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Structural noise characterization and flaw detection in austenitic stainless steels using ultrasonic signals, wavelet analysis and significance testing

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The aim of this study is to characterize the structural noise in order to better detect flaws in several heterogeneous materials (steels, welding, composites …) using ultrasonic waves. For this purpose, a continuous wavelet transform is applied to ultrasonic Ascan signals acquired using an ultrasonic Non Destructive Testing (NDT) device. The time-scale representation provided, which highlights the temporal evolution of the spectral content of the Ascan signals, is relevant but can lead to misinterpretation. The problem is to identify if each pattern from the wavelet representation is due to the structural noise or a flaw. To solve it, a detection technique based on statistical significance testing in the time-scale plane is used. Typical structural noise signals are then described using an autoregressive model which seems relevant according to the spectral content of the signals. The approach is tested on experimental signals, obtained by ultrasonic NDT of metallic materials (austenitic stainless steel) then of a welding in this steel and indeed enables to separate various components from the signal that is two kinds of structural noise and flaw echoes.

1 Introduction

The Austenitic Stainless Steels (ASS) are used in various applications, in particular in the parts of the primary circuit of the nuclear reactors. Among the methods used for the characterization of the ASS damage, the Non Destructive Testing (NDT) is proved to be effective to detect various types of defects, whose presence is likely to imperil industrial installation functioning. The ultrasonic inspection is the best NDT method applied to the Austenitic Stainless Steels. The ultrasonic waves generated in this material propagate in two different ways: coherent and incoherent waves. The incoherent waves are called structural noise, due to the phenomenon of diffusion inside the material. Thus their presence can mask the acoustic signature of the sought damage. Ultrasonic NDT of the Austenitic Stainless Steels are of interest for both theoretical and experimental aspects. Many studies have been interested in the structural noise, particularly for characterizing signals resulting from stainless steel material [1, 2], defect detection [3, 4] and noise reduction [5, 6].

In this contribution a new approach is presented which consists in characterizing the structural noise in austenitic stainless steel, where flaws, welding and other different echoes are present. This is carried out by using both Continuous Wavelet Transform (CWT) and hypothesis testing in order to differentiate structural noise from other echoes in the ultrasonic signal. The CWT gives a time-scale or a time-frequency representation which may be difficult to interpret. The aim of this study is to provide some quantitative interpretations of each pattern (amplitudes of the time-scale representation) in order to know if these patterns correspond to structural noise or flaws. Thus hypothesis testing requires structural noise characterization. The basis of this approach is the computation of the Power Spectral Density (PSD) of the ultrasonic signal revealing a structural noise that can be done from an autoregressive model.

This study is inspired by geophysical research [7, 8], which shows this approach is well adapted to separate various the signatures in the time-frequency plane. Our goal is to separate the signature of structural noise from the others signatures such as flaws. In the paper, we describe wavelet analysis, because it is an essential signal processing tool for the study, the material studied, i.e. austenitic stainless steel and the approach used which consists in characterizing the structural noise and detecting the flaws in these material. Some results are then reported.

2 Continuous Wavelet Transform

The wavelet transform can measure the time's evolution of the spectral contents of a signal. The continuous wavelet transform CWT is defined for a signal $x(t)$ [9] by:

$$W_x(\tau,s)=\int_{-\infty}^{+\infty} x(t)\,\frac{1}{\sqrt{s}}\,\psi^*(\frac{t-\tau}{s})\,dt\,, \qquad (1)$$

* conjugate function.

The CWT enables to measure the interaction of the signal $x(t)$ with a function which is called the analyzing wavelet considered for a scale s in the neighbourhood of the time τ. This analyzing wavelet $\psi_{\tau,s}(t)$ such that:

$$\psi_{\tau,s}(t)=\frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s})\,, \qquad (2)$$

results by dilation or compression with the parameter s and translation with the parameter τ of a mother wavelet $\psi(t)$.

The use of several scales through the wavelet transform enables to obtain a time-scale representation where the components of the signal will be split up into various scales during time. One can note that the scales are inversely proportional to the frequencies present in the signal and then it is easy to go from a time-scale representation to a time-frequency plane. Very often, the representation used is the wavelet power spectrum (energetic representation) defined as the square of the modulus of the wavelet coefficients [10] $|W_x(\tau,s)|^2$.

