THE RELIABILITY OF THE ULTRASONIC CHARACTERIZATION OF WELDS BY THE ARTIFICIAL NEURAL NETWORK

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Abstract
Increasing automation of NDT inspection procedures has conducted to an expanded quantity of acquired data, which must be interpreted in a short amount of time. Therefore, for cost-effectiveness, the process requires reliable automated data interpretation techniques. In this work we develop an intelligent tool, which proceeds with an automatic classification algorithm and a pattern recognition scheme of A-scan data. After a defect classification based on shape/amplitude, the system processes through learning, thanks to an automatic apprenticeship stage. A previous study on learning techniques has concluded that: for NDT data interpretation, the main advantage of case-based reasoning systems is their ability to learn rapidly from classification made by the operator, who transfers automatically his reasoning on the basis of his experience and know how. Therefore, the model needs the presence of the operator during the interpretation process, because of the required high reliability of the testing. The resulted system will provide intuitive operator guidance in the case of data complexity and performs classification of the different events derived from defects, noise and component geometry.

Introduction

The application of Ndt techniques to estimate material quality depends on a large body of knowledge based on operator's competence and experience. In manual testing particularly, the identification of relevant from non-relevant indications as well as defect characterisation is highly examiner dependant. The volumetric/non-volumetric type of indication detected during an ultrasonic weld inspection has a decisive influence on weld acceptance or repair. Usually, during the examination procedure the ultrasonic operator is alone, depending only on his own observation of the signal features, such us echo shape, amplitude level, defect position within the joint geometry, rotation of the transducer around the defect location, etc. These parameters to which, for some of them no figure can be put, are combined by the operator in a non explicit way to lead to the diagnosis. This signal shape recognition joined with heuristics rules; ensure a natural extension in the exploitation of artificial intelligence tools. The system drawn here by the artificial neural networks method is based on an automatic classification and learning algorithm of A-scan data from defects, thanks to an automatic apprenticeship stage. However, for accuracy and effectiveness needs, our classification scheme has been accompanied by an ultrasonic 'level 2' IAEA certified inspector.

Neural network background

An artificial neural network (Ann) is a network of nodes connected via adjustable weights. The weights can be adapted so that a network learns a mapping represented by a set of example input/output pairs. An Ann can in theory reproduce any continuous function $F^n \rightarrow$

F^m, where n and m are numbers of input and output nodes. Most applications use feed forward Ann's and the back propagation (BP) training algorithms. There are numerous variants of the classical BP algorithms which assume a fixed Ann architecture. They train only weights in the architecture that includes both connectivity and node transfer function [1]. The neural network impose strong requirements on the data and the inspection, however when these are accomplished, then good automatic classification system can be developed. Networks used for classification have commonly as much input neurones as there are features and as much output neurones as there are classes to be separated [2].

Ultrasonic data features for defect recognition

Drawing an automatic recognition of weld defects requires a powerful formalism. The chosen methodology is based on the fact that the classification is considered as a closed system, with well known inputs and outputs.
A detailed knowledge of the interaction between ultrasonic waves and defects, the propagation medium and the conditions in which ultrasonic investigations are curried out, are all elements of basic importance in defect recognition. The strategy is to extract some parameters, enabling the featuring of the pulse echo envelope reflected from a defect on A-scan images obtained using a single transducer, about the maximum reflection transducer position and the transducer-defect distance variation. Some of the knowledge rules for the most important defects are drawn in table1.

Table 1. Defect recognition rules from manual testing

Defect Type	Echo form	Echo form after transducer movement from the defect location		
		M^{vt} // to the joint	$M^{vt} \perp$ to the joint	Around the joint
Porosity	With jagged aspect	The echo disappears rapidly	The echo declines quickly	The echo is nearly constant.
Porosity group	Set of small echoes with stiff fronts	The global echo persists, with mobility of the sub echoes position.	Same conditions as // movement.	Same conditions as the other movements.
Slag Inclusion	has an irregular front	The echo persists but its shape changes	The echo go away rapidly	The echo decreases gradually
Imperfect Penetration	The echo is high with stiff front.	The echo behaviour subsists	As for // movement	The echo disappears
Lack of fusion	As for lack of penetration	Same conditions. The only	Same conditions. differentiation is	Same conditions. about the defect position.
Cracks	High echoes superposition, with stiff front	The echo persists	The echo persists	The echo reduces and raises without going out

