Welding defect pattern recognition in TOFD signals Part 1. Linear classifiers

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Non-destructive tests have been increasingly used as an inspection method to assure the quality and reliability of products and equipment. Among non-destructive testing techniques, ultrasound is one of the most applied in industry, for detecting and sizing up discontinuities in materials, evaluating their properties, measuring thickness, etc. Some difficulties in metallic material inspections by other methods, such as radiography, to detect cracks that are parallel to the X-ray beam, have been eliminated by using the TOFD technique, which sends an ultrasound beam to the interior of the material being inspected but at an angle in relation to its surface. Although TOFD has high speed inspection, high sizing reliability and low rate of incorrect results, the classification of defects through ultrasound signals generated by the TOFD technique is still frequently questioned, because it depends heavily on the knowledge and experience of the operator. The use of computational tools for the pattern recognition, such as the artificial neural networks, has offered a new way to classify the defects detected using this technique. This study shows how to obtain the best hierarchical and non-hierarchical linear discriminators, in order to distinguish the main defects in welded joints detected by the TOFD technique, using the technique of neural networks for its implementation. The results are very promising.

1. Introduction

There are many types of NDT and each type offers advantages and disadvantages, depending on the material being inspected, the type of discontinuity, the medium in which the material is, and so on. Thus, the choice of the most appropriate method depends on the desired application. Nowadays, with the ever-increasing competition among industries, the use of NDT has risen significantly, as shown by the high number of studies developed in research centres and universities in this area.

Radiography has been widely used to detect and to size discontinuities in welded joints of metallic materials. However, the ultrasound technique is moving in to replace radiography, especially because X-rays produce ionising radiation (which represents a certain danger to the operator), besides the need to develop the film, which takes some time to give the results. Unlike the tests with penetrating radiation, the ultrasonic test does not require special safety features or any other accessories. The time-of-flight diffraction (TOFD) technique[1] is an important non-destructive test that has eliminated the difficulties found in sizing defects that are parallel to the X-ray beam, sending to the interior of the material an ultrasound beam inclined in relation to the surface of the area being inspected[2,3]. Before the use of TOFD, the detection and sizing of discontinuities with ultrasonic techniques usually used the amplitude of the echo obtained and related each amplitude directly to the dimension of the discontinuity.

Despite the advantages of the ultrasound over the radiographic test, the classification of ultrasound defects is still frequently questioned for being very subjective, since the analysis and the identification of defect types depend exclusively on the experience and knowledge of the operator.

The increasing progress in computational techniques, mainly the development of neural networks, has greatly stimulated research into the development of automatic systems for the inspection and the classification of defect patterns[4,5,6]. Neural networks consist of algorithms that learn how to simulate some functions of the brain, such as pattern recognition, creation of associations, signal processing and learning by experience or training. Although they are less complex than the human brain, the neural networks can process enormous amounts of data in a short period of time that typically could only be analysed by a specialist. The network's training or learning by examples, exactly like the human brain, is one of its most important characteristics[7,8].

In this study, hierarchical and non-hierarchical linear classifiers are implemented by using artificial neural networks. The performance of such classifiers is evaluated in the classification of the following types of defects in welded joints detected by the TOFD technique: lack of fusion (LF), lack of penetration (LP) and porosity (PO). One type of signal from regions presenting no defect (ND) was also defined to evaluate the capability of these classifiers to identify signals from regions with defect or regions presenting no defect.

2. Principle of the TOFD technique

First reported by Maurice G Silk in 1975, the TOFD is a technique that uses the time-of-flight of the ultrasonic signals that are diffracted by the upper and lower tips of the defects as a reference for its sizing (Figure 1)[1,9].

The TOFD technique is based on the interaction of the ultrasonic waves with the extremities of the discontinuities. The issue of diffracted spherical waves is the result of such interaction. The detection of these diffracted waves makes it possible to establish the presence of discontinuities. The difference in the time-of-flight of the registered signals is related to the discontinuity height, and consequently it allows to set its sizing. The signal amplitude is not used to calculate the dimension.