3 Materials

The approach is tested on experimental signals obtained by an ultrasonic scan of metallic materials: a rolled austenitic stainless steel, then a welding in this steel.

This material is tested using a transversal wave with a 60° angle of orientation. The transducer used for this control has a central frequency of 2 MHz. The signals are acquired with a sampling rate of 50 MHz. For this test, 643 Ascan are recorded. Fig.1 shows the Bscan image obtained from this material, along two axes: axis z represents space (the depth of the material) and axis y represents a set of Ascan signals collected step by step over the width of the material.

In this image, four areas are distinguishable, area 1 represents echoes of rebounds due to the mounting–block of the transducer, area 2 represents structural noise in the base metal, area 3 represents a strong raising noise and area 4 represents echoes of defects.

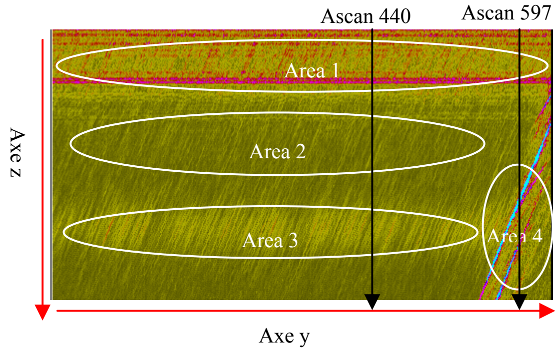

Fig.1 Bscan image of the austenitic stainless steel.

Two Ascan signals n°440 (Fig.2) and n°597 (Fig.3) are extracted. The first signal is without any defect and the second one crosses two defects (area 4). Both signals are corrupted by the same structural noise (area 2). The second part of the signals (at the bottom of the Bscan image) highlights a more energetic structural noise (area 3) than the first part as shown in Fig.1. A rebound echo can be observed (area 1) due to the mounting-block of the transducer at the early beginning of the scan.

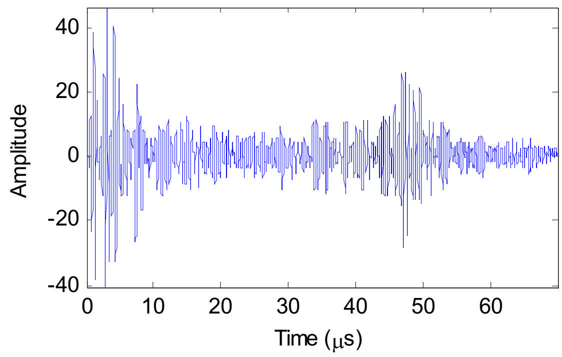

Fig.2 Ultrasonic signal Ascan 440.

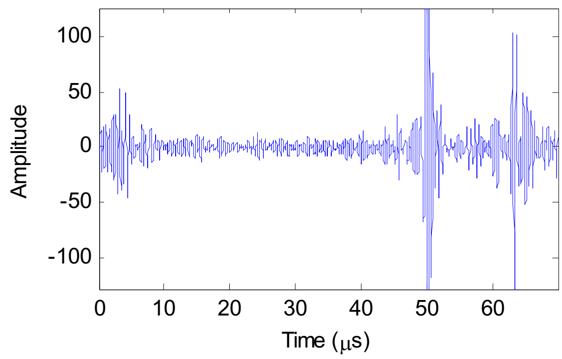

Fig.3 Ultrasonic signal Ascan 597.

4 METHOD

The first step of the study is the representation in a time-scale plane (Fig 4) of the wavelet power spectrum of an Ascan signal. Then the aim is to provide quantitative information to make easier the interpretation of each pattern (composed of several high coefficients of the wavelet power spectrum $|W_x(\tau,s)|^2$) to know if these patterns correspond to the structural noise or to some flaws. For this purpose hypothesis testing is carried out based on two formulations:

- The pattern corresponds to the structural noise
- The pattern indicates something else such as for example the signature of a flaw.

Thus the hypothesis testing requires to characterize the structural noise. The basis of this approach is to compute the Power Spectral Density (PSD) of some ultrasonic signals revealing a structural noise, using an autoregressive model.

