CLASSIFICATION OF PULSE-ECHO AND TOFD ULTRA-SONIC SIGNALS USING ARTIFICIAL NEURAL NETWORK

Jordana Luiza Barbosa da Costa Veiga
PUC-Rio
veiga@centroin.com.br

Antonio Alves de Carvalho
UFRJ - COPPE
alvez@metalmat.ufrj.br

João Marcos Alcoforado Rebello
UFRJ - COPPE
jmarcos@metalmat.ufrj.br

Abstract. *The use of welded structures is extremely common nowadays. But its inspection deserves care and attention to increase the reliability in these structures.The present work evaluates the application of artificial neural networks for the pattern recognition of ultrasonic signals using the pulse-echo and TOFD (Time of Flight Diffraction) techniques in weld beads. Four conditions of weld bead were evaluated: lack of fusion (LF), lack of penetration (LP), porosity (PO) and non-defect (ND). The defects were intentionally inserted in a weld bead of AISI 1020 steel plates of 20 mm thickness and 300 mm length and were confirmed using radiographic tests. In this study a standard classifier implemented by an artificial neural network of the backpropagation type. The ultrasonic signals acquired from pulse-echo and TOFD were introduced, separately, in the network with and without preprocessing. The preprocessing was only used to smoothen the signal improving the classification. The results obtained show that it is possible to classify ultrasonic signals of weld joints by the pulse-echo and TOFD techniques using artificial neural networks showed a performance superior a 73% of success for test. Although the preprocessing of the signal improved the classification performance of the signals acquired by the TOFD technique considerably, the same didn't happen with the signals acquired by the pulse-echo technique..*

Keywords: *Nondestructive Tests, Ultrasonic Technique, Artificial Neural Network, Pattern Recognition*

1. Introduction

Ultrasonic is one of the most used nondestructive tests for the detection, localization and measurement of flaws present in engineering materials under inspection. Among the ultrasonic techniques the pulse-echo method is the most commonly used in industry, mainly due to its simplicity and efficiency. However, the accurate measurement of defects perpendicular to the inspection surface is one of the limitations of the pulse-echo technique. In order to overcome this difficulty the TOFD (Time of Flight Diffraction) technique is used, which apply to the interior of the material one angular ultrasound beam in relation to the surface of the inspection. Until now (Erhard and Ewert, 1999, Raad and Dijkstra, 1998) the detection and measurement of flaws by ultrasonic techniques have only used the amplitude of the echo obtained and related it directly to the size of the flaw.

Despite a high velocity of inspection, a high probability of detection and a low number of false results, the classification of defects based on ultrasonic signals is still much questioned, since it is not possible to relate the amplitude and/or the position of the signal directly with the type of defect (Carvalho et al., 2002, Ogilvy, 1993). However this classification depends basically on the ability and knowledge of the operator.

The correct classification of the type of flaw present in the material reduces measurement errors, increasing the confidence in the test and consequently the safety of the material in future applications.

The continued advances in computational techniques, mainly the development of the sciences related to artificial intelligence, like artificial neural networks, has given a large impetus in the research development of automatic inspection systems and classification of defect patterns (Masnata and Sunseri, 1996, Siqueira, 2002, Margrave et al., 1999). The neural networks consist of algorithms that try to model some functions of the human brains such as pattern recognition, the creation of associations and learning from experience or training.

In this work, pattern classifiers are implemented using artificial neural networks (ANN) for the recognition of classes of ultrasonic signals obtained in the inspection of weld beads by the pulse-echo and TOFD techniques, with the aim to improve the reliability in the structural integrity of the materials. The performance of these classifiers is evaluated in the classification of signals in four conditions of weld joints: lack of penetration (LP), lack of fusion (LF), porosity (PO) and non-defect (ND), Fig. 1.