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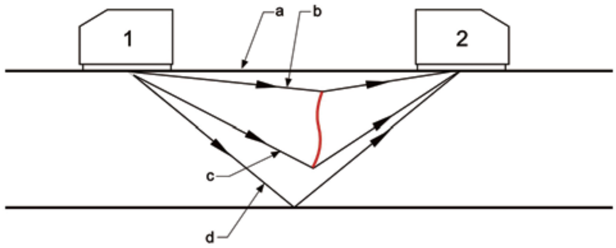

Figure 1. Typical arrangement for the TOFD technique: (1) Transmitter; (2) Receiver; (a) Surface wave; (b) wave diffracted by the upper tip of the defect; (c) wave diffracted by the lower tip of the defect; and (d) backwall echo

The conventional configuration for the TOFD technique consists of two transducers, one emitter and one receiver, aligned on either side of the weld bead, so that the region of interest is entirely within the area covered by the sonic emitter (Figure 1). The transducers of longitudinal waves are usually used, since they have a higher propagation speed than transversal waves, they do not suffer superposition of other types of waves and offer an easier identification of defects and better construction of images[10].

The 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 Figure 2.

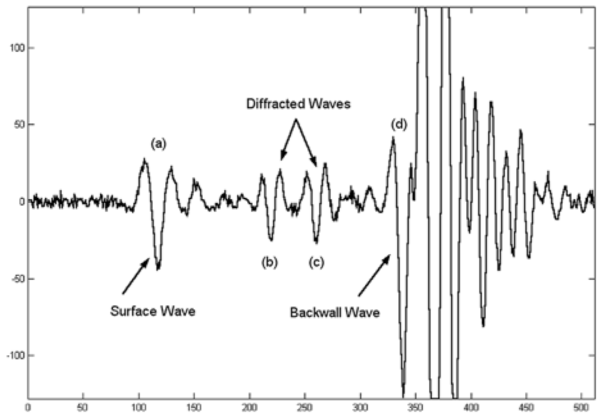

Figure 2. Typical model of the signal obtained (A-scan) by the TOFD technique in a region with one discontinuity

The first signal coming into the receiver after the acoustic impulse is usually the surface wave that propagates under the upper surface of the tested specimen. In the absence of discontinuities, the second signal that comes will be the backwall echo. These two signals are usually used as a reference. Any signals diffracted from discontinuities will come between the surface wave and the backwall echo, since they correspond to the shortest and longest distances respectively between the transmitter and the receiver.

For identical reasons, the diffracted signal at the upper tip of a discontinuity will come before the signal generated at the lower tip. The calculation of the discontinuity height is based on the difference in the time-of-flight of both diffracted signals.

3. Materials

Inspections with the TOFD technique were performed on twelve test samples of steel plate AISI 1020, 20 mm in thickness, 300 mm in length, 50° V-bevel and welded by the shielded process. Different defects, such as lack of fusion (LF), lack of penetration (LP) and porosity (PO) were inserted into the test samples during the welding process, generating defect patterns. The position, type and dimension of each inserted defect were previously recorded by means of ultrasonic tests, pulse-echo tests and radiography.

3.1. Acquisition of signals

An automatic system of inspection was used for the acquisition of several A-scans obtained with the normal transducer displaced in relation to the direction of the sonic beam. This system consisted of a vehicle with magnetic wheels, especially designed to transport one pair of 5 MHz normal transducers, and 60° angle wedge for longitudinal waves; a conventional ultrasound equipment; an A/D converter; a microcomputer (PC) and a program developed at the Non-Destructive Testing Laboratory – LABOEND/COPPE/UFRJ that controls the vehicle and stores the signals from the inspected weld region.

3.2. Selecting signals

After the inspection of twelve test samples, a total of 240 signals (A-scan), equally divided into the four classes (LF, LP, PO and ND), were selected for processing with the neural networks. From the 60 signals selected for each class, 40 signals were used during the network training stage, and 20 signals were reserved to test the capability of the classifier to identify signals not presented during the training process. Each A-scan has 512 points.

