On Line Analysis and Interpretation of Ultrasonic Images to Improve the Selectivity of the Control Installations for Steel Pipes

François DENEUVILLE [1], Nicolas NOURRIT[1], Sébastien PETIT [1], Alejandra SEGURA [1], Bernard BISIAUX [1]

[1] NDT/Stats Department, VRA – V&M France – Vallourec Group, Aulnoye-Aymeries, 59620 France; Phone: +33 3276 96695, Fax +33 3276 74030; e-mail: francois.deneuville@vallourec.fr, nicolas.nourrit@vallourec.fr, sebastien.petit@vallourec.fr, alejandra.segura@vallourec.fr, bernard.bisiaux@vallourec.fr.

Abstract

The ultrasound non destructive testing methods are based on the comparison of the amplitude of the signal of response compared to the amplitude of calibration standard flaws. They therefore presuppose a high correlation between the depth of a detected flaw and the amplitude of the signal, which is generally false. The idea described in this paper consists in the use of the capacities of acquisition in production lines of the ultrasonic raw data and the reconstruction of "ultrasonic images" of pipes. Thereafter, a system automatically analyzes these images using image-processing techniques and expert systems using neural networks. The system described can then evaluate on line the gravity of the acquired ultrasonic indications much more reliably than with a single threshold.

Keywords: Ultrasound, Imagery, Flaw detection, Neural networks, Tubes.

1. Introduction

Non-destructive tests play an important role in many industrial sectors. Their purpose is to detect flaws inside a given part without damaging it. Examples of non-destructive examinations used are ultrasonics, Eddy currents, radiography, magnetic particle inspection and thermography. The choice of technique depends mainly on the application and the required degree of precision. At present, the high technicality of manufacturing processes and new requirements of customers and standards dictate that these non-destructive tests constantly need to develop.

Our work focuses mainly on ultrasonic non-destructive testing and is applicable to a wide range of industrial sectors, essentially in the field of metallurgy, owing to the simplicity of the principle: its implementation and its relatively low cost. A great many techniques are involved in perfecting the test, particularly with regard to signal and image processing methods which have improved considerably in recent years. The present study concerns the use of image processing technologies and expert systems using neural networks in order to locate and estimate the type and depth of the flaws. This paper proposes a new concept for the ultrasonic testing of steel pipes and is the subject of a patent published in January 2007.

At present, non-destructive techniques are based on the comparison of the amplitude of the signal from an inspected pipe and the amplitude of the signal from a calibration standard flaw. Studies of the correlation between the amplitude of the flaw response and the depth of the flaw have shown that the correlation is very low. On the basis of this finding, we are seeking to improve our estimation of the criticality of a flaw by using all the parameters available from the ultrasonic image rather than simply its amplitude. In order to attain this interpretation, it is necessary to follow three steps:

- Acquisition and reconstruction of the image
- Extraction of potential flaws using filtering and image processing tools
- Interpreting and characterizing the flaws (type, depth) by means of neural networks.

2. Description of the Work Performed

2.1 Conventional ultrasonic testing of steel pipes

Among the various ultrasonic testing techniques, it is the immersion technique that is the most suitable for pipes. It consists in immersing part of the pipe inside a tank containing the probes. This technique is extensively used industrially as it enables to inspect automatically the entire pipe.

The imperfections encountered in pipe manufacturing process include longitudinal and transverse flaws of varying obliquities and at various angles, and imperfections in the wall thickness, as illustrated in figure 1. The aim of our study is to improve our knowledge of these imperfections.

