Ultrasonic Grain Noise Reduction using Wavelet Processing. An Analysis of Threshold Selection Rules

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Abstract. Several specific signal processing techniques have been proposed to improve the detection capabilities in some ultrasonic NDT applications where the testing signals are buried in grain noise. This type of noise originates from the echoes of multiple scatters (grain boundaries) and presents a spectrum frequency very similar to that of the target echoes. For this reason conventional averaging and/or filtering techniques are not useful for coherent grain noise reduction. On the other hand, wavelet processing offers great flexibility and is a well established technique for removing noise from signals. It is usually based on a thresholding of the coefficients in the transformed wavelet domain, using different threshold selection rules, like Universal, Minimax and SURE, that in general have been proposed for the case of additive white Gaussian noise. In this work, Discrete Wavelet Transform processing is used for de-noising ultrasonic pulse-echo traces. Thresholds for each decomposition level are estimated from its wavelet coefficients. The efficiency in noise reduction is evaluated by means of the signal-to-noise ratio SNR enhancement. Synthetic ultrasonic traces have been generated by inserting a single flaw signal into different grain noise registers, which are obtained from a frequency domain model that includes frequency-dependent material attenuation and scattering. An analysis of the SNR of the processed traces is performed and the efficiency of different threshold selection rules is evaluated. In addition, experimental pulse-echo ultrasonic traces, obtained from a CFRP (carbon fiber reinforced plastic) composite block, have been also processed.

1. Introduction

Noise encountered during the inspection process in ultrasonic non-destructive testing (NDT) applications is one of the main factors disturbing the reliability and accuracy of quantitative evaluation methods. Ultrasonic grain noise originates from the interference of multiple echoes produced by randomly located scatters (grain boundaries). This type of noise presents a frequency band very similar to that of the echoes issuing from the defects to be detected. Therefore, conventional averaging and/or filtering techniques can not reduce this type of noise. Several specific signal processing techniques have been proposed to improve the detection capabilities in ultrasonic inspection applications where the testing signals are buried in coherent grain noise (speckle), including Split Spectrum Processing [1-3], Time-Frequency distributions and Wavelet Transform Processing [4-9].

Wavelet de-noising methods usually employ a thresholding and/or pruning of the coefficients in the transformed domain. In this work, discrete wavelet transform (DWT) processing is used for de-noising ultrasonic pulse-echo traces contaminated with grain noise, using level-dependent thresholds, as proposed in Ref. [10] for correlated noise. The efficiency in noise reduction has been evaluated by means of the signal-to-noise ratio (SNR) enhancement. Synthetic grain noise registers have been generated by using a frequency domain model which includes frequency dependent material attenuation and frequency dependent scattering. A single ultrasonic flaw-echo signal is incrusted, at a fixed position, with different values of the input SNR. The mean value and the standard deviation of each set of processed traces have been computed and used as indications of the efficiency of different thresholding procedures. Several experimental pulse-echo ultrasonic traces, obtained from a CFRP (carbon fiber reinforced plastic) composite block, have been also processed with the same set of parameters. They were acquired by means of a digital oscilloscope, Tektronix TDS 744 of 2GSamples/s, with a data length of 5000 samples and were transferred via GPIB to a computer for further processing.

2. Wavelet Transform Processing for De-noising

Wavelets are families of functions obtained by dilation and translation of a single prototype function called "mother wavelet", $\psi(t)$.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

The continuous-time wavelet transform (CWT) of a signal $x(t)$ is obtained following the next expression:

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right) dt \qquad (2)$$

The above expression produces a very redundant transform, thus, in order to avoid this redundancy, the translation, b; and dilation, a, parameters can be discretized. One of the most popular discretization methods consists of changing the dilation a by 2^j and the translation b by $2^j n$, resulting the dyadic wavelet. The dyadic discrete wavelet transform (DWT) of a signal $x(t)$ can be obtained by using:

$$DWT_x(j,n) = CWT_x(2^j, 2^j n) = \int_{-\infty}^{\infty} x(t)\, \frac{1}{\sqrt{2^j}}\psi\left(\frac{t}{2^j} - n\right) dt \qquad j,n \in Z \qquad (3)$$

The previous expression produces an orthogonal, non-redundant, wavelet decomposition. The DWT of a signal can be computed by means of a digital filter bank tree combined with decimation blocks [11]. At each level of the filter bank tree, the input is decomposed into two frequency bands, one with the high frequencies and the other with the low frequencies. The output of the filters is downsampled and the low frequency branch constitutes the input for the filters in the next decomposition level.

The discrimination between signal and noise in the wavelet domain usually employs a thresholding of the wavelet coefficients. It is based on the idea that the signal, with certain waveform structure, is concentrated on a few coefficients in the wavelet domain, while the noise, with a more random structure, is spread over a higher number of wavelet coefficients. In its simplest version, wavelet de-noising can be summarized as (i) wavelet transform of the noisy register; (ii) pruning and/or thresholding of the coefficients in the transformed domain; (iii) reconstruction of the de-noised signal by the inverse transform.