Ultrasonic neural network classifier

Choosing the architecture of a neural network for a particular problem usually requires some prior knowledge of the problem's complexity. Both theoretical studies and simulations, show that larger than necessary, networks tend to overfill the training data and thus have poor generalisation, while too small a network will have difficulty learning the training samples [3]. Currently, there are no formal methods to customise or select the right network structure. In this study, the Ann classifier is trained to represent some decision between the 2 classes about planar and volumetric defects to be recognised. In the figure.1 the input layer characterises the envelop shape of the defect signal called the defect map, received from a numerical oscilloscope on 1024 samples in a vectored representation. And the output layer is a Boolean representation of the 2 classes.

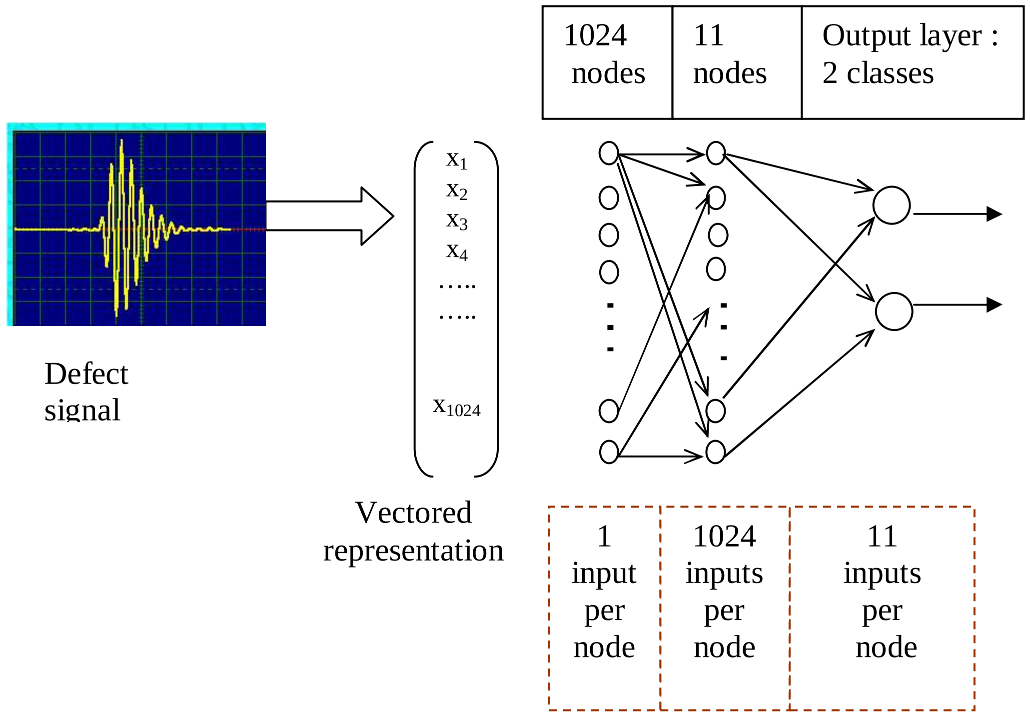

Figure 1: Network architecture

Learning process

After initialising the network neurones, the learning starts with applying the training vector to the network input. This vector is processed through the different layers. At the network's output the error between the actual and the desired output is measured. This error is afterwards minimised by back propagating it through the network. The neurones and their weight's matrices in the network are then corrected. This is repeated for all training patterns until the convergence of the algorithm to a small error. The program starts with random initial weights and learns with different maps. Since the back propagation algorithm requires differentiability along the signal path of the network, we adopt as a transfer function at each unit the 'Sigmoid' function [1] as follows:

$$F= 1 / 1+ e^{-\Sigma a x +b} \qquad (1)$$

a : is the weight; x : is the input ; b : is randomly selected in [-0.5 , 0.5] at start state and modified during training.