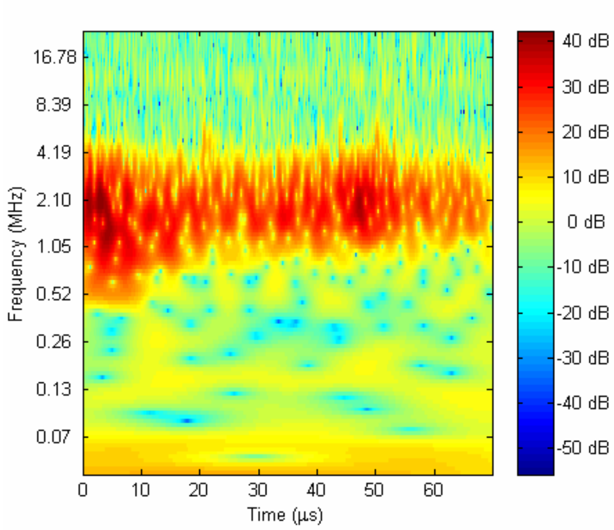

Fig.4 Wavelet power spectrum in dB of Ascan 440.

4.1 Autoregressive modeling

By autoregressive modeling, it is possible to synthesize a signal whose statistical properties (particularly the autocorrelation function) matches those of a sample of the structural noise. It consists in filtering a white noise of variance σ^2, with an autoregressive filter composed of p coefficients $a_i\,(i=1\ldots p)$. The coefficients of the filter as well as the variance of the white noise are obtained by resolving the system of equations of Yule-Walker [12]. The synthesized signal y_k is written then at time k :

$$y_k = u_k - \sum_{i=1}^{p} a_i \; y_{k-i} \, , \qquad (3)$$

where u_k is the white noise of variance σ^2. One of the major interests of this model is that the power spectrum density (PSD) of the autoregressive signal (AR) is written in an analytical way:

$$S_y(f) = \frac{\sigma^2}{\left|1+\sum_{i=1}^{p} a_i \; e^{-2j\pi i f T_e}\right|^2} \, , \qquad (4)$$

T_e indicates the sampling rate of the signals. Thus this PSD highlights the frequency content of the structural noise modeled. The major difficulty of autoregressive modeling is the choice of the order *p,* which can be set arbitrarily. However, there are criteria $J(p)$ (Final Prediction Error and Akaike's Information Criterion), to estimate the number of parameters $\hat{p}$ [12].

Final Prediction Error:

$$J(p) = FPE(p) = \frac{N+p}{N-p}\sigma_p^2. \qquad (5)$$

Akaike's Information Criterion:

$$J(p) = AIC(p) = 2p + N\log\sigma_p^2, \qquad (6)$$

N is the number of samples of the signal and σ_p^2 is the white noise variance of a model of order p. The estimated order $\hat{p}$ of the model corresponds generally to the minimal value of the criteria:

$$\hat{p} = \underset{p}{Arg\,Min}\, J(p) \qquad (7)$$

4.2 Hypothesis testing

Hypothesis testing is introduced to determine whether a pattern of the time-scale plane corresponds or not to some structural noise. It has been reminded in [7] that when the amplitudes of a temporal signal are distributed according to a Gaussian probability density function (PDF), then the square of the spectrum modulus follows a chi-squared χ_2^2 PDF with two degrees of freedom. In addition, Torrence and Compo explain that if a time series can be modeled as an autoregressive process, each vertical slice of its wavelet power spectrum has the frequency content described in eq.(4). Consequently, the wavelet power spectrum of the signal follows for each scale a chi-squared PDF such as [7,8]:

$$\frac{|W_x(\tau,s)|^2}{\frac{1}{2}P_s} \sim \chi_2^2, \qquad (8)$$

P_s corresponds to the spectral content of the signal for the frequency kf_e/N, associated with the scale s. f_e indicates the sampling rate. According to eq.(4):

$$P_s = S(k\,f_e/N) = \frac{\sigma^2}{\left|1+\sum_{i=1}^{p} a_i\, e^{-2j\pi ik/N}\right|^2}. \qquad (9)$$

It is then possible to define a confidence interval (95% for example) for which the wavelet power spectrum is distributed according to a chi-squared PDF with two degrees of freedom. Thus the values of the time-scale plane outside the interval indicate the presence of defects. The decision rule depends on the value:

$$G(\tau,s) = \frac{|W_x(\tau,s)|^2}{\frac{1}{2}\gamma P_s}, \qquad (10)$$

with:

$$\mathrm{Prob}\left(\frac{|W_x(\tau,s)|^2}{\frac{1}{2}P_s} > \gamma\right) = \alpha, \qquad (11)$$

and γ the threshold corresponding to $\alpha = 0.05$.

