Ultrasound material backscattered noise analysis by a duo wavelet-regression analysis

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Internal material defects detection by ultrasound non destructive testing is widely used in industry, ultrasonic data are obtained from travelling waves inside the matter and captured by piezoelectric sensors. The natural inhomogeneous and anisotropy character of steel made material causes high acoustic attenuation and scattering effect. This adds complexity to data analysis. In this research we address the non linear features of back scattered ultrasonic waves from steel plates and welds. Indeed structural noise data files captured from specimens, and processed by a wavelet energy filtering approach, show significant insights into the relationship between backscattered noise and material microstructures. This algorithm along with correlation coefficients, residuals and interpolations calculations of processed ultrasonic data seems to be a well-adapted signal analysis tool for viewing material micro structural dimension scales. Experiments show a challenging 3D interface between material properties, calculations and ultrasonic wave propagation modelling. As well as they indicate a quasi linear signal energy distribution at micro structural levels. It suggests probable incidence of microstructure acoustic signatures at different energy scales of the material phases. Multi polynomial interpolations of the processed noise data exhibit an attractor shape which should involves chaos theory noise data.

1 Introduction

Acoustical characterization is an important item in materials testing; it takes significant status during fabrication and "in service inspection" process. Ultrasonic techniques have been commonly used in power and petrochemical industries for nearly 50 years. However, cast or welded austenitic components remain difficult to reliably and effectively examine. In some devices grains orientations produce ultrasonic beam divergence and splitting mainly in the case of multi-pass welds when the re-melting process after each pass causes complex solidification process. Anisotropic grains large size compared with acoustic pulse wavelength, affects coarsely ultrasound propagation; by causing severe attenuation, changes in velocity and energy scattering [1]. Sound beam refraction and reflection arising at grain boundaries induce defects incorrectly reported, specific volumes of materials not examined or both [2]. Various industrial inspections on dissimilar components confirm the consequence of these physical phenomena on ultrasonic inspection implementation. Some experimental studies as in [3] and [4] confirm grain size influence on attenuation and noise, in addition to a frequency filtering when the wavelength is equal to the average grain diameter. Therefore, it seems to be essential to make relationships between material micro structural features and ultrasonic beam acoustic characteristics. And try to examine micro structural parameters which are the source of attenuation and structural noise origin. As ageing and environment consequence on failure mechanisms cannot be sufficiently predicted by traditional methods, computational modelling of materials behaviour is becoming a reliable tool to emphasize scientific investigations and to match up theoretical and experimental approaches. This requires not only development of improved processing techniques but also better understanding of material structure. These conditions implicate multiple length scales analysis and multiple implementation steps.

In this paper we present a new structural noise features analysis based on an energy smoothing algorithm. The new de-noising algorithm performs an accurate signal analysis as well as detection of little defects of 1mm. The following experiments obtained from structural noise signal captured from a steel plate, will give significant insights into the relationship of backscattered noise and microstructures which can help to micro structural dimension scales understanding

2 Ultrasonic s noise features : overview and challenge

Since ultrasonic signal is transient, non-stationary, and limited in time and frequency, extraction and analysis of the useful information remain difficult. Basically, flaw visibility is corrupted by electrical, pulse, ringing, structure noises or spurious signals. Commonly acoustic noise is assumed to be gauss random variable with zero averaging and limited band power spectrum function [1] [2]. Various signal processing techniques were investigated to interpret waveform data and extract useful information for further diagnostic and predictive purpose. In the literature, there are three main categories of waveform data analysis: time domain, frequency domain and time frequency analyses. The first calculates typical attributes as descriptive statistics (mean, peak, standard deviation, high order statistics etc.), and extract features by the use of autoregressive parametric models. However the complexity of the model order estimation carries on complicated modelling. In frequency domain, spectral analysis is certainly the oldest technique that presents the hidden view of the signal. Incompatible for transitory signals and non stationary data, its efficiency is limited. To solve this problem, time-frequency distribution approved several reliable techniques such as short-time Fourier transform (STFT), Wigner-Ville distribution and wavelet transform. Wavelet transform is one of the most successful processing techniques able to withdraw the non stable characteristics of the signal.