4. Hierarchical and non-hierarchical linear classifiers

In this study, each input of the neural network is represented by a vector $\vec{x}$, dimension: 512 (one signal with 512 points), or geometrically, by one point in a space of dimension 512, called space of inputs. A linear discriminator for the class C_j separates the inputs of this class from the others, through one linear inequation of the first order.

$$\vec{x} \in C_j \Leftrightarrow u_j > 0 \quad \text{.....................................(1)}$$

where:

$$u_j = \sum_{i=1}^{512} w_{ji} x_i + b_j = \vec{w}_j^t \vec{x} + b_j \quad \text{.......................(2)}$$

each class C_j has its own discriminator, defined by $\vec{w}_j$ and b_j.

In the input domain, the separator of the class C_j, that is, the geometric place of the points that fulfills $u_j = 0$, is a plane which is perpendicular to the vector $\vec{w}_j$ and distant from the origin $-b_j / \left|\vec{w}_j\right|$, a distance measured in the direction of $\vec{w}_j$. Usually, it is regulated to $\left|\vec{w}_j\right| = 1$, adjusting the value of b_j not to alter the inequation (1). In this case, u_j measures the distance from the input $\vec{x}$ to the separator, and u_j is usually the success probability measurement of the classification for that specific input[7,11].

The excellent linear discriminators are those that maximise the precision probability of the classification. One practical way to implement them is through a one-layer neural network, with only one neuron per class as described by Haykin[7]. This technique was used in this study. With a set of training available, networks with supervised learning were used, where the algorithm of the error backpropagation was used for training of the neural network.

The geometric display of the separators in this case was difficult, due to the input space dimension (512), although in a bidimensional space it can be done easily. In Figure 3, the shaded area shows the domain of hypothetical inputs of classes C_j and its respective separators S_j (that, in this case, are represented by the straight lines).

Each separator S_j divides the input space into two semi-spaces (in this case, two semi-planes), one with $u_j > 0$ and one with $u_j < 0$. The

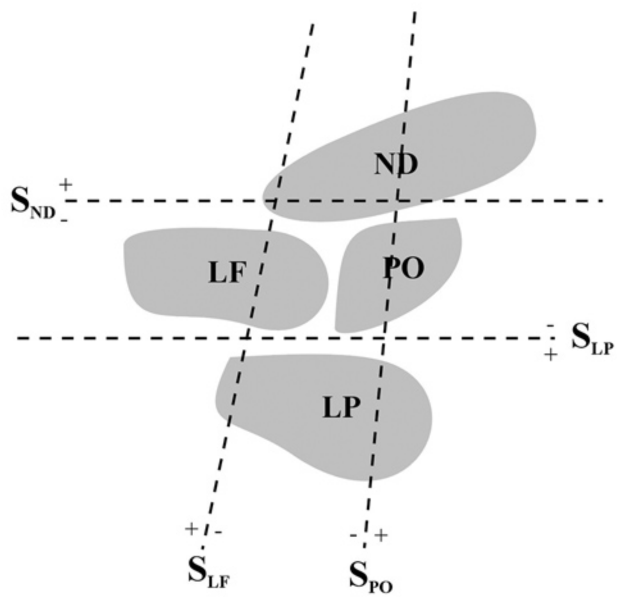

Figure 3. The four classes C_j, j = LP, ND, PO and LF, and their respective non-hierarchical separators S_j with the polarities indicated. The most external classes LP and ND are almost perfectly separated, and the most internal classes PO and LF are imperfectly separated

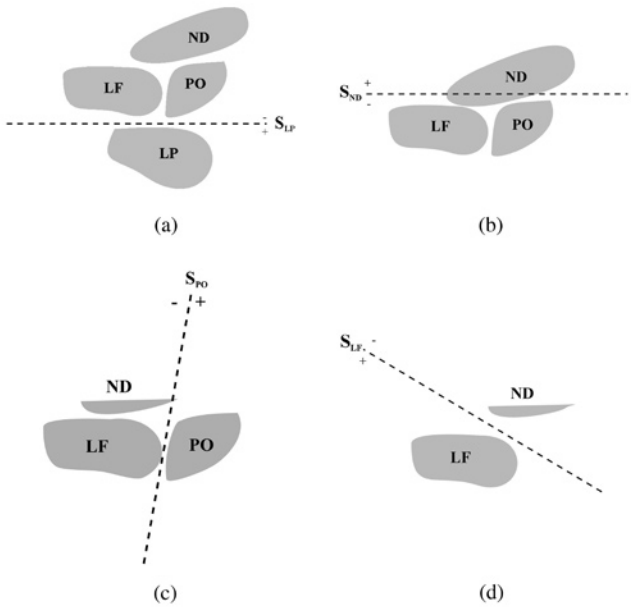

Figure 4(a) and (b): After the exclusion of the inputs classified as LP and ND, the other discriminators can assume positions that are much more efficient in separating the remaining classes, mainly S_{PO}, (c), and the same happens after the exclusion of the inputs classified as LF (d)