Two hypotheses are considered:

- H_0: the signal is part of the structural noise if $G(\tau,s) \le 1$
- H_1: the signal is a defect if $G(\tau,s) > 1$

These decisions are made in any point of the time-scale plane with a confidence interval $1-\alpha$.

5 EXPERIMENTS AND RESULTS

5.1 Autoregressive modeling of the structural noise

The signal chosen for autoregressive modeling (Fig.5) is extracted from the image Bscan (Fig.1) corresponding to the area 2. This signal is distributed normally, which is checked by the test of Shapiro and Wilk [13]. The order of the model is estimated by the Akaike's criteria. The minimum of the two functions FPE eq.(5) and AIC eq.(6) are obtained for the order p =53 (Fig.6).

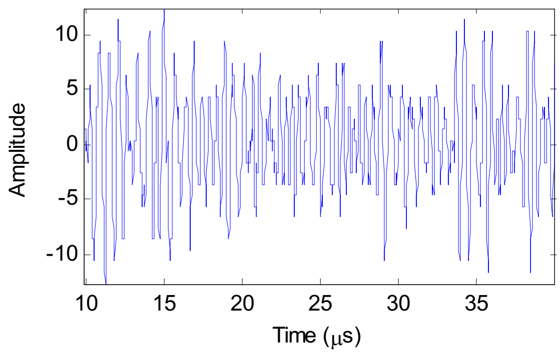

Fig.5 Structural noise signal.

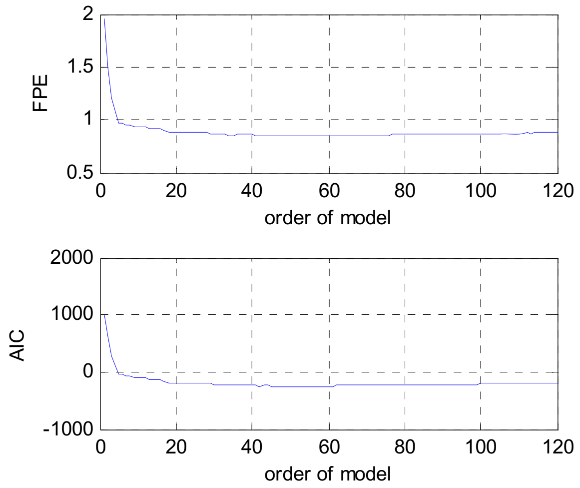

Fig.6 Akaike's criteria for the choice of the autoregressive model order.

Fig.7 illustrates the autocorrelation functions of the structural noise and the AR signal of order 53. Fig.8 illustrates the theoretical Power Spectrum Density obtained by eq.(9), and the PSD of both signals, autoregressive (AR) of order 53 and structural noise, computed by means of Welch periodograms.

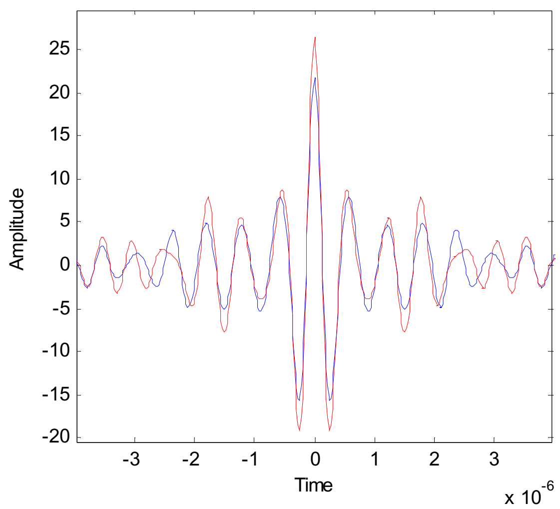

Fig.7 Autocorrelations of the structural noise signal (blue) and the AR signal of order 53 (red).