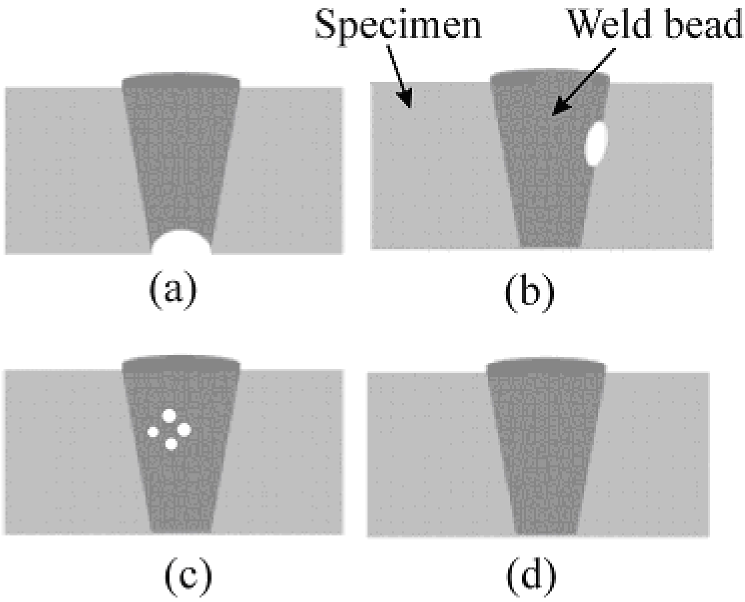

Figure 1. Schematic drawing of the four studied conditions of the weld bead: (a) lack of penetration, (b) lack of fusion, (c) porosity and (d) non-defect.

2. Pulse-echo Technique

Pulse-echo is the most commonly used ultrasonic technique for material inspection. This technique involves the detection of an echo that is produced when an ultrasonic signal is reflected by a flaw present in the material being tested. However in this case only one transducer is used to emit (emitter) the ultrasonic pulses and receive the reflected signals (receptor). This method is used for the detection, localization and measurement of any defects present in the material. Based on the location of the defect an inspector makes its classification (Figure 2). The size of the defect is directly related to the amplitude of the signal reflected, if the ultrasonic beam meets a reflecting surface, part or all of the energy is reflected. The percentage of energy that is reflected is directly dependent on the size of the reflecting surface in relation to the size of the ultrasonic incident beam (ASNT, 1991, Metals Handbook,1994).

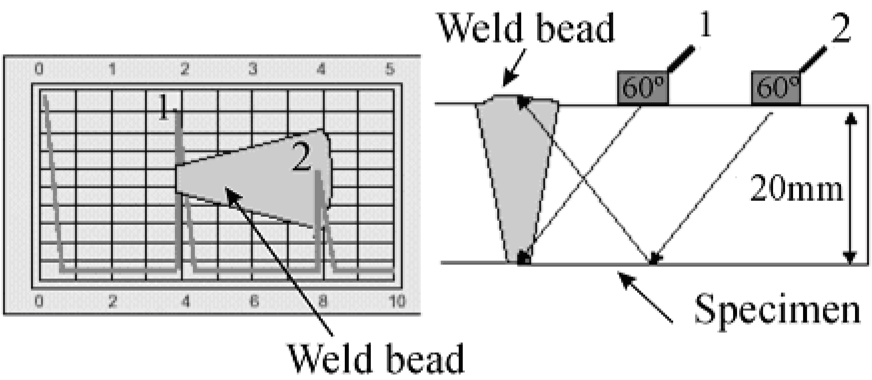

Figure 2. Ultra-sonic inspection using the pulse-echo technique.

3. TOFD Technique

This method relies on the diffraction of ultrasonic energy from ’corners’ and ’ends’ of internal structures (primarily defects) in a component under test. This is in contrast to conventional pulse-echo methods, which rely on directly reflected signals.

The TOFD technique is based on the interaction of ultrasonic waves with the extremities of the flaws. This interaction results in the emission of diffracted waves in many angles. The detection of these diffracted waves makes it possible to establish the presence of flaws. The difference in the time of flight of the diffracted signals is related to the flaw height, and consequently it allows to set its sizing. The amplitude of the signal is not used to estimate the size of the flaw.

The conventional configuration for the TOFD technique consists of two transducers, one emitter and one receiver, aligned at both sides of the weld bead, so that the region of interest is entirely within the sonificated area by the emitter (Figure 3).

