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Defects Clustering using Kohonen Networks during Ultrasonic Inspection

Thouraya Merazi Meksen, Bachir Boudraa, Malika Boudraa

Abstract— **In Non Destructive Testing (NDT) of materials, the ultrasonic waves propagating in a structure are reflected or refracted from the presented discontinuities. The reached waves are received and converted to electrical signals containing informations about the internal defects. The characterization of those defects is an important task and the use of tools of signal processing gives an appreciated help in the decision making for the human operators.**
This work is a contribution for the defect characterization. The Neural Networks are used in order to classify reached signals allowing to distinguish between signals reflected from two different defects (cracks and inclusions) included in a welding.

Index Terms **— Non Destructive Testing, Ultrasonics, Defect Recognition, Classification**.

I. 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[1]. In the last decade, ultrasonic techniques have shown to be very promising for non destructive testing 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 inform 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. Automated signal classification systems can be obtained to recognize different classes of signals in an accurate and consistent manner [2,3,4]. However, it has been shown that for realistic flaws, it is apparent that the characterization is complex. The variability of ultrasonic response from the same type of defects appears to be very large. A realistic goal is to recognize them in flat defects, like cracks and lack of fusion, and volumetric, like porosity and slag inclusions.

Thouraya Merazi Meksen, t_merazi@yahoo.fr
Bachir Boudraa. Malika Boudraa, mk.boudaa@yahoo.fr
University of Sciences and Technology H.Boumedienne.
BP 32, EL Alia, 16 111, Algiers, ALGERIA.

In spite of all modern automated inspection methods, defect classification is still a difficult task. Much works, essentially based on pattern recognition techniques and artificial intelligence methods has been published. The perhaps most commonly used feature classification is the rise time, pulse duration and fall time. These features are calculated from the envelope of the signal using time instants corresponding to the 10% and 90% amplitude level. However, reliability of these features may be considerably impaired for realistic defects. In spite of very different shapes of waveforms, the rise time, pulse duration and fall time are often rather similar. It is evident that more powerful features are needed.

Jiao Shuxiang et al.[5] has developed a statistical pattern recognition approach. In this method is applied on the rectified signal and presents thus, the disadvantage of blurring the frequency character. Four features are selected for the classification: The Autoregressive Model Coefficient, The standard Deviation, the Pearson Correlation and the Dispersion Uniformity Degree. A classification Tree is created and applied to recognize the peak position and the amplitude.

Discrete Wavelet Transform (DWT) has several interesting features for this application. The impulse-like nature and the locality of the basis functions in the DWT make it suitable for modelling ultrasonic signals. If an analysing window is centered on an ultrasonic pulse, it is possible to examine at which position and scale this pulse has significant energy, which is reflected in the wavelet coefficients produced by DWT[6].

Nowadays, neural networks can be treated in order to improve the diagnostic of experts in the classification of the pattern recognition of defects in weld bead and to obtain a reliable and fast tool for automatic classification of defects. In reference [7], authors covered the use of different flaw

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detection methods comparing them with their proposed one. The experiment aimed to determine whether a given ultrasonic signal contains a flaw echo or not. The proposed method is based on radial basis function networks, one of the most powerful neural network techniques. In paper [8]an evaluation of various types and configurations of neural networks developed for the purpose of assisting in accurate flaw detection in steel plates is illustrated.

T.D'orazio addressed the problem of developing an automatic system for the analysis of ultrasonic data in order to detect and classify internal defects in three composite materials with different thicknesses [9]. A three- layer neural network is used and the classification technique used to compare ultrasonic signals and to detect classes of similar points. The training was performed using the back propagation algorithm.

Somme success using neural networks had also been reported with the use of the Hopefield method and a back propagation algorithm [10, 11].

This work will present a signal selection based on a self organizing algorithm. The idea is to cluster the signals in the similarity space and to use this result in order to distinguish between signals corresponding respectively to non defect, flat defects (cracks), and volumetric defects. This paper is organized as follows: In the second section, ultrasonic non destructive inspection is described. Section three outlines the pre-processing steps which allow the enhancement and the normalization of signals. Section four describe the proposed signal selection algorithm an presents some results. Section five draws the conclusion.