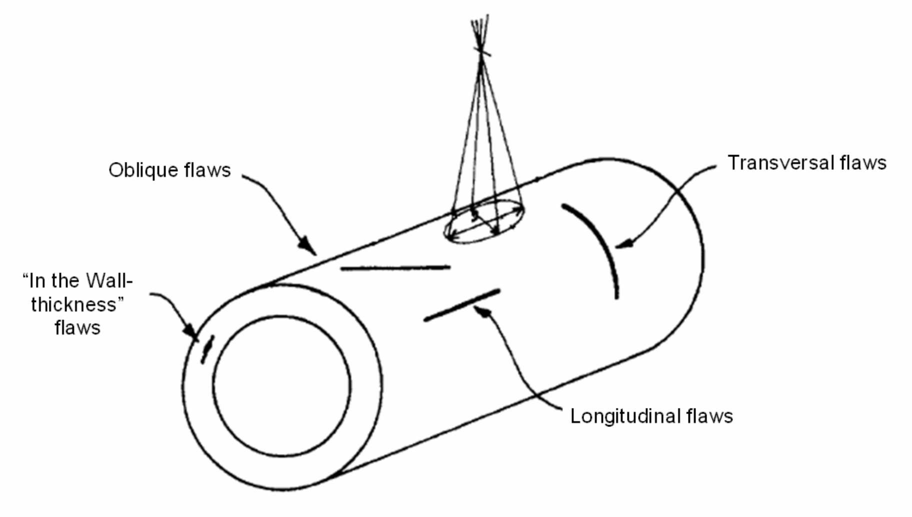

Figure 1 - Types of flaws

Conventionally, the inspection tank contains two probes for detecting longitudinal and sometimes oblique flaws, and two probes for inspecting transverse flaws, as well as a probe for wall thickness measurement and for inspecting imperfections in the wall thickness.

All the probes for longitudinal and transverse inspection are arranged diagonally opposite to each other in order to inspect the pipe in two directions of deflection so that any flaws positioned at an angle can be detected.

The interpretation involves comparing the signals received from the inspected pipe with those from a calibration standard containing reference flaws. This reference pipe serves to establish the positions of the time selectors on the Ascan for detecting internal and external flaws. The position of these selectors involves setting limits for the time base and signal amplitude according to the response obtained from the reference flaws in the internal and external surfaces, as shown in figure 2. If the amplitude of a particular echo exceeds one of the selectors, the pipe will be classed as suspect and will be either repaired or scrapped.

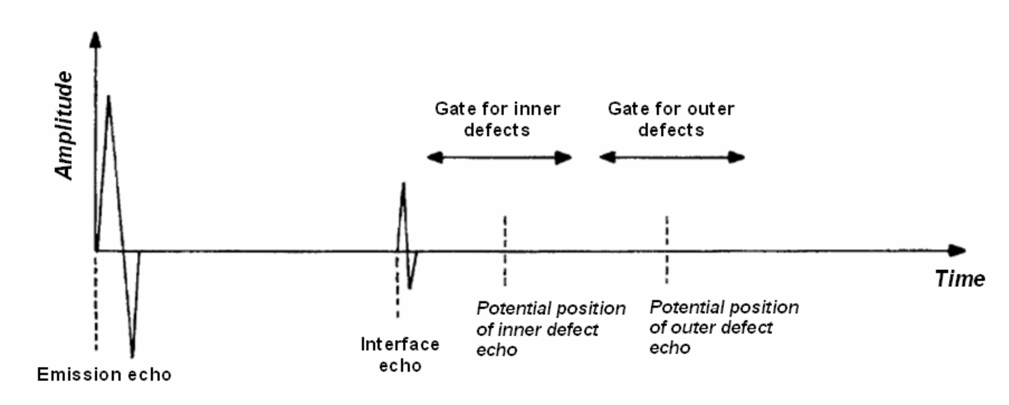

Figure 2 – Settings of selectors (or gates) on received A-scans

The gravity of the imperfections is estimated on the assumption that the amplitude of their echo will be proportional to their depth. When we analyse the following distribution:

$$K = \frac{Amplitude}{Amplitude\ de\ réf.} = f(profondeur)$$

we obtain a very poor correlation (around 0.3 to 0.4). This is why we are exploring image processing and shape recognition techniques in order to achieve more reliable and more precise interpretation of flaws.