Several applications of wavelet transform for defect detection were proposed, using continues wavelet transform enriched with recent techniques, discrete or multiresolution analysis and wavelet packet transform [9] [10]. An interesting synthesis of these techniques is presented in [11]. Similar to the time frequency distribution, wavelet is a time scale representation. It expresses the signal in a series of oscillatory functions with different frequencies at different times. Its main advantage is its ability to produce high frequency resolution at low frequencies and high time resolution at high frequency, for signal with long duration low frequencies and short duration high frequencies. This provides facilities to noise cancellation in natural signals [2] [6] [7].

The aim of this work is to *propose a new method* based on wavelet analysis optimization. In this paper, wavelet multiscale analysis was investigated with *a forecast viewpoint*, as a powerful computational tool for noise discrimination and features extraction. *This idea has*

emerged after having examined continuous, discrete, wavelet packet and dual transforms on natural signals from heterogeneous materials, mostly welding defects signals. More details of this works are given in [12] [13] [14]. In this work the structural noise features are extracted by a new energetic smoothing algorithm which permits the identification of the noise analyzing function and invalidation of the noise random nature. The energetic extraction of the noise and the useful signal has provided easy filtering with enhanced defect detection in natural ultrasonic signals from steel pieces with artificial flaws and welding defects

3 The energy approach

Since useful ultrasonic energies are clustered in the signal central frequency band and the defects energy fit lower frequencies than the structural noise. So the energetic analysis provides a larger view of the signal energetic configuration and permits as well as easy extraction of the noise.

Wavelet basis functions as described in the Mallat's book [7] are constructed by dyadic dilation (index j) and translation (index k) of a mother wavelet:

$$\psi_{jk} = 2^{-j/2} \psi (x/2^{-j} - k) \tag{1}$$

Wavelet transform is characterized by two functions the scaling function (2) and its associated wavelet (3):

$$\phi(x) = \sqrt{2} \sum_{k \in z} h(k) \phi(2x - k) \tag{2}$$

$$\psi(x) = \sqrt{2} \sum_{k \in z} g(k) \phi(2x - k) \tag{3}$$

Where g (k) is a suitable weighting sequence and h (k) is the refinement filter

The orthogonal aspect of wavelet transform provides for any function f(x) *vectors of atoms* composed by detail coefficients (4) and approximation coefficient (5) which characterize the atomic decomposition of f(x):

$$d_j(k) = \langle f, \psi_{jk} \rangle \tag{4}$$
$$c_j(k) = \langle f, \phi_{jk} \rangle \tag{5}$$

Subsequently wavelet transform with a depth j can be adjusted by (6):

$$f(x) = \sum_{j=1}^{J} \sum_{k \in z} d_j(k) \psi_{jk} + \sum_{k \in z} c_j(k) \phi_{jk} \tag{6}$$

3.1 From atomic representation to energy distributions

The purpose of the energy distributions is to distribute the energy of the signal over time and frequency. The starting point is that since the energy of a signal x can be deduced from the squared modulus of either the signal or its Fourier transform, we can interpret $|x(t)|^2$ and $|x(v)|^2$ as energy densities, respectively in time and in frequency. It is then natural to look for a joint time and frequency energy density $\rho_z(t, v)$, such that:

$$E_z = \iint_{-\infty}^{+\infty} \rho_z (t, v) \, dt \, dv \tag{7}$$

3.2 Wavelet smoothing method

Smoothing is an estimation technique that takes into account both past and future observations, and can be more accurate than filtering [22]. Generally, wavelet smoothing and wavelet de-noising can be used to enhance signal to noise ratio. The difference between these two processes is that smoothing removes high frequency components of the transformed signal regardless of their amplitudes, while denoising removes small amplitude components of the transformed signal regardless of their frequencies. However, it is not easy to choose a suitable strand value for de-noising which is significant to the noise suppression achievement without signal loss. For this reason, wavelet smoothing provides fine visual quality of the processed scales (spectra), which is more suitable to signal features extractions. Sachs in [19] gives a rich report on wavelet smoothing by non linear thresholding for non stationary time series de-noising and signal recovery. In any case, the literature designs two classes of smoothers: linear, including local polynomial smoothing, loess, spline and kriging, and nonlinear, such as running medians and other median-based smoothers [20] [21] [22]. In contrast to their performance for data containing only Gaussian noise, linear smoothers do not respond well to data containing impulsive noise, or noise generated by microstructures. Non linear energetic smoothing algorithms are more suitable.

4 New approach and algorithm

If the above methods are suitable their implementation needs several algorithms and experiments, for detecting best analysing functions and best threshold regulation rules. In fact "Hwang, Mallat" theorem indicates the presence of maxima at the finer scales where singularities occur, in addition when the wavelet is the nth derivative of a Gaussian, the maxima curves are connected and go through all of the finer scales [7]. As the 8th Gaussian derivative is the analysing function in our experiments, the core of the "Hwang, Mallat" theorem offers us the opportunity to investigate the spirit of the minima maxima smoothing energetic analysis.

The new filtering algorithm is based on the energy content of the wavelet coefficients via an energy smoothing of the noise function [23].

4.1 The algorithm

While ultrasonic energies are concentrated in the central frequency band, therefore different frequencies close the band are represented in the transform domain by very weak amplitudes and can be scattered without loss of information.

But how the structural noise can be removed? The idea is to approximate it with an analysing function. The proposed algorithm illustrated admits the development of a noise analysing function with an easy filtering process. In this algorithm, the extraction from the signal of the noise energetic coefficients is based on the removal of the maximum energetic coefficients vector from the original signal wavelet decomposition by the 8th derivative gauss

function. In contrast the computation of the noise energetic threshold is achieved from the wavelet coefficients of the noise Morlet scalogram. An inverse wavelet transform procedure gives us statistical noise characterization. The Morlet function is selected after a correlation process between wavelet bases and extracted noise database from ultrasonic signals captured from welds, welding defects and artificial flaws. Then the filtering is performed 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 8th derivative of the Gaussian i.e. a subtraction between two continuous wavelet representations of the same signal is performed.

5   Experiments

Steel material used in these experiments is a rich element which can undergo quenching and tempering, see chemical analyses in table 1. Metallographic investigations reveal ferrite and pearlite structure (figure 1). Grain size varies between 40 and 60 µm and hardness testing gives an average value of 120 HV. Structure noise function extracted and analyzed by the de-noising algorithm [9], undergoes computing mismatching and correlation process between interpolation and residuals coefficients. See example of pure signal filtering in (Figure 2). Obtained results, point to occurrence of quasi linear energy distribution in (figure 3), which could advise to apparent energy scales incidence of micro structural acoustic signatures. In (figure 4) residuals display fitting indications from first samples noise data obtained after multi-interpolation stages. This must be correlated with ultrasonic frequency band and material behavior. (Figure 5) reveal particular residual distributions of Fourier transform noise function, after several polynomial interpolations. This will recommend relationship exploration with some material properties.
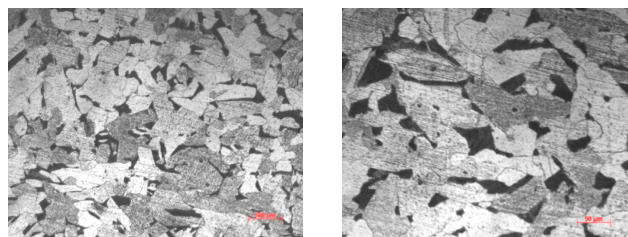

