defined by the Self organizing Map algorithm outputs and is independent of the quantity of initial data.The economy of memory is important and the defect location and characterization will be faster when analyzing only the sparse matrix elements.

**V. CONCLUSIONS**

In this work, a method to detect and locate cracks by analyzing a sparse matrix built from TOFD signals has been described. A first layer of a neural net selects a point from the reached signal if an echo signal is presented in the zone of interest. The co-ordinates of this point which correspond respectively to the probe position and the time of flight of the signal are stored and used as inputs for a self organizing map network. Outputs will represent a group of points corresponding to the defect presented in the structure. Results of the application of this technique have been promising in terms of speed, and robustness. This would make the proposed system suitable for implementation in situations requiring near real-time processing and interpretation of large volumes of data giving thus an important help in the decision making.

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