II. ULTRASONIC INSPECTION

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

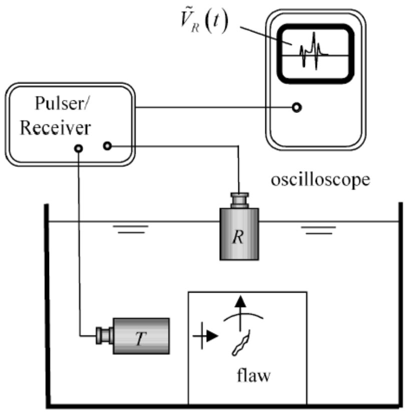

Fig. 1. Signal acquisition system for Ultrasonic inspection

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:

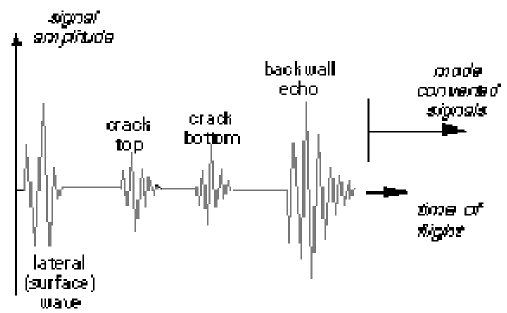

Fig. 2.Example of ultrasonic A-scan signal

III. PRE-PROCESSING

In this work, signals are acquired from structures where the defects were intentionally inserted into the welding (figure 3).

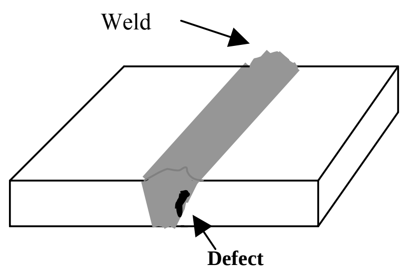

Fig. 3. Test block containing the defect included in the weld

The interaction between the ultrasonic beam and the reflector does not always take place in an ideal manner. In most cases a portion of the beam strikes the reflector and sometimes only part of the reflected wave can be received. So, reflected wave is often very low (Figure 4) and enhancement is an important pre-processing phase.

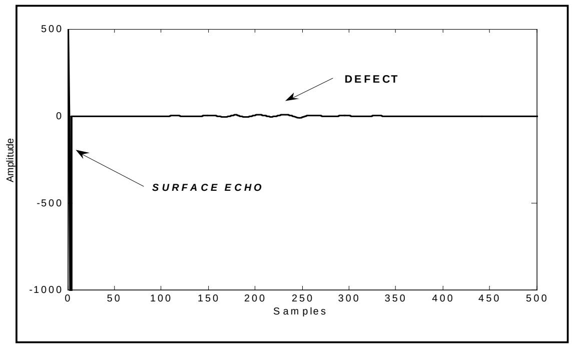

Fig. 4. Echo signal obtained in this work, corresponding to the crack contained in a welding. It shows at what point the defect echo is small in comparison

In this work, a Hamming filter is first applied to the reached signal in order to eliminate the front echo and the back echo, useless for the interpretation and too high in comparison with the defect echo making its observation improbable.

Noise removal may be obtained:

(i) By averaging
Averaging is a useful way to eliminate the random white noise from the signal when:

- There are enough data to do the averaging.
- The time to get enough data is acceptable.
- The time consumed by the averaging is acceptable.

The main advantage of this method is that it will not distort the original signal definitively.

(ii) By zero-phase shift filter
Because the noise in the ultrasonic testing is mainly high frequency low pass filter or band stop pass is desired. For this special application, because the peaks positions should not been changed after filtering, it is necessary to design a zero-phase shift filter to reduce the noise for the reached ultrasonic signal.

The last step consists in reducing the number of samples to a fixed one equal to the number of the neural inputs used in the training phase. In this work the Fourier transform is first applied in order to transform the signal from the time domain to the frequency domain. This is then followed by an inverse Fourier Transform with a fixed number of samples, 200 in this case. The temporal signal obtained thus contains always 200 samples. Figure 5 shows a block diagram of the overall scheme.