Figure 1. Ferrite pearlite structure (X50 & X100)
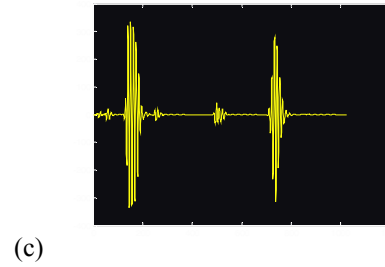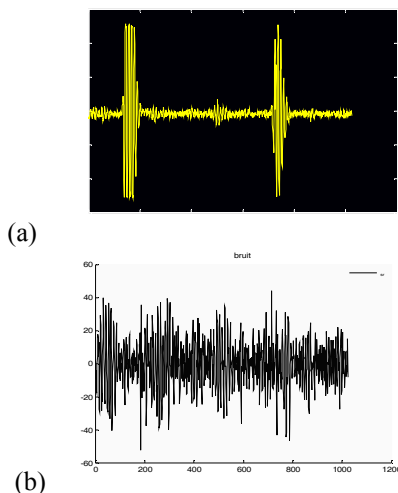

(a)

(b)

(c)

Figure 2. Signal and noise analysis: (a) Natural signal from steel piece of 35 mm, inside 1 mm flaw indications captured by a 5 MHz Krautkramer transducer. (b) Extracted functional noise. (c) Smooth filtered signal where the flaw indications are amplified and noise totally withdrawn.
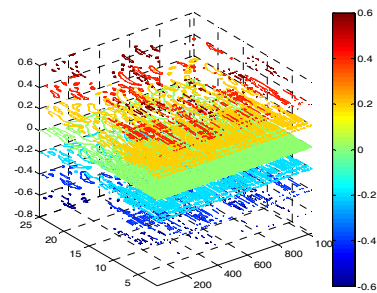

Figure 3. Noise functional analysis displays different energy scales
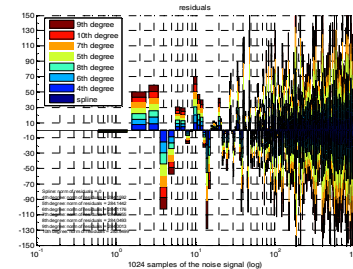

Figure 4. Residuals of the structure noise after several interpolations
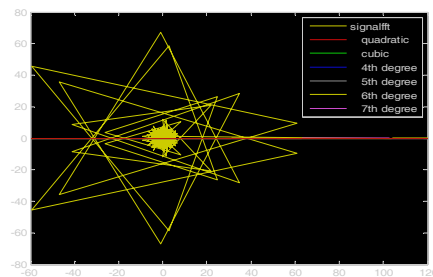

Figure 5. Attractor shape after multi-polynomial interpolations

Table 1: XRF Chemical analysis

Cr	1.36%
Ni	0.90%
Mn	0.85%
Si	0.52%
Al	0.45%
Cu	0.13%
S	0.00218%
Mo	0.048%

Mg	0.04%
Sb	0.02%
P	0.01%
V	0.01%
Fe	balance
C	0.126%

6   Conclusion

Non linear denoising of ultrasonic signals captured from welds, with multiscale approximation using thresholding, permits an adaptive representation of the signal discontinuities. The new energy algorithm involving the energetic matter of the signal and the noise, by means of minimisation of a smoothing functional is promising. In this algorithm no signal decomposition is performed and the threshold level is determined by an arithmetic process of the maximum and the minimum wavelet coefficients energetic level. Therefore the structural noise is approximated by a wavelet function, and the denoising process is carry out by discrimination between two wavelet functions. This algorithm is powerful when the selected analyzing functions are the best matching mother wavelet functions to signal and noise information. In reverse case, a scaling function must be composed for the generation of the experimental wavelet functions. The approximation of the structure noise by the Morlet function, offers the prospect to investigate a multiscale material microstructure characterization, in an attempt to extract some useful microstructure material features as presented in Fig 9, where we can observe different levels of the structural noise energy concentration at different scales, extracted from a steel plate by ultrasonic testing with 5Mhz piezoelectric tranducer. In reality, if anisotropic noise is related to local variations in texture or shapes of macro etches, the relationship of this ultrasonic property to microstructure is not well understood, and up to now no careful theory has been presented to quantitatively describe these relationships [24]. Chaos theory seems to be helpful for this issue.

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