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THE MULTIRESOLUTION ANALYSIS FOR ULTRASONIC NON DESTRUCTIVE EVALUATION

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Abstract

Acoustical characterization is an important item in materials testing and takes an increasing place during the fabrication and the "in service inspection" processes. Indeed, ultrasonic techniques have been commonly used in power and petrochemical industries for nearly 50 years and the often used technique is the echo-graphic in which the waves reflected by the material structures are observed and analyzed. Since, the performance of ultrasonic techniques are often affected by the physical structure of the component and by background noise, the effects of aging and environment on failure mechanisms cannot be sufficiently predicted by the traditional methods. However computational modelling of materials behaviour is becoming a reliable tool to emphasize scientific investigations and to match up theoretical and experimental approaches. With the continuous progress in computational power new ultrasonic testing systems are expected to be discovered and implemented. This requires not only development of improved processing techniques but also a better understanding of material structure. These conditions implicate multiple length scales analysis and multiple implementation steps, which are available only by means of simulation models. Therefore, increasing efforts are focused on ultrasonic multiscale modelling methods for signal interpretation; the multi-resolution models are the mainly investigated approaches. In this work a multiresolution ultrasonic signal analysis is accomplished and an enhanced energetic smoothing filtering algorithm is proposed for an advanced material behavior characterization.

Introduction

The performance of ultrasonic examination techniques in stainless steel austenitic structures, clad components, and welds are often strongly affected by the materials anisotropy and heterogeneity. The major problems encountered are beam skewing and distortion, high and variable attenuation and high background noise [1].

Ultrasonic techniques have been routinely used in industry for nearly 50 years and yet, cast or welded austenitic components remain difficult to reliably and effectively examine. In some components grains orientations cause deviation and splitting of the ultrasonic beam. It is especially true in the case of multi-pass welds when the re-melting process after each pass causes complex solidification process. The large size of the anisotropic grains, relative to the acoustic pulse wavelength strongly affects the propagation of ultrasound by causing severe attenuation, changes in velocity and scattering of ultrasonic energy [1]. Refraction and reflection of the sound beam occur at the grain boundaries resulting in defects being incorrectly reported, specific volumes of materials not being examined, or both. Conventional ultrasonic techniques are less applicable on these materials because of the commonly very low signal to noise ratio achieved and of the uncertainty of the flaw location.

Since the ultrasonic signal is non stationary, the extraction and the analysis of the useful information remain difficult. Due to its computational efficiency, one powerful tool to enhance the signal noise ratio of ultrasonic signal is the multi resolution analysis. The wavelet analysis is a multi-resolution time scale method which enables to perform a time localized analysis of signals [2]. It is a powerful tool for signal filtering, but requires increasing test speed with greater test validation data bank. However, to enhance the flaw characterisation, methods based on "thresholding" have given good results only when the signal to noise ratio is high [3]. In this work a multiresolution signal analysis is performed and the noise features are extracted by an enhanced energetic smoothing algorithm which has allowed the identification of the noise analyzing function. In this juncture the random nature of the noise in the spatial domain has been overcome. The energetic characterization of the noise and the signal information has allowed an easiest filtering of the ultrasonic signal with good material behaviour characterisation.

Multiresolution modeling method: an overview

A multiresolution decomposition enables us to have a scale-invariant interpretation of the signal. This decomposition defines a complete and orthogonal representation called the wavelet representation [2]. The wavelets are used to build a basis in which are represented the details that are obtained between a resolution and the next finer one**.** Details bases, like resolution bases, ore obtained by translating a single unit called a wavelet. The order of approximation of the multiresolution is equal to the number of the wavelet vanishing moments. It also represents the wavelet's ability to detect the isolated singularities of a signal [4].

Wavelet shrinkage [5] is a way of noise reduction by trying to remove the wavelet coefficients that correspond to noise. Since noise is uncorrelated and usually small with respect to the signal of interest, the wavelet coefficients that result from it will be uncorrelated too and probably be small as well. The idea is therefore to remove the small coefficients before reconstruction. Of course this method is not perfect because some parts of the signal of interest will also result in small coefficients, indistinguishable from the noisy coefficients that are withdrawn [5]. There are two popular kinds of wavelet shrinkage: one using hard thresholding and one using soft thresholding. For hard thresholding all wavelet coefficients smaller than a certain threshold are simply eliminated. For soft thresholding a constant value is subtracted from all wavelet coefficients and everything smaller than zero is removed. The process is recursive until a pre-defined decomposing level of the signal [6].

Wavelet transforms modulus maxima are related to the singularities of the signal. More precisely, the “Hwang, Mallat” [4] theorem proves that there cannot be a singularity without a local maximum of the wavelet transform at the finer scales**.** This theorem indicates the presence of a maximum at the finer scales where a singularity occurs. The uncertainty principle can be applied to our subject as follows: Higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency. This means that, a certain high frequency component can be located better in time than a low frequency component. On the reverse, a low frequency component can be located better in frequency.