Conclusion

Since Ndt is an "expert" oriented field, the ability of learning systems to offer a framework for emphasising the manner in which decisions are made, and then to formalise the path by which they are reached, is exceptionally essential for automation purpose [4]. Feature

extraction is a very important aspect of solving the problem of pattern recognition, and neural networks of various types and structures have been found to be efficient tools for identifying such systems. In this paper we have worked on artificial flaws from steel plates, and on some natural defects from welds, for which the obtained signals are sampled on 1024 points. And for each defect location, we have taken several signals dealing with different transducer positions. The learning is performed on about 90 patterns. Future work concerns the search of an optimal configuration of the global network in which a sub net of each defect family will be included, so that to obtain a more categorical apprenticeship stage.
The figure 2 displays the main interface of the system. And figure 3 shows the software environment by which the operator has to record his observations if the signal is speckled or is kept on during the movements of the transducer' perpendicular, circular and parallel) from the defect position. At this stage the system begins the defect recognition analysis.

(a) (b) (c) (d)

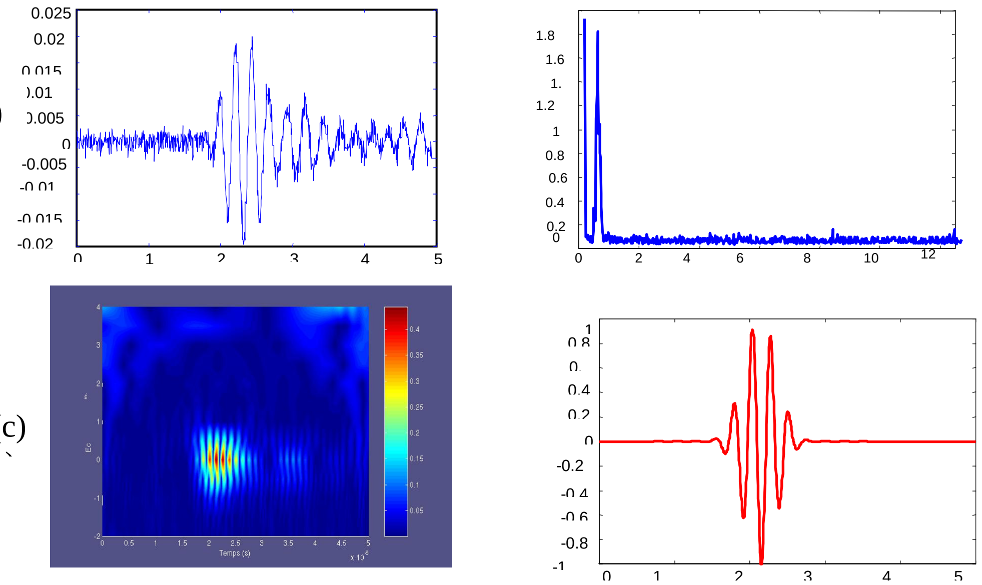

Figure 2: a: Group of porosity signal; b: its FFT; c: the defect wavelet, d: the result signal

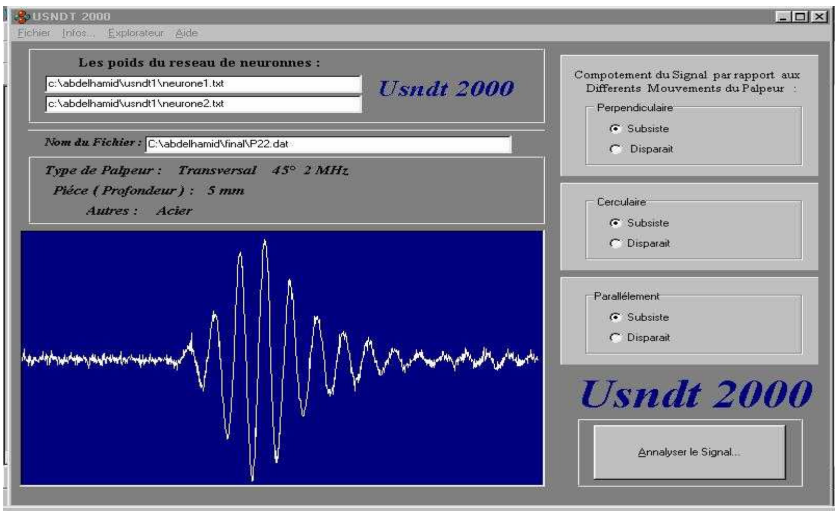

Figure 3. Software behavior

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