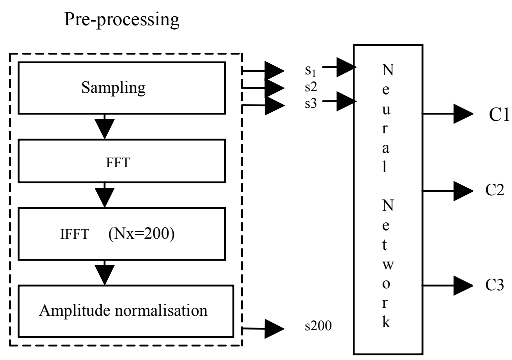

Fig. 5. Algorithm of different steps:
from the signal acquisition to the network outputs.

Signals are then normalized in order that maximum equals 1. The figure below shows the result obtained from the signal on figure 4.

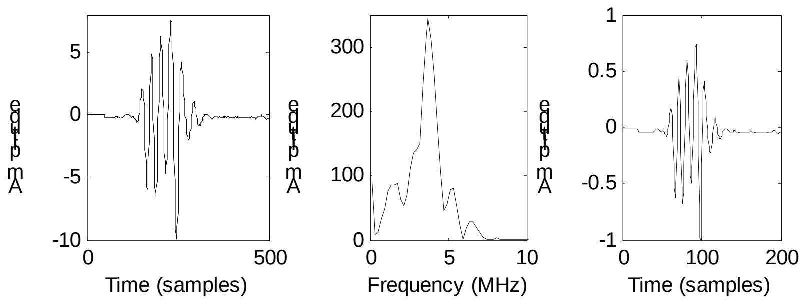

Fig. 6. (a): Filtered signal; (b): spectrum of the filtered signal;
(c): Normalized signal.

IV. CLUSTERING USING KOHONEN NET'S

An Artificial Neural Network is a simple mathematical model whose purpose is to represent the human brain behaviour in different situation**.** This mathematical model consists of a generic interpolation equation that is function of the components exciting the system (human neurons) and its associated response. In this work, the neural net's was used for the recognition of ultrasonic signal classes.

Kohonen Self organizing Algorithm is often used to cluster datasets in an unsupervised manner [12]; The Kohonen learning rule allows the weights of a neuron to learn an input signal. The weights are updated after the presentation of each signal. To do this, the distance (usually the Euclidian one) is computed between the input vector (signal) and each weight vector as in (1).

$$d_k = \| x(t) - w_k(t) \| \quad k = 1 \ldots N \qquad (1)$$

Where Nx is the number of the output neuron.

In the second step, the algorithm searches for the winning neuron d_w , i.e. the neuron that best matches the input neuron and is characterized by the minimum distance from the input vector.

$$d_w (t= \min((d_{k(t)}) \quad k = 1 \ldots N \qquad (2)$$

In the third phase the algorithm updates the weights of the winning neuron and of the neurons that lie in a use defined neighbourhood as follows:

$$W_k (t+1) = w_k (t) + \alpha (t)\, h_{kw} (t) \,\| x(t) - w(t) \|$$
$$k = 1 \ldots N$$

Where α (t) is the learning rate, that modulate the weights update and h_{kw} is the neighbourhood function that depends, given a time t, on the winning neuron under consideration k.

In this work, three neurons corresponding to three classes of signals (no defect, flat defect and volumetric defect) are implemented.

V. CONCLUSION

A large amount of research work has been conducted using various NDT techniques in the detection and identification of weld defects. Ultrasonic inspection has proven to be effective in the assessment of internal defects. In this work Probabilistic Neural Networks has been used in order to classify reached A-scan signals in order to give a help to the operators in the decision-making phase regarding the importance to distinguish between soft defects like inclusions and dangerous defects like cracks. The tests was done on defects intentionally included in two different welding joints and for each type of defects 60 signals were used in the training phase and 20 in the testing phase. In classifying the defect class with non defect class, 99% of signals were well classified. However the PNN confused 30% between cracks and inclusions. This indicates that this work can be performed considering additional features.

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