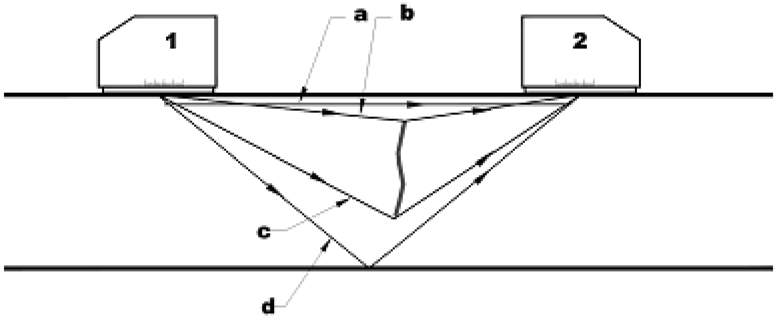

Figure 3. A typical layout for the TOFD technique. (1) emitter, (2) receptor, (a) lateral wave, (b) diffracted wave by the top of the defect, (c) diffracted wave by the bottom of the defect and (d) back-wall echo.

A-scan mode is the most typical form of the ultrasound signal, and it consists of the signal itself, amplitude versus time, which is displayed on the ultrasound equipment screen. A typical signal (A scan) of the TOFD is shown in Fig. 4.

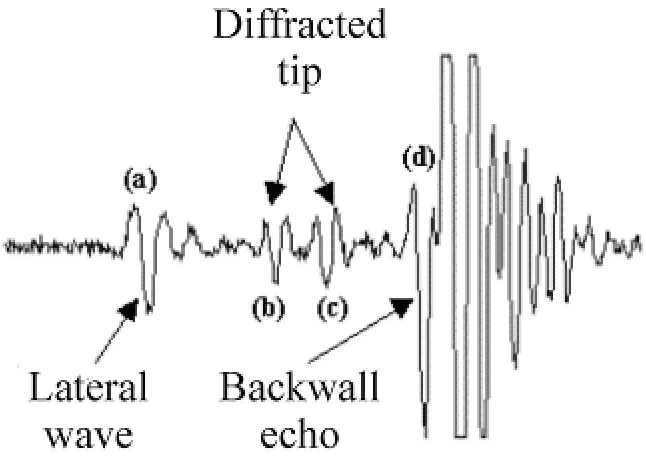

Figure 4. A typical model of an A-scan signal generated by the TOFD technique obtained from a flaw.

4. Artificial Neural Networks

Artificial neural networks (ANN) are mathematical models that have the objective, in a simple and objective way, to simulate the human brain. And so, a model should have the fundamental capacity of a brain - learning, which permits carrying out tasks that are considered typical of the human brain, such as patterns recognition, creation of associations, systems identification and clustering etc.

Despite being much less complex than the human brain, neural networks have the capacity to process large quantities of data in a short space of time that could normally only be analyzed by a specialist. The training or learning of the network from samples, like with the human brain, is one of its most important characteristics (Haykin, 1994, Wasserman, 1989).

5. Experimental Procedure

The ultrasonic tests, in this work, were performed on twelve specimens made of steel plates AISI 1020, thickness: 20mm and length: 300mm, V-type bevel with inclination: 50^o, root distance of about 2mm and welded by shielded process. Different defects, such as lack of fusion, lack of penetration and porosity, were inserted in the specimen during welding. The LP defects are incomplete fill and the LF defects are side-wall fusion. The size of LP defects are between 2 and 32 mm, and the size of LF defects are between 5 and 20 mm.

For the pulse-echo technique, angular transducers with 4 MHz central frequency and 60^o sonic beam incidence on the material and an ultrasound equipment with analog signal output were used in the test. The signals were digitized by oscilloscope in order to be treated in a PC-type microcomputer.

The inspections with TOFD technique were made using the same specimens as with pulse-echo technique. Transducers of 5 MHz frequency and wedge for longitudinal waves of 60^o sonic beam incidence in the material were used. The position, the type and the size of each of the defects inserted are known through the use of radiographic tests of the weld beads.

For inspection of the ultrasonic TOFD test, an automatic inspection system was used in the acquisition of various signals A-scan, obtained by the normal dislocation of the transducer in relation to the direction of the sonic beam (Wasserman, 1989). The automatic inspection system consist in a device of magnetic wheels, especially projected to transport a pair of transducers, one conventional ultrasound equipment, an A/D converter board, a PC microcomputer and a software that carries out the control of the device and data recorded from the region of the weld being inspected.

