Signal Processing Techniques for Ultrasound Automatic Identification of Flaws in Steel Welded Joints – A Comparative Analysis

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Abstract

The purpose of this work is to compare the effects of different signal processing techniques applied as preprocessing steps for a steel welded joints automatic flaws identification system. Three types of defects (lack of penetration, porosity and slag inclusion) were artificially produced during the welding process of two carbon-steel plates. Ultrasound inspection using the phased-array technique was performed in the welded joint. The ultrasound signals were pre-processed in two different ways through both Fourier and wavelet transforms and further classified using an artificial neural network. The effects produced by each pre-processing technique on the classifier flaw detection and identification efficiencies were evaluated.

Key-words: Ultrasound inspection, Signal Processing, Neural Networks, Welded Joints

1. Introduction

During the manufacturing of a part or after some time of use imperfections or defects that are often imperceptible to a visual inspection shall appear. A proper inspection procedure able to detect and identify the defects is required in order to assure reliability and prevent system damage or failure. In this contest, the ultrasonic testing is applied to detect internal discontinuities present in the equipment. Welded joints are present in a great number of facilities and equipments and are subject to different kinds of imperfections and defects.

Among the conventional ultrasonic techniques, the pulse echo configuration is widely applied. The results of an ultrasonic inspection are usually obtained by experienced operators that analyze the receive echoes characteristics and decide whether it corresponds to a normal condition or a defect. Recently, different signal processing techniques [1, 2] were applied to the ultrasonic signals aiming at facilitating the detection of abnormal conditions. Automatic classification systems based on Artificial Neural Networks (ANN) have also been use to produce materials condition indication [3, 4].

This work presents a comparative study on the application of digital signal processing techniques, such as the discrete Fourier and wavelet transforms, as preprocessing steps for a neural network based steel welded joints flaws identification system.
2. Theoretical Foundation

2.1 Ultrasound Inspection

The purpose of the ultrasonic test is the detection of internal discontinuities in industrial equipment and components [5]. Due to its simplicity of application and the need for contact with only one surface, the pulse-echo configuration is widely used [6]. The pulse-echo test uses only one transducer to send and receive ultrasonic waves, verifying the location and dimensions of the discontinuities [7].

In ultrasonic testing, one of the main factors that significantly affect the reliability and accuracy of a measurement is the noise (electronic or acoustic) produced during the inspection. Thus, techniques for digital signal processing and computational intelligence are employed to extract relevant information from the signals and provide more reliable results [8].

2.2 Discontinuity in Welded Joints

In industry, welding is one of the most applied metal joining processes. There are basically two types of welding, which are based on pressure or fusion. In pressure welding the parts to be joined together are turned into a viscous state by absorbing power provided by pressure (usually no additional material is required). Among the pressure welding processes we can mention friction and ultrasonic welding.

In the fusion welding thermal power is applied to produce heat capable of melting the base material. Among the fusion-welding processes, we can mention: MIG / MAG, TIG, coated electrodes, plasma, submerged arc, etc. In fusion welding, only the parts to be joined are heated and the rest of the specimen remain at much lower temperatures [9].

A discontinuity can be defined as any break (or imperfection) in the typical structure of a welded joint. Thus, it is characterized as a discontinuity any non-homogeneity of the physical, mechanical or metallurgical characteristics of the welded material. However, for welded joints, the existence of a discontinuity does not mean the existence of defects.

The discontinuities in welded joints can be classified into two types:

- Dimensional: these discontinuities arise from changes in size or shape of the weld. Among the dimensional discontinuities one can point out the incorrect profile of the welded joints and misalignment, which is associated with inappropriate sizing or positioning of the parts.

- Structural: these discontinuities are related to lack of material or the presence of spurious material in the welded region. Its severity depends on the extent and geometry of the weld. Porosity and lack of penetration are some examples of structural discontinuities.

2.3 Signal Processing

The direct comparison of time-domain signals acquired during an ultrasonic inspection does not always allow the detection and identification of defects in welded joints. Depending on the characteristics that one wants to analyze, more sophisticated mathematical tools shall be required.
The Fourier and the wavelet transforms have the potential to significantly increase the accuracy of ultrasonic non-destructive testing, as they reveal the discriminating information by reducing redundancy and noise [8].