2.2 General Description of the proposed method

Figure 3 illustrates the system according to the following steps:

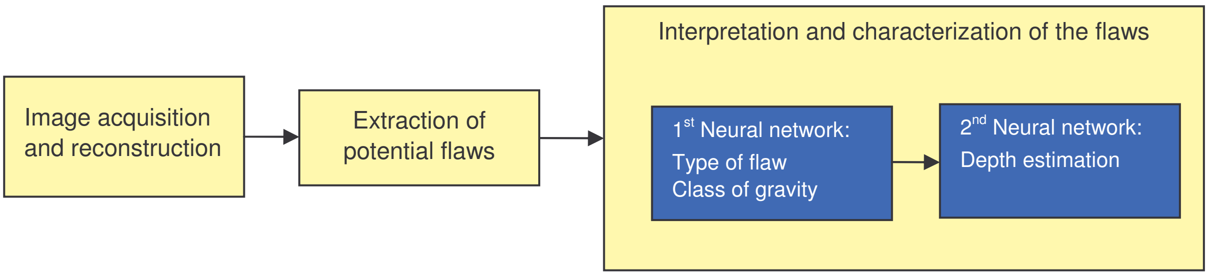

Figure 3 – Diagram of the proposed method

The first step is the acquisition of ultrasonic signals for image reconstruction. The next step combines signal processing and image processing techniques for recognizing the zones of imperfections. The third step includes the interpretation of the imperfection zones using two neural networks to estimate the type and depth of the flaws. Each of these steps will be more detailed below.

2.3 Acquisition and reconstruction of the image

Based on the same principle as a conventional inspection, the idea we propose is to recover and process the signals received by the probes in order to interpret and assess the criticality of the imperfections.

The inspection tank used is the same as for the conventional inspection, containing two sets of probes for longitudinal inspection, two sets for transverse inspection and one set of probes for wall thickness measurement and inspecting imperfections in the wall thickness. In the same way as for the conventional inspection, the longitudinal and transverse probes are arranged with opposing deflection directions in order to be able to detect tilting flaws.

The images processed in our approach are complementary Cscans pairs. The X-axis of the Cscans corresponds to the probe position along the length of the pipe and the Y-axis corresponds to the probe position around the circumference of the pipe (see figure 4). Each point of the Cscans corresponds to the maximum amplitude received in the selectors from ultrasonic shots, and are representing in colour scales. Probe positions along the pipe are measured, either by means of an angle coder or a Doppler laser system.

Figure 4 illustrates the reconstruction of the Cscan images acquired by the probes for the longitudinal inspection corresponding to each deflection direction named “direction 1 and direction 2" respectively.