Ultrasonic multiresolution analysis for signal de-noising: Description and results

Many studies have been conducted on the use of the wavelet theory for ultrasonic signal de-noising, but no one has been done on the structural noise features and its possible analyzing wavelet function. In the framework of the automation of the ultrasonic signal analysis project, we haven’t make the exception, and we have followed the exploration of the multiresolution theory, from the continuous transforms to the discrete ones without disregarding the wavelet packet. Thus, the original ultrasound image is transformed into a Multiscale wavelet domain, and the wavelet coefficients are processed by a threshold method, the de-noised image is the output image obtained from the inverse wavelet transform of the threshold coefficients.

With the use of the discrete transforms the signal is decomposed in approximations and details coefficients which represent the low and high frequencies respectively, and the original signal is passed through a high pass wavelet filter and a low pass wavelet filter. In the second level of the decomposition, only the output of the low pass filter is once again passed through a pair of high pass and low pass filters by dawn sampling. And this is repeated a finite number of times. So a signal that has 2^n points can be decomposed into n levels, which will produce 2^{n+1} sets of coefficients, where the level n has 2^n coefficients [6]. This decomposition in effect halves the time resolution, and doubles the frequency resolution, and requires an increased computing time and memory space. Even, the reconstruction at each level is performed only on the approximations, and the informations brought by the details are discarded [7].

The wavelet packet transform is a signal analysis tool that has the frequency resolution power of the Fourier transform and the time resolution power of the wavelet transform. It can be applied to time varying signals, where the Fourier transform does not produce useful results, and the wavelet transform does not produce sufficient results. The wavelet packet algorithm applies recursively the wavelet transforms to the high and low pass results at each level, generating 2 new filter results. The signal reconstruction is realised with all coefficients without information loss. Therefore, a wavelet packet decomposition of the whole signal, requires more and more computing time and memory space, than the discrete one, and needs a lot of experiments for the threshold regulation.

The continuous wavelet transforms provide good filtering results only for the highest frequencies, and require a discriminating noise threshold study for the low frequencies, which needs many experiments on each defect signature [8].

To overcome these critical situations we have chosen to perform in a first step, a filtering of the frequencies that are outside the frequency band by a continuous filter bank, and in a second step a filtering of the frequency band by the wavelet packet transform. The tree decomposition has needed only 3 levels which have been considered as a threshold limit, with an improved computing time [8].

Since the choice of analysing wavelet affects the success of the filtering, we have chosen for the continuous filtering process the 8^{th} derivative Gauss function as the analysing function, consequently to a correlation procedure between ultrasonic signals and the Gauss wavelet family described in [8]. And for the discrete filtering, 3 different mother wavelets were investigated in an attempt to find out that the best matches the shape of the analysed signal. These wavelets are the Symlet, the Coiffet and the Debauchees (figure 1). The Debauchee of order 8 was the most suitable and was used in the wavelet packet filtering process[8] .

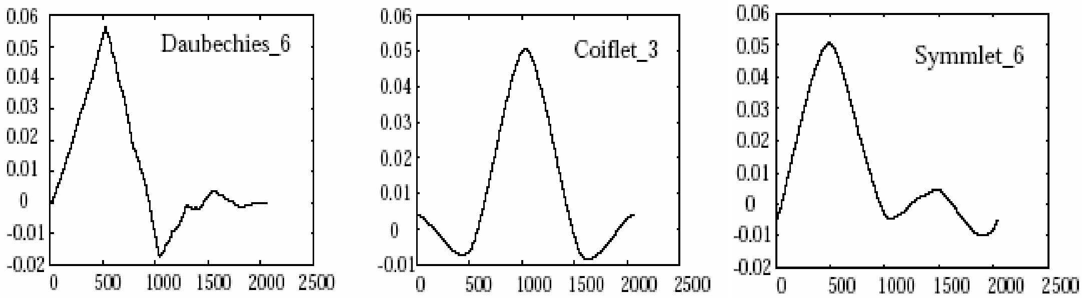


Figure1: Several tested wavelet at different vanishing moments

If this analysis is satisfactory its implementation is very complex, it needs several algorithms and lot of experiments, for finding out the best analysing functions and the optimized algorithms. At this stage, a look at “Hwang, Mallat” theorem [4] indicates the presence of a maximum at the finer scales where a singularity occurs and when the wavelet is the n^{th} derivative of a Gaussian, the maxima curves are connected and go through all of the finer scales [4].

This approach lets us to investigate the spirit of the smoothing analysis applied to the multiresolution process. These investigations guided us to the construction of the new filtering method that we called the “minima-maxima energetic smoothing algorithm”.