### 2.3.1 Fourier Transform

The signal analysis in the frequency domain by applying the Discrete Fourier Transform is a widely used tool for revealing the different frequency components of signals [10, 11]. The frequency spectrum is obtained by the decomposition of the signal in sinusoids of different frequencies [12].

Equation 1 represents the Discrete Time Fourier Transform (DTFT) [1].

\[ X(e^{jw}) = \sum_{n=-\infty}^{\infty} x[n]e^{-jwn} \]  

### 2.3.2 Wavelet Transform

The wavelet transform is a signal processing technique that allows a more accurate analysis than the Fourier transform, as it explores both time and frequency domains. Wavelets are functions that satisfy certain mathematical requirements and are used to represent data or other functions [13].

In order to perform the wavelet analysis, a prototype function, called an analyzing wavelet or mother wavelet, is required. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. The original signal can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions). Considering this, data operations can be performed using just the corresponding wavelet coefficients [13].

Analysis with wavelets can be seen as a detailed breakdown, where one seeks the most basic components of the signals. When dealing with digital signals, an efficient way to implement the Discrete Wavelet Transform is through multi resolution analysis. Using a pyramidal filtering algorithm (as illustrated in Figure 01) it is possible to obtain the approximation (low-frequency) and detail (high-frequency) [14]. The number of levels of decomposition is defined based on the nature of the signal [12]. The outputs of the wavelet filters (low pass and high pass) can be represented, respectively, by Equation 2 and 3. The reconstruction abilities of a wavelet filter depends on the choice of the mother wavelet function [15, 16, 17].

\[ y_{\text{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n - k] \]  

\[ y_{\text{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n + 1 - k] \]
2.4 Neural Networks

The detection, classification and sizing of defects by analysis of ultrasonic signals require time, and previous experience of the operator. In this context, decision support systems based on Artificial Neural Networks (ANN) are important to optimize this process and make it more reliable. ANNs are inspired by the human brain biological models and present a parallel distributed structure, which gives the networks increased computing power and a wide range of applications [18].

Neural networks have nodes or processing units. Each unit has links to other units, in which they receive and send signals. These units are the simulation of neurons, receiving and relaying information. The most important property of neural networks is the ability to learn from their environment and generalize to examples unseen in the training set [18].

The backpropagation algorithm is a method of training multi-layer networks (MLP, multi-layer perceptron), responsible for considerable expansion of the field of applications of ANNs. The training of ANNs by backpropagation involves error feedback from the input training vector and the associated adjustment of synaptic the weights [19]. A backpropagation artificial neural network was used by Thavasimuth [3] to classify ultrasonic signals in stainless steel AISI 304, obtained by the pulse echo technique, improving the detection sensitivity.

3. Methodology

3.1 Test Object

The test object used in this work consisted of a sheet of carbon steel welded joint. Both shielded metal arc welding and tungsten inert gas (TIG) processes were applied. The test object dimensions are specified in Figure 02. During the welding process, some defects such as porosity, slag inclusion and lack of penetration were purposely and randomly inserted throughout the piece. The exact locations of these imperfections were obtained through an x-ray inspection.

The signal acquisition of the pulse-echo testing was performed in two lines parallel to the weld bead. The first line was drawn with a distance of 37.50 mm from the weld and the second with 43.30 mm, as shown in Figure 02. These distances were chosen in order to reduce the interference from the near field of the transducer over shorter distances to the weld bead.
4. Results

The signal acquisition was performed by a system comprising a pulse generator, an oscilloscope and a personal computer. During the ultrasound scan, 100 signals were obtained for each class of the problem (no defect, lack of penetration, porosity and slag inclusion). The results obtained by the neural classifier are presented through the confusion matrix and the geometric mean of the efficiencies of each class. The confusion matrix elements $a_{ij}$ correspond to the number (usually in %) of elements of class $i$ identified by the classifier as belonging to class $j$. Its diagonal ($i=j$) brings the discrimination efficiency for class $i$.

In the signal preprocessing, Fourier and wavelet transforms were applied separately (as illustrated in Figures 03 and 04). In the following, the neural networks training was performed using with ~70% of the available signals from each region. Finally, we performed the neural network testing using ~30% of the signals.