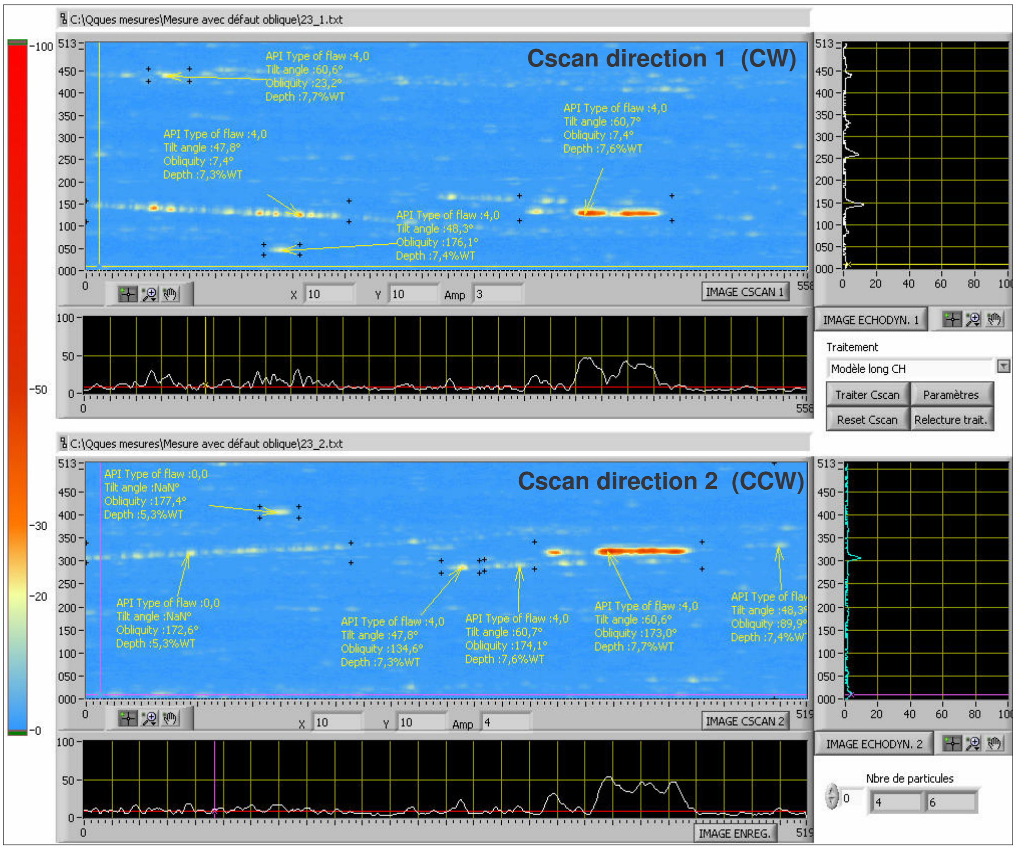

Figure 4 – Example of a Cscans pair (2 deflection directions) from a longitudinal flaws inspection

2.4 Extraction of potential flaws

The aim of this step is to determine the zones of potential imperfections in the Cscan images. The selected zones will be analysed later by the neural networks.

The zones of imperfections are extracted by means of a threshold that adapts to the current noise level of the image. The method is based on the theory of signal detection in white noise, which can rest on two assumptions H0 and H1:

H0: measurement = white noise (of average "*m_b*" and standard-deviation "*std_b*")

H1: measurement = defect signal + white noise

Statistical tests were conducted to determine whether it is assumption H0 or H1 that applies. These statistical calculations are made in real time on all the points of the image.

According to this method (known as the "Gaussian additive noise" method) we can use Neyman-Pearson's criteria to determine a detection threshold according to the probability of false alarms (pfa) given by the formula (1).

$$pfa = \int_{seuil}^{\infty} \frac{1}{\sqrt{2\pi} \cdot std\_b} \cdot e^{-(x-m\_b)^2 / 2 \cdot std\_b^2} dx = Q\left(\frac{seuil - m\_b}{std\_b}\right) \qquad (1)$$

A cumulative Gaussian function was used, generally named Q. By inverting this function, the threshold can be obtained using formula (2).

$$Threshold = std\_b \cdot Q^{-1}(pfa) + m\_b \qquad (2)$$

Use of such kind of adaptive threshold avoids the false alarms which occur with a fixed threshold. False alarms are due to background noise from various sources: water inside the pipe, electric buzzing, phenomena due to the material structure of the inspected product, ...

The zones of potential imperfections are defined from the points above the threshold identified on the image. To correctly delimit the zones a specific combination of contour (Robert gradient), expansion and erosion image processing algorithms is used. The ultrasonic data in the corresponding image zone are thus obtained for each imperfection and used for the subsequent neural network analysis.

2.5 Interpreting and characterizing the flaws

An imperfection in a pipe may be defined by its position, type and depth. In the interpretation proposed, the type and depth of a flaw are determined separately using two neural network processes with the same general structure.