inputs belonging to the class C_j and that are classified incorrectly are represented by points in the semi-plane where u_j is positive. Notice that there are regions in the positive semi-space of two or more separators: one input in this region will be assigned to two or more classes. On the other hand, there might be regions in the negative semi-space of all separators: one input in this region will not be assigned to any class. In this situation, it can be considered that u_j is the probability measurement of one input belonging to the class C_j and 'tie-breaking' the result, taking the class with the greatest u_j, which is the most probable one to include the input, as being the answer.

It can also be clearly observed that the most 'external' classes are more easily separable, while the 'internal' ones are hardly separable (Figure 3). However, if these 'external' classes are removed, other classes that had previously been 'internal' will become 'external', and then can be separated easily (Figure 4). This introduces the concept of hierarchical classification, where the 'external' classes are classified first, that is, those with high precision level, and only afterwards, the 'internal' classes are classified[12].

As Figure 4(b) shows, there is a small region of ND that is not correctly classified by the separator S_{ND}, being situated in the negative semi-space. In this case, this set of signals regarding the class ND is not removed from the system, and the discriminator of the class PO is found, not only to separate PO from LF, but also from such set of signals belonging to the class ND.

It is important to point out that these figures are simplified illustrations that describe the method used to obtain hierarchical and non-hierarchical classifiers. Their sole purpose is to show the operating principle of these classifiers, and not to represent the exact condition of the signals used in this study.

The algorithms are constructed after obtaining the discriminators of each class. The flow diagram of a non-hierarchical classifier is shown in Figure 5.

The input vectors are multiplied by the vectors $\vec{w}_j$ of each class and added to the corresponding bias b_j, generating u_j. The result of this operation that is greater than zero corresponds to the selected class. In this situation, it is possible to have no class being indicated (when all outputs are negative), or the occurrence of more than one indication (when more than one output is greater than zero).

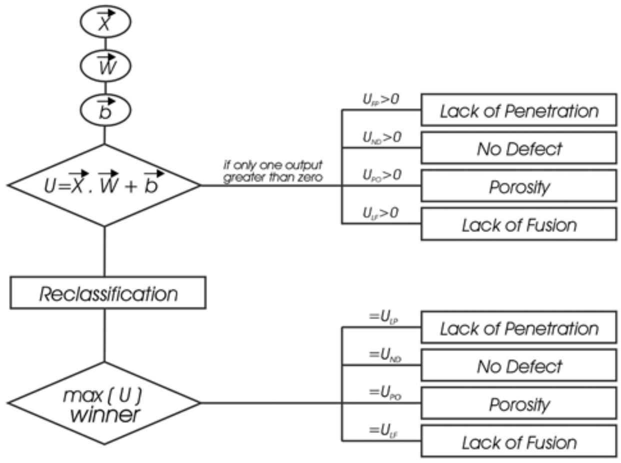

Figure 5. Algorithm of the non-hierarchical linear classifier

In this case, one reclassification criterion, or a 'tiebreak', can be used, in which the greatest value of u_j indicates the class. For both cases (with or without reclassification), the tables of defect-type confusion, precision and errors were constructed, based on the results obtained[12].

Unlike the non-hierarchical classifier, the hierarchical classifier first classifies the most easily separable classes. The algorithm of this classifier is shown in Figure 6[12]. Its performance was similar to the non-hierarchical classifier. The algorithms of the non-hierarchical and hierarchical classifiers are compared below, in terms of precision percentage.