In the present study, for the pulse-echo signals, one non-linear (with hidden-layer) pattern classifier was implemented with a supervised feedforward neural network backpropagation type. By varying the number of neurons on the hidden layer and observing the classifier performance and error at the end of the training, it was possible to obtain a suitable number of neurons from the hidden layer for this study. The neural network used has a hidden layer of 30 neurons, and 1 neuron (corresponding to the condition to be classified) on output layer. One artificial neuron may have many inputs (x_i), each of them associated to a weight function, synapses (w_{ij}) . The outputs of all added synapses (v_i) are submitted to an activation function ($h(v_i)$), in order to restrict the output signal amplitude. Any collection of input dates will generate a certain output (y_i), as a boolean output, for example.

For TOFD signals, a linear pattern classifier was implemented with a supervised feedforward neural network backpropagation type. The performance of this linear classifier justified the non-utilization of a classifier with hidden layer.

This neural network was fed with ultrasonic signals that represent the four conditions of the weld bead: ND, LF, LP and PO, for both techniques, separately. Each signal has its own characteristics, and this is the information that the network uses to resolve the different classes, as exemplified in Fig. 5 for pulse-echo signals and Fig. 6 for TOFD signals. For each condition of pulse-echo, 30 signals for training and 20 signals for tests were acquired, for TOFD, 40 signals for training and 20 signals for tests were acquired.

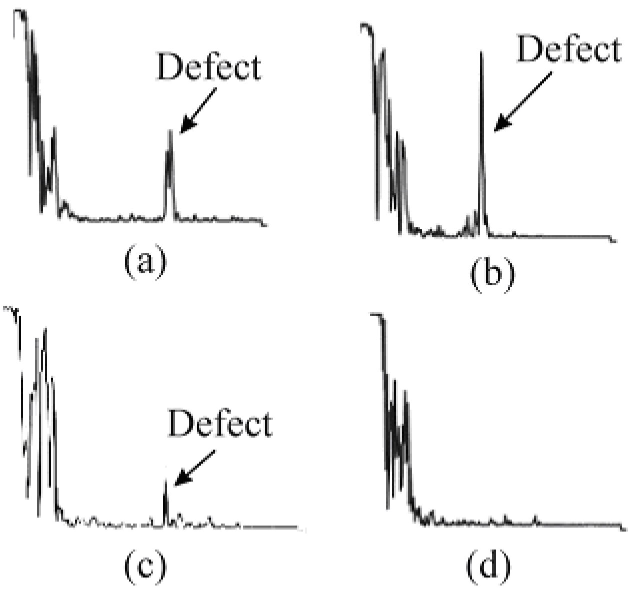

Figure 5. Example of characteristic pulse-echo signals: (a) LF, (b) LP, (c) PO and (d) ND.

The neural network was initially fed with pulse-echo signals. The performance in classifying the four studied classes was evaluated. Another group of signals was acquired, this time for the TOFD technique and, again, the classifier performance was evaluated. Finally, both signals were preprocessed with the application of one low-pass filter to smoothen the signal. These preprocessed signals were used, again, as inputs for the classifier.