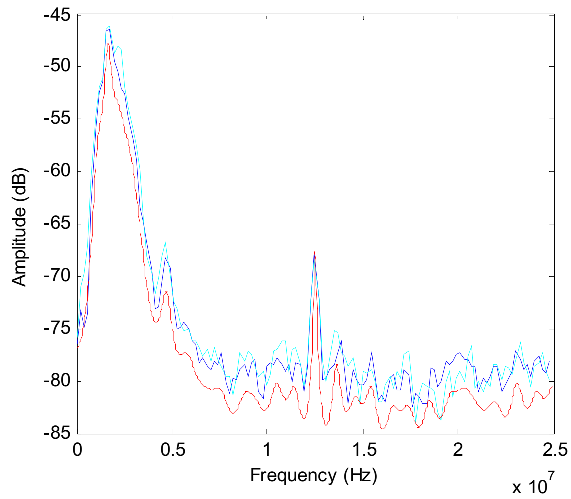

Fig.8 DSP (dB) of the structural noise signal (blue), the AR signal of order 53 (cyan) and theoretical (red).

From the comparisons of the temporal properties (Fig.7) and the frequency content (Fig.8) of the structural noise signal and the AR signal, the autoregressive model for the structural noise seems relevant.

5.2 Time –scale plan study

In this study the Morlet wavelet is used [9]. The wavelet power spectrum of the signal Ascan 440 (Fig.2) is presented in Fig.9. The result related to the signal Ascan 597 (Fig.3) is given in Fig.10.

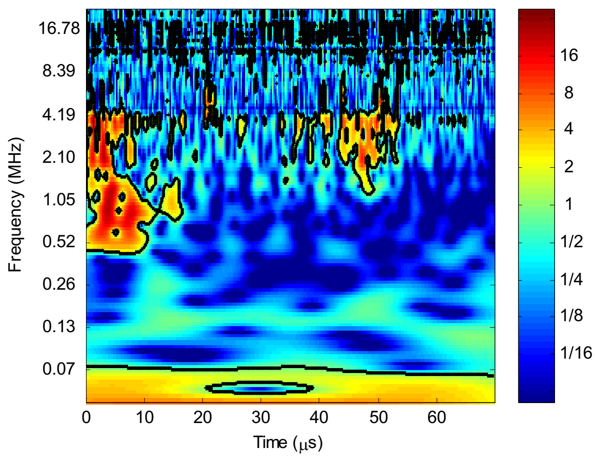

Fig.9 Wavelet power spectrum of Ascan 440.

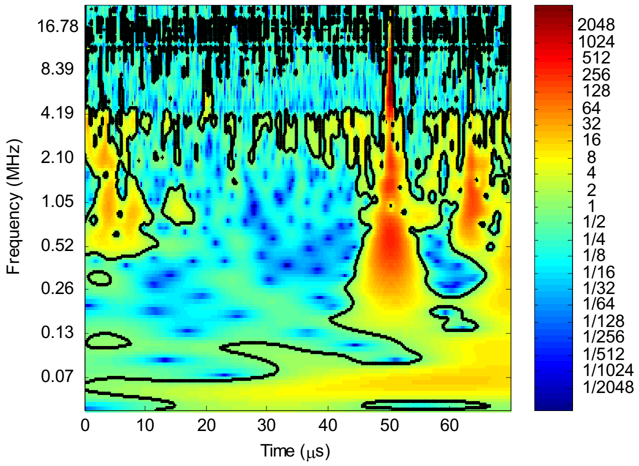

Fig.10 Wavelet power spectrum of Ascan 597.

The contours in Fig.9 and Fig.10 correspond to the values of $G(\tau, s)$ eq.(10) higher than 1. According to the hypothesis testing described in paragraph 4.2, these contours indicate the areas where the signal cannot be considered as structural noise with a confidence interval of 95%. Indeed Fig.9 shows clearly the echoes due to high level noise and the echoes of rebound. Fig.10 also shows the echo of rebound and the echoes of defect.

6 CONCLUSION

Through the results obtained and their analyze, the approach implemented, based on modeling the structural noise and hypothesis testing in the time-scale (or time-frequency) plane, seems of great interest. Indeed, the method leads to differentiate the various echoes from the structural noise in an ultrasonic signal Ascan. We also showed how the structural noise could be modeled using an autoregressive model. A similar study could be applied to other materials with strong structural noise such as the centrifuged cast steels and the concretes. This approach could be used to consider the height of the plane defects emerging, which is based on the difference of time of flight between echoes of diffraction and echoes of corner, the echoes of diffraction being often drowned in the structural noise in particular for the centrifuged cast steels.

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