6. Presenting and discussing the results

6.1 Non-hierarchical linear classifiers

With this type of classifier, each class shall be separated from the others, independently of being linearly separable or not. This section shows the results obtained from the data of the training and test done with the non-hierarchical classifier. It must be pointed out that the purpose of such data is to evaluate the performance of the classifier for data that were not used during the training. Tables 1

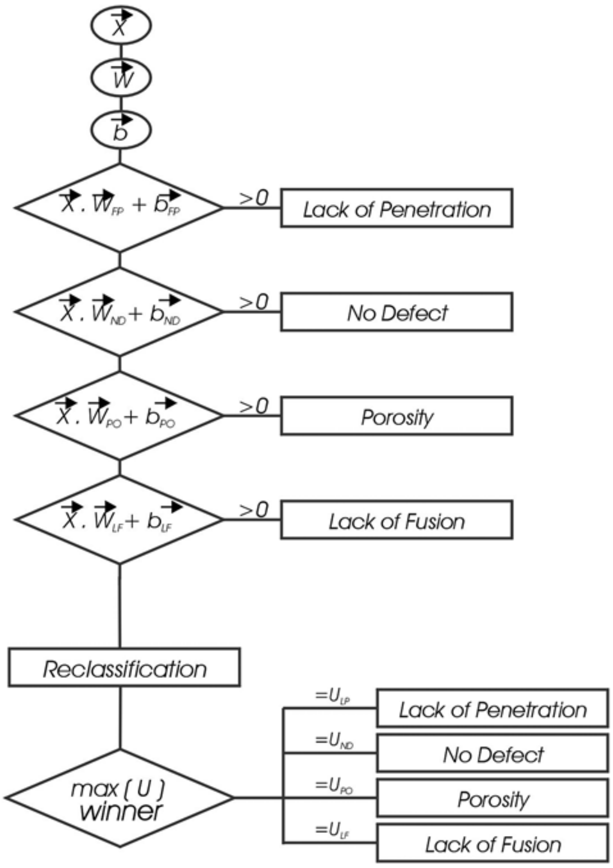

Figure 6. Algorithm of the hierarchical linear classifier

and 2 show the results obtained from the training data, and Tables 3 and 4 show the results obtained from the test data. It can be seen that in Tables 2 and 4 the general result for the training data (85%) is higher than the general result for the test data (71.25%). This is because it is easier to classify a signal that was supplied to the network during the training process.

Table 1 shows the results for the non-hierarchical linear classifier without any 'tiebreak' criterion at the output. Table 1 also shows the values in percentage for when no class was identified, or when more than one class was activated. With the data in Table 1, it is possible to observe that the lack of penetration defect (LP) has the best performance (95%), indicating that this is the most easily separable class. This result was obtained due to the fact that the backwall echo position is slightly altered by this type of defect. The result obtained for the class presenting no defect was the second best (87.5%), followed by the porosity defect (82.5%). The worst performance obtained was for the lack of fusion defect (75%), because this class (LF) is characterised by two peaks, which may not be very evident in the signal, and consequently its classification is more difficult. It might be thought that the signal class presenting no defects would be the most easily separable one, since it has the simplest signals, but in fact it is not so. This was probably a consequence of noise present in the signals that was mistakenly considered a defect.

During the more conservative process (without any 'tiebreak' criterion at the output), there was no confusion among the classes. However, during the reclassification, the signal is forced to belong to a class.

Table 2 shows the performance percentage of the classifier with the 'tiebreak' criterion based on the greatest output value of signals that were classified or that were classified more than once. Although a better performance was expected for this process, this was not confirmed for the training signals, and such signals

Table 1. Table of confusion, successes and errors – non-hierarchical linear classifier. Original signals – training signals – without criterion of reclassification (%)

	Neuron winner						Successes	Errors	Without classification
	LF	LP	PO	ND	None	More than one			
LF	75	0	0	0	25	0	75	0	25
LP	0	95	0	0	5	0	95	0	2
PO	0	0	82.5	0	17.5	0	82.5	0	17.5
ND	0	0	0	87.5	12.5	0	87.5	0	12.5
						TOTAL	85	0	15

Table 2. Table of confusion, successes and errors – non-hierarchical linear classifiers. Original signals – training signals – with criterion of reclassification (%)

	Neuron winner				Successes	Errors
	LF	LP	PO	ND		
LF	75	10	2.5	12.5	75	25
LP	0	95	2.5	2.5	95	5
PO	2.5	5	82.5	10	82.5	17.5
ND	0	5	7.5	87.5	87.5	12.5
				TOTAL	85	15

were reclassified incorrectly, having in Table 2 the same results obtained in Table 1. However, it will be interesting to observe this improvement for the test signals later on.