For type recognition, we have classed our flaws into four types, being those most often encountered in our production processes. These flaws are illustrated in figure 5:

- Type 1: Straight flaw
- Type 2: Slightly tilted flaw
- Type 3: Highly tilted flaw
- Type 4: Wide flaws

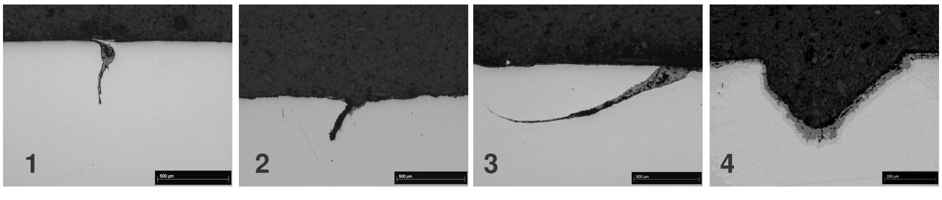

Figure 5 – Types of flaws considered in this study

In general, the neural networks used are the classifying type with probabilities of belonging to each class. As shown in figure 6, the first neural network allows the gravity of the flaw to be estimated by classifying the flaws into three groups according to their depths:

- Green: the indication is definitely an imperfection of no importance ;
- Orange: suspect zone to be further investigated using the second model ;
- Red: the indication is definitely a serious flaw.

This same neural network also serves to classify the flaw detected into one of the four types defined above (Type 1 to Type 4).

The second neural network allows precise depth estimation on the flaws of the previous intermediate group ("Orange"). As relation between flaw depth and ultrasonic response is highly dependent of the flaw type, this second neural network uses the previous results of type estimation as input parameter, in order to reach an accurate level of estimation.

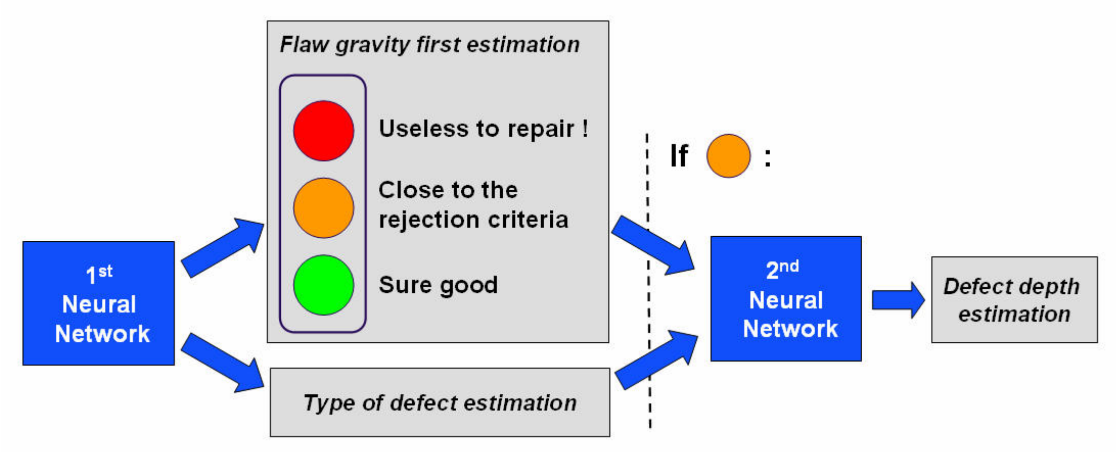

Figure 6 – How the neural networks operate

In general, the input parameters of the neural networks are characteristics of the pairs of Cscan images. They are made up of the ratio of the maximum amplitude to the amplitude obtained from the reference pipe, the width of the echo ("echodynamic"), the position of the echo representative of obliquity and the length of the flaw among others. These parameters are taken from the zones of imperfections previously detected. Other parameters are also taken into account, such as the probe characteristics, pipe dimensions, etc.

3. Validation in semi-industrial conditions

The learning process for the neural networks was based on response data from around 2500 simulations, 150 artificial flaws and 100 natural flaws. The simulations were obtained using the commercial software CIVA developed by the CEA.