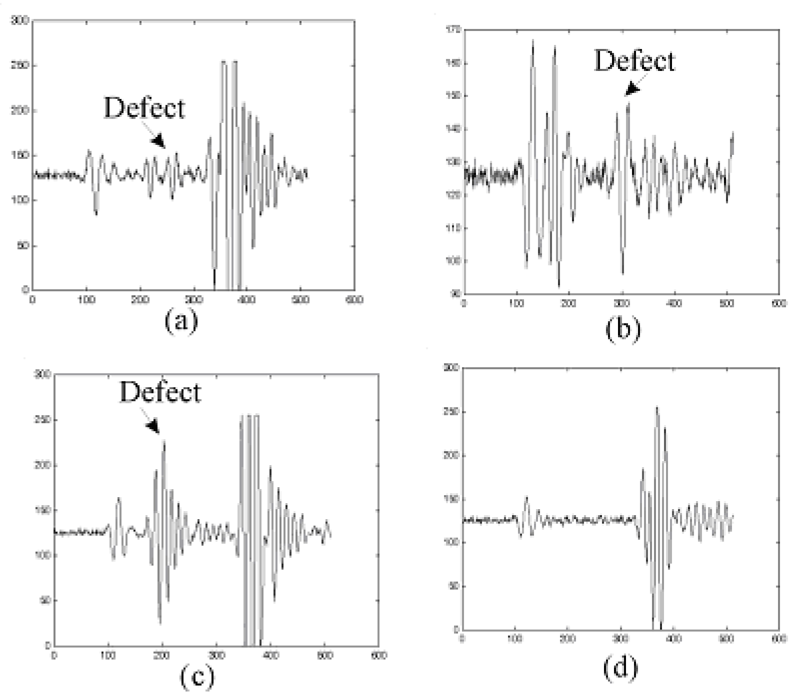

Figure 6. Example of characteristic TOFD signals: (a) LF, (b) LP, (c) PO and (d) ND.

6. Results and Discussions

Tables 1 and 4 show the results of "confusion" between classes for training and test for the pulse echo and TOFD, respectively. The tables 2, 3, 5 and 6 show the general results for the pulse echo signals, preprocessed pulse echo, TOFD and preprocessed TOFD in that order. Table 2 shows that the results of the pulse echo signals for training (97.5%) were better than those for test (73.75%). This difference between the training signals and the test signals was also observed in the preprocessed pulse echo signals, rate of success of 100% for training and 77.5% for test (Table 2). The TOFD signals without preprocessing presented a rate of success of 96.25% for training and 76.25% for test (Table 5) and with preprocessing 98.75% for training and 97.5% for test (Table 6). This difference is due to the fact that it is easier for the ANN to classify a signal known during the training process, than a totally unknown signal (test signal). All the tables show the results of the classifier with the decision criteria at the output, which means that the signal can be classified even when the network doesn't indicate any class or indicates more than one class as true. When this occurs, the output class will be the one with the largest algebraic value at the output of the network. The tables 1 and 4 show the results for the classification of each class, also showing the "confusion", which occurs between the classes.

Table 1 shows that for the training data the LF and ND classes were separated, while the LP and PO classes presented error in the classification. For the test data the LF, PO and ND classes presented rate of success of 85%, 65% and 90% respectively. The good performance of ND class can be explained by the absence of echoes, making the signal cleaner. The LP class showed a rate of success of 55%. The low rate of success presented by this class can be explained by the fact that the signal presented a large variation in shape, with amplitude alterations of the peak of the defect, which caused a confusion, mainly, with the FF and ND classes.

The results of the preprocessed pulse echo signals presented in Table 3 show that all the classes were well separated during the training, and that the test data also presented the same tendency of success as the pulse echo test without preprocessing, the ND class was the best separated with 95% of success, followed by LF (90%), PO (70%) and LP (55%). A possible reason for the low rate of success for the class LP is that during the processing some relevant information may have been suppressed from the signal, reducing the characteristics for the identification of the class by ANN.

Table 4 presents the results of the TOFD technique. It can be seen that during the training of LF and PO classes no showed errors, and the worst classification was for the ND class with a rate of success of 87.5%. For the test data, the best results was obtained with the LP class with 90% of success, followed by PO with 80% and LF with 70%. The worst result was for the ND class with 65%. The good performance presented by the LP class can be explained by the fact that the signal of this class did not have a back-wall echo, which caused low confusion with the other classes. While the low rate of success presented by ND class can be explained by the presence of noise in the signal, which was eliminated with the preprocessing, bringing a significant improvement of the performance of ANN. The same explanation could be the reason of the errors in LF class, due to the improvement after preprocessing, as well as the fact that when the defect is very small the diffraction of the upper and lower ends of the defect are very close to each other, becoming only one echo, increasing the confusion. It can also be seen that there was a considerable confusion between the classes by the ANN, the presence of noise is a possible explanation justifying the need of a preprocessing to smoothen the signal.

In Table 6 can be observed that there was a considerable increase in the success rates of the results for the preprocessed TOFD technique, for the test data (97.5%) in relation to the test data without preprocessing (76.25%). This confirms what was said previously, that is, the noise present in the signal (unnecessary information being supplied to the classifier) was creating difficulties for the classification.