How it works? As the ultrasonic energies are concentrated in the frequency band, so the different frequencies beside the band are represented in the transform domain by very weak amplitudes and can be scattered without loss of information. But what about the structural noise ? The idea is to approximate it with a wavelet function. The proposed algorithm allows the development of a noise analysing function and an easy filtering process (figure2):

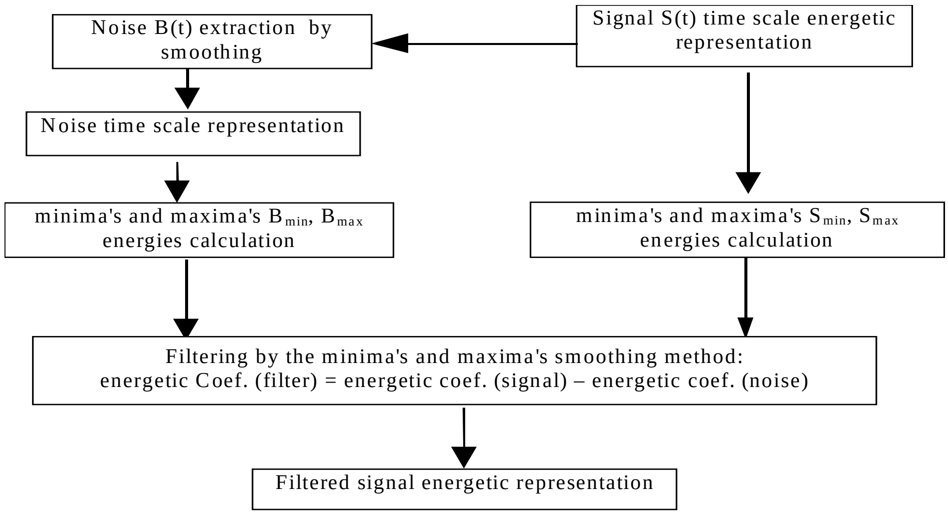


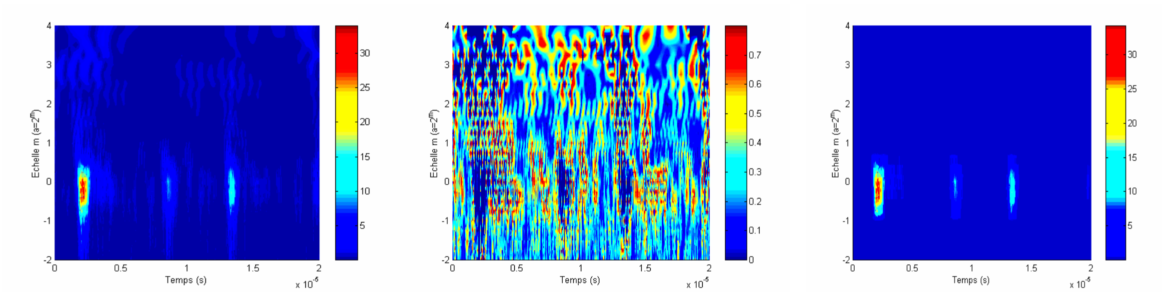
Figure 2: Energetic Smoothing Algorithm decomposition

In this algorithm, the noise energetic coefficients extraction is based on an elimination of the maximum energetic coefficients vector from the signal which has been decomposed by the 8^{th} derivative gauss function. And from a time scale noise mapping with the Morlet function, we do a computation of the noise energetic threshold. An inverse procedure gives us statistical noise characterisation.

Then the filtering is performed with the named "min-max smoothing method" based on an energetic subtraction of the maximum noise energetic coefficients vector analysed by the Morlet from the minimum signal energetic coefficients vector analysed by the 8^{th} derivative of the Gaussian (a subtraction between two wavelet representations is performed).

Conclusion

Noise filtering of the original signal can be achieved if only a few wavelet coefficients representative of the signal are retained. In this work, the discrete transforms has needed extensive tree decomposition for each signal, and an amount of time computing for the choice of the best averaging. Even, the reconstruction of the signal components was not complete due to the waste of some useful information from the filter bank tree [7]. The wavelet packet analysis allowed a biggest decomposition and a lot of time computing with a refined signal reconstruction [7]. A combination between continuous transforms and wavelet packet transforms gave enhanced results but an extensive data bank experiments was required for the use of the appropriate analyzing functions[7][8]. As a result, advances in the automatic threshold control were based on the investigation of the noise features. In this study the proposed algorithm has enabled the identification of the ultrasonic structural noise analyzing function by which the random nature of the noise was surpassed. The algorithm runs on a one cycle for each data analysis and provides an output image with high quality parameters see experiment in figure3 of an ultrasonic signal time scale representations of 1mm circle signal, and the filtering result.



a - Input signal (8th Gauss) *Energetic coefficients calculation*

b – Noise extraction (Morlet) *noise coefficients calculation*

c – Filtered signal *by smoothing*

Figure 3: Mini-max smoothing filtering method

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