Semi-industrial validation of the obtained neural networks was conducted on 90 samples of natural imperfections previously detected in the factory. The validation was conducted on the basis of a comparison between the estimations given by the neural networks and the results given by the conventional method with standard threshold. Results from each method were compared to real characteristics of the imperfections, which was obtained by micrographic analyses done after destruction of the samples.

The validation trials show a correct estimation of the type of flaws on 81% of the considered 90 samples.

In comparison with the conventional method, the gravity and depth estimations given by the proposed system is closer to real flaw gravity observed after samples destruction. On the 90 considered samples, a correlation of $R^2 = 0.75$ was obtained with the proposed system.

A detailed analysis of the validation results shows that the proposed system mainly offers a better gravity evaluation on tilted flaws, through the evaluation adjustment permitted by knowing the type of flaws. On straight flaws, improvement is less marked, but a gain is still observed, through the use of more parameters than conventionally.

4. Perspectives of the Method

Improvements of this concept are already in progress. The main way of improvement consists into three-dimensional ultrasonic image processing techniques, which will offer an even better knowledge of the imperfections. Work on the three dimensional reconstruction of ultrasonic images has already begun through a partnership with the Roberval Laboratory of the University of Technology of Compiègne (France). The figure 7 shows an example of prototype and first results. The aim is to obtain three dimensional micrographic images of the flaws from non-destructive ultrasonics testing, by using in addition the time of flight data.

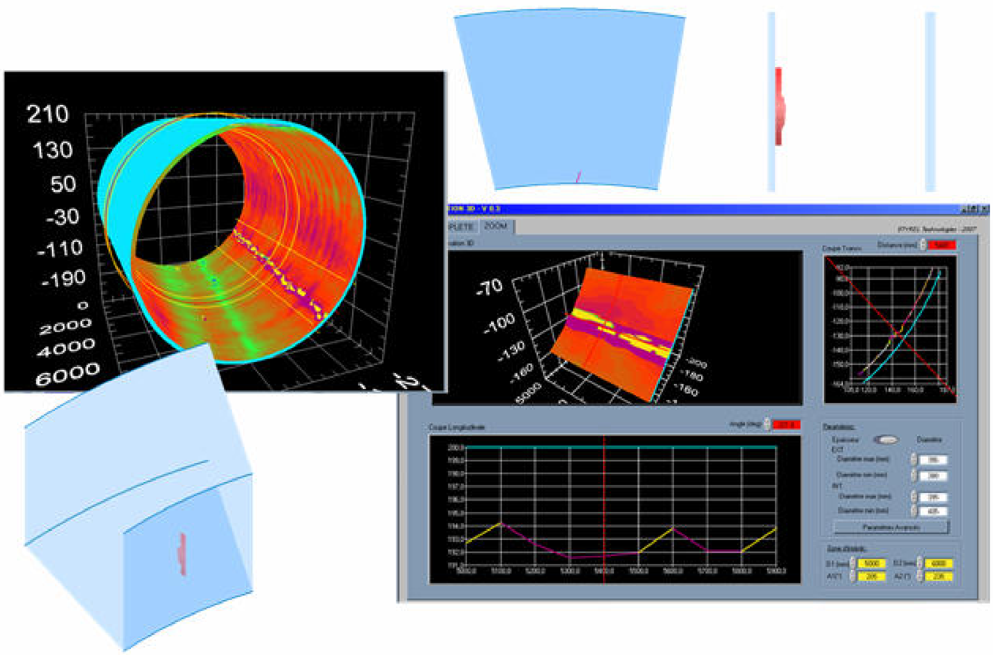

Figure 7 - Improvement of the method by 3D processing

5. Conclusion

This research work offers a new concept in the ultrasonic testing of steel pipes. By estimating the depth and the type of flaws, it gives us a better understanding of our flaws. The tool has been validated industrially and is used in parallel to the conventional inspection to allow better process control.