It is possible that these signals belong to these reclassified classes and that the error occurred during the classification carried out by the operator. Besides this supposition, such error may also be related to the low signal/noise ratio, characteristic peaks of the class that had little emphasis, or even the relative position among the classes, etc. This questioning encourages even further the elaboration of this study, showing that it may even happen in the conventional process of inspection, due to the difficulty presented by the technique.

Table 1 also summarises the performance of these classifiers in terms of global percentages of correctly classified observations, errors and output with no classification (all outputs of negative network or more than one positive network). First, for the case without any 'tiebreak' criterion at the output, and afterwards, with the classification by the greatest value (Table 2). In this way, it was possible to obtain the general performance of this type of classification algorithm. The precision percentage found was 85%, which is a reasonable result considering that a linear classifier was used.

Tables 3 and 4 show the results for the test data, indicating, as mentioned before, that the performance of such data (71.25%) is inferior to the results for the training data (85%). However, there is coherence with the training results, the class LP being the most easily separable (90%) and the class LF the least separable (55%). Tables 3 and 4 also show that one improvement occurred with the reclassification of the test data, although the reclassification process did not improve the performance of the classifiers of the training signals.

6.2 Hierarchical classifiers

The order used in the separation of the classes (separation hierarchy) was chosen considering the results of the non-hierarchical process (Tables 1 and 2), starting with the class that presented the best precision rate towards the class that presented the worst rate.

Table 5 shows the first results found for the hierarchical classifier. The performance of this classifier was better than the performance of the non-hierarchical classifier, even with the most demanding criterion (classification only when just one output is greater than zero, that is, with no reclassification). The precision rates of 100% for LF and PO confirm that these are the two linearly

Table 3. Table of confusion, successes and errors – non-hierarchical linear classifier. Original signals – test signals – without criterion of reclassification (%)

	Neuron winner						Successes	Errors	Without classification
	LF	LP	PO	ND	None	More than one			
LF	55	0	0	0	35	10	55	10	35
LP	0	80	0	0	10	10	80	10	10
PO	5	0	65	5	25	0	65	10	25
ND	0	0	5	55	30	10	55	15	30
						TOTAL	63.75	11.25	25

Table 4. Table of confusion, successes and errors – non-hierarchical linear classifier. Original signals – test signals – with criterion of reclassification (%)

	Neuron winner				Successes	Errors
	LF	LP	PO	ND		
LF	55	15	25	5	55	45
LP	5	90	0	5	90	10
PO	10	0	70	20	70	30
ND	0	10	20	70	70	30
				TOTAL	71.25	28.75

classifiable classes. Another important point of interest regarding the precision rates of 100% for LF and PO is that these classes exceeded ND and LP, which were the most easily separable classes in the non-hierarchical process. In theory, it can be explained by the fact that, with the removal of the most external classes, the classification of the most internal classes becomes easier (Figure 4). During the reclassification stage, the training signals were incorrectly reclassified, and the results obtained with the 'tiebreak' criterion at the network output, shown in Table 6, are the same as shown in the previous case (Table 5), without any increase in the precision rate. However, considering the test signals, there was a small improvement in the global precision rate in the reclassification process, which can be observed when comparing Table 7 to Table 8.

When comparing the non-hierarchical classifier to the hierarchical classifier, it is clear that the results of the hierarchical classifier are better, mainly regarding the classes LF and PO. Tables 5 and 6 show the general results of this type of classifier for the training data. The precision rate of 96.25% shown in Table 6 is significantly higher than the precision rate of 85% shown in Table 2.