Summarizing, it can be concluded that using a pattern classifier, implemented by ANN, it is possible to classify the classes of the signals from the welds as much by the pulse echo technique as by the TOFD technique, with a reasonable rate of success (73.75% for the pulse echo and 76.25% for the TOFD technique, both for test data). However, the application of preprocessing to the signal produces a reasonable improvement in the results of TOFD (97.5%), but the same did not occur for the pulse echo technique (77.5%).

Table 1. Table of "Confusion" - Training and Test Signals - Pulse-echo Signals

	Training Signals				Test Signals			
	LF	LP	PO	ND	LF	LP	PO	ND
LF	100%	0%	0%	0%	85%	5%	10%	0%
LP	3.3%	93.4%	0%	3.3%	20%	55%	5%	20%
PO	0%	0%	96.7%	3.3%	15%	0%	65%	20%
ND	0%	0%	0%	100%	5%	0%	5%	90%

Table 2. Table of Success and Errors - Training and Test - Pulse-echo Signals

	Training		Test	
	Success Rate	Error Rate	Success Rate	Error Rate
LF	100%	0%	85%	15%
LP	93.3%	6.7%	55%	45%
PO	96.7%	3.3%	65%	35%
ND	100%	0%	90%	10%
TOTAL	97.5%	2.5%	73.75%	26.25%

Table 3. Table of Success and Errors - Training and Test - Preprocessed Pulse-echo Signals

	Training		Test	
	Success Rate	Error Rate	Success Rate	Error Rate
LF	100%	0%	90%	10%
LP	100%	0%	55%	45%
PO	100%	0%	70%	30%
ND	100%	0%	95%	5%
TOTAL	100%	0%	77.5%	22.5%

Table 4. Table of "Confusion" - Training and Test Signals -TOFD Signals

	Training Signals				Test Signals			
	LF	LP	PO	ND	LF	LP	PO	ND
LF	100%	0%	0%	0%	70%	0%	25%	5%
LP	0%	97.5%	2.5%	0%	5%	90%	5%	0%
PO	0%	0%	100%	0%	10%	5%	80%	5%
ND	5%	2.5%	5%	87.5%	5%	5%	25%	65%

Table 5. Table of Success and Errors - Training and Test -TOFD Signals

	Training Signals		Test Signals	
	Success Rates	Error Rates	Success Rates	Error Rates
LF	100%	0%	70%	30%
LP	97.5%	2.5%	90%	10%
PO	100%	0%	80%	20%
ND	87.5%	12.5%	65%	35%
Total	96.25%	3.75%	76.25%	23.75%

Table 6. Table of Success and Errors - Training and Test - Preprocessed TOFD Signals

	Training Signals		Test Signals	
	Success Rates	Error Rates	Success Rates	Error Rates
LF	100%	0%	100%	0%
LP	95%	5%	90%	10%
PO	100%	0%	100%	0%
ND	100%	0%	100%	0%
Total	98.75%	1.25%	97.5%	2.5 %

7. Conclusions

Using a pattern classifier implemented by neural networks it is possible to classify patterns of ultrasonic signals from welds by the pulse echo technique and by the TOFD technique with a reasonable rate of success (73.75% for pulse echo and 76.25% for the TOFD technique, both without preprocessing).

Preprocessing applied to the signal with the objective to reduce the levels of noise present produced a considerable improvement in the classification of the signals acquired by the TOFD technique. The same was not observed for the pulse echo technique.

Based on the analysis of the results it can be concluded that the signals evaluated: the pulse echo, with and without preprocessing and TOFD with and without preprocessing, the TOFD signal with preprocessing presented the best rate of success. It can also be concluded that of the four classes evaluated: lack of fusion, lack of penetration, porosity and non defect, the class which showed the best classification by ANN was lack of fusion followed by the non defect class. The increase in the number of training signals, adequately including representative data of all classes to be resolved, is a factor that can help to increase the ANN performance.

For an on-line production system, where processing time could be a problem, both the pulse-echo technique and the TOFD technique presented a rate of success higher than 73% for tests, without preprocessing. However, if the processing time is not a problem, as for example, for auxiliary inspectors on decision, the TOFD technique showed better results with preprocessing signal.

8. Acknowledgements

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10. Responsibility notice

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