Figure 05 illustrates typical time-domain echo signals for all four classes. The largest amplitude appears for lack of penetration. Typical signals corresponding to porosity and slag inclusion present low amplitude and a profile very similar to the signal without defect.

![Figure 02 - Dimensions of the steel sheet.](image)

![Figure 03 - Neural classifier based on the Fourier analysis.](image)

![Figure 04 - Neural Classifier based on the wavelet analysis.](image)
Figure 05 – Typical pulse-echo signals for lack of penetration, porosity, slag inclusion and no defect regions.

Typical frequency-domain signals are illustrated in Figure 06. As it was observed in the time-domain, the characteristic signal of lack of penetration is the one with the largest peak amplitude. The remaining three graphs are quite similar.

The Figure 07 represents the wavelet transform coefficients for the four classes addressed at this work. The first half of each graph corresponds to the approximation coefficients and second half to the detail coefficients. The characteristic lack of penetration signal after the wavelet transform is once again the one with the highest peak amplitude. The graph of the slag inclusion region is very similar to the lack of penetration, but with lower amplitude. The other remaining two graphs are very similar to each other.

Table 01 illustrates the results obtained by the neural classifier fed from the discrete Fourier (FFT) coefficients. It can be observed that the greatest efficiency was obtained for the slag inclusion class (82 %). A high confusion among the no-defect, porosity and slag inclusion signals was observed. The biggest error was observed for the region without defect (33 %). A geometric average efficiency of ~74 % was achieved.

The results obtained by the neural classifier fed from the discrete wavelet coefficients are illustrated in Table 02. In this case, the discrimination efficiency was considerably improved if compared to the previous discriminator (which was based on the Fourier coefficients). Efficiencies of ~90% are obtained for the no defect, porosity and lack of penetration signals. The average efficiency was ~88 %, indicating that the wavelet transform provides relevant information for signal classification.
Figure 06 – Typical FFT signals for lack of penetration, porosity, slag inclusion and no defect regions.

Figure 07 – Typical wavelet coefficients obtained for lack of penetration, porosity, slag inclusion and no defect regions.
Table 01 – Confusion matrix obtained by feeding a neural classifier with the discrete Fourier coefficients.

<table>
<thead>
<tr>
<th>Class</th>
<th>Without Defect</th>
<th>Lack of Penetration</th>
<th>Slag Inclusion</th>
<th>Porosity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Defect</td>
<td>67</td>
<td>6</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Lack of Penetration</td>
<td>7</td>
<td>72</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>Slag Inclusion</td>
<td>13</td>
<td>16</td>
<td>82</td>
<td>9</td>
</tr>
<tr>
<td>Porosity</td>
<td>13</td>
<td>6</td>
<td>7</td>
<td>76</td>
</tr>
</tbody>
</table>

Table 02 – Confusion matrix obtained by training a neural classifier with the discrete wavelet coefficients.

<table>
<thead>
<tr>
<th>Class</th>
<th>Without Defect</th>
<th>Lack of Penetration</th>
<th>Slag Inclusion</th>
<th>Porosity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Defect</td>
<td>94</td>
<td>7</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Lack of Penetration</td>
<td>2</td>
<td>90</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Slag Inclusion</td>
<td>2</td>
<td>1</td>
<td>80</td>
<td>5</td>
</tr>
<tr>
<td>Porosity</td>
<td>2</td>
<td>2</td>
<td>8</td>
<td>88</td>
</tr>
</tbody>
</table>

5. Conclusions

In this work, two carbon steel plates were welded using the TIG and coated electrodes processes. At the time of welding, some defects were inserted: porosity, slag inclusion, and lack of penetration. Tests were carried out using ultrasonic pulse echo technique, with a transducer angle of 45°. The ultrasonic pulse-echo technique is frequently used in industry mainly due to its simplicity and efficiency. A decision support system based on an artificial neural network classifier was designed for the ultrasound inspection of the steel welded joint. The available signals obtained during the inspection were preprocessed using both the Fourier and wavelet transforms. The obtained results were quite satisfactory. With the Fourier transform, has achieved an average efficiency of ~74% and with the wavelet transform ~88%. These results indicate that the wavelet coefficients carry relevant information for signal characterization in steel welded joints welding inspection.

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7. References