Table 5. Table of confusion, successes and errors – hierarchical linear classifier. Original signals – training signals – without criterion of reclassification (%)

	Neuron winner					Successes	Errors	Without classification
	LF	LP	PO	ND	None			
LF	100	0	0	0	0	100	0	0
LP	0	95	0	0	5	95	0	5
PO	0	0	100	0	0	100	0	0
ND	0	0	0	90	10	90	0	10
					TOTAL	96.25	0	3.75

Table 6. Table of confusion, successes and errors – hierarchical linear classifier. Original signals – training signals – with criterion of reclassification (%)

	Neuron winner				Successes	Errors
	LF	LP	PO	ND		
LF	100	0	0	0	100	0
LP	0	95	2.5	2.5	95	5
PO	0	0	100	0	100	0
ND	5	2.5	2.5	90	90	10
				TOTAL	96.25	3.75

Table 7. Table of confusion, successes and errors – hierarchical linear classifier. Original signals – test signals – without criterion of reclassification (%)

	Neuron winner					Successes	Errors	Without classification
	LF	LP	PO	ND	None			
LF	75	0	20	5	0	75	25	0
LP	10	90	0	0	0	90	10	0
PO	5	5	80	5	5	80	15	5
ND	0	5	20	65	10	65	25	10
					TOTAL	77.5	18.75	3.75

Table 8. Table of confusion, successes and errors – hierarchical linear classifier. Original signals – test signals – with criterion of reclassification (%)

	Neuron winner				Successes	Errors
	LF	LP	PO	ND		
LF	75	0	20	5	75	25
LP	10	90	0	0	90	10
PO	5	5	85	5	85	15
ND	0	5	30	65	65	35
				TOTAL	78.75	21.25

It also increased from 71.25% shown in Table 4 to 78.75% shown in Table 8 for the test data. This result can be considered very good, as a linear classification criterion was used for the classification of the defects.

When analysing the errors occurred during the reclassification shown in Tables 2, 4, 6 and 8, it can be seen that none of the studied classes was systematically taken as being another class by mistake. Table 9 shows a summary of all the results obtained with the original signals.

Table 9. Summary of results for linear classifier and original signals (%)

Original signals				
	Non-hierarchical		Hierarchical	
	Training	Test	Training	Test
Number of signals	160 signals	80 signals	160 signals	80 signals
Successes	85	71.3	96.25	78.75
Reclassification	0	7.5	0	1.25
Errors	15	28.75	3.75	21.25

In order to obtain the results presented so far, the signals that were used during the training and the test of the linear classifier were the original signals of the inspection, that is without any type of preprocessing, such as low-pass filters, or any other denoise technique, etc.

With the purpose of improving the performance of the classifier, the inputs presented to the neural network were preprocessed. The preprocessing consisted in the envelope calculation of each of the 160 signals through an application of the digital filter Savitzky-Golay[13]. After such preprocessing, all the previous stages were repeated.

Table 10 shows a summary of all the results obtained when the preprocessed signals were used as the input of the neural network. A significant improvement can be seen in all the stages executed, that is with or without hierarchy, with or without reclassification,

Table 10. Summary of results for linear classifier and preprocessed signals (%)

Preprocessed signals				
	Non-hierarchical		Hierarchical	
	Training	Test	Training	Test
Number of signals	160 signals	80 signals	160 signals	80 signals
Successes	94.38	83.75	99.375	96.25
Reclassification	3.75	11.25	0	0
Errors	5.625	16.25	0.625	3.75

and both for the training and test signals. This is explained by the fact that the preprocessing pointed out certain relevant information the signal contained, characteristics of each class, suppressing the irrelevant information that could have made the classification more difficult.

7. Conclusions

The linear classifiers of pattern implemented by neural networks are very efficient in the classification of the studied classes. The classification criterion by hierarchy optimised the performance regarding the non-hierarchical classification. Besides, the preprocessing of the signals eased the use of such classifiers, increasing their performance in the classification significantly. The results presented for the test data, just a little different regarding the training data, confirmed their identification capability to identify new signals.

In general, the results obtained are very promising, giving contributions that are important to research into the development of an automatic system for the detection and classification of welding defects inspected using the TOFD technique. It is expected that non-linear classifiers can offer even better performances.

This study did not inspect other types of defects, such as crack, undercutting, slag inclusion, etc. However, the same procedure studied here can be applied to the classification of these classes, which will be done in future studies.

Usually, the ultrasonic inspection process using the TOFD technique is automatic. With the results presented in this study, there is a possibility of automating the result-evaluating stage.

8. Acknowledgement

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