There are different ways to apply the thresholds to the wavelet coefficients. The most common methods are hard and soft thresholding, illustrated in figure 1, which correspond to the following laws:

hard thresholding:
$$x_H = \begin{cases} 0 & |x| \le T \\ x & |x| > T \end{cases} \tag{4}$$

soft thresholding:
$$x_S = \begin{cases} 0 & |x| \le T \\ x - T & x > T \\ x + T & x < -T \end{cases} \tag{5}$$

where T is the threshold value. These methods set to zero the coefficients with absolute values below the threshold, since they are considered to contain fundamentally noise, and keep or shrink the coefficients over the threshold. Each method has different statistical performance: hard thresholding keeps the coefficients, creating discontinuities at $x = \pm T$; soft thresholding avoids those discontinuities by shrinking the coefficients, but it can produce high attenuation of the signal, especially when the threshold values are big. For all these reasons, the suitability of one or the other method depends on each particular application.

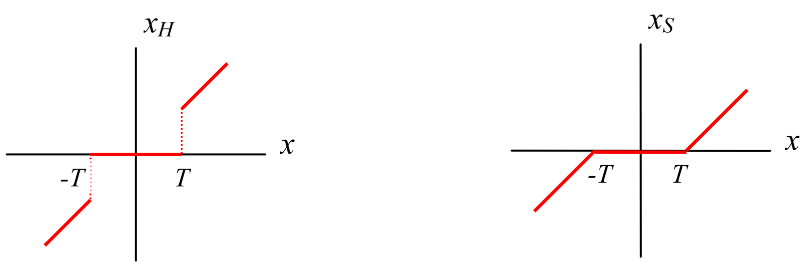

Figure 1. Hard x_H and soft x_S thresholding procedures

3. Threshold Selection Rules

The Discrete Wavelet Transform of the input ultrasonic traces is obtained as a first step of the de-noising method. The usual discrimination between signal and noise consists of a thresholding of the coefficients in the transformed wavelet domain. Different threshold selection rules have been proposed, generally from investigations assuming additive white Gaussian noise [12-15]. The threshold selection rules used in this work are summarized in Table 1, where N represents the number of wavelet coefficients, $\hat{\sigma}$ is their standard deviation, and λ^* are the values presented in Table I of Ref. [13].

Table 1. Summary of threshold selection rules used in this work.

Name	Expression	References
Universal T^U	$T^U = \hat{\sigma}\sqrt{2\ln N}$	[14,15]
Minimax T^{Mm}	$T^{Mm} = \hat{\sigma}\lambda^*$	[13]
SURE T^S	Eqs. (11-12) of [14]	[14]

3.1 Level dependent thresholds

Specific thresholds for each decomposition level were suggested in [10] for signals contaminated with correlated noise. This approach is also followed in this work for de-noising ultrasonic traces contaminated with grain noise. Thresholds are estimated for each decomposition level from the computed wavelet coefficients, according to the expressions shown in Table 1. In this case N represents the number of coefficients at the given scale, and $\hat{\sigma}$ their standard deviation.

4. Synthetic Ultrasonic Traces

Synthetic noise registers have been generated using a structural noise model based on the superposition of backscattered signals from the grain boundaries [6] and developing the necessary software. The implemented frequency-domain model assumes single scattering, frequency dependent material attenuation, frequency dependent scattering, a Gaussian distribution of the scatters, and an accurate model for the two-way transducer response. An additional white Gaussian noise N(0,1), which can be related to the measurement system, is added to the previously normalized grain noise. Figure 2.a shows a typical synthetic noise register, computed for a sampling frequency f_s = 64 MS/s, with attenuation factor α_0 = 1.8E-26 and N=4096 points [6]. Figure 2.b shows the clean ultrasonic echo signal, which corresponds to the pulse-echo impulse response of the reference piezoelectric ultrasonic transducer. Figures 2.c and 2.d show the corresponding frequency bands.

A clean echographic signal with amplitude $A = \mathrm{F} / \sigma_t$ is added at the central position of the noise register, where σ_t is an estimation of the standard deviation of the ultrasonic trace and F is an index of the input SNR. In this way, several sets of 500 ultrasonic traces with the same factor F were generated. In this work, the following values of F are used: 2, 2.5, 2.75, 3, 3.25, 3.5, 3.75, 4, 5, and the signal-to-noise ratio SNR of the traces is calculated by means of the following expression:

$$\mathrm{SNR} = 10 \cdot \log\left(\sum_{i=1}^{Nts}\left(ts_i^2 / Nts\right) \Big/ \sum_{i=1}^{Ntn}\left(tn_i^2 / Ntn\right) \right) \qquad (6)$$

where ts_i are the amplitudes of the trace points located in a time window around the zone where the signal was incrusted (target zone, with Nts points), and tn_i are the amplitudes of the points in the rest of the trace (Ntn points). The time window is centred with the incrusted signal and has the same length. These quantities can be computed for the raw input traces (SNRin) and for the processed traces (SNRout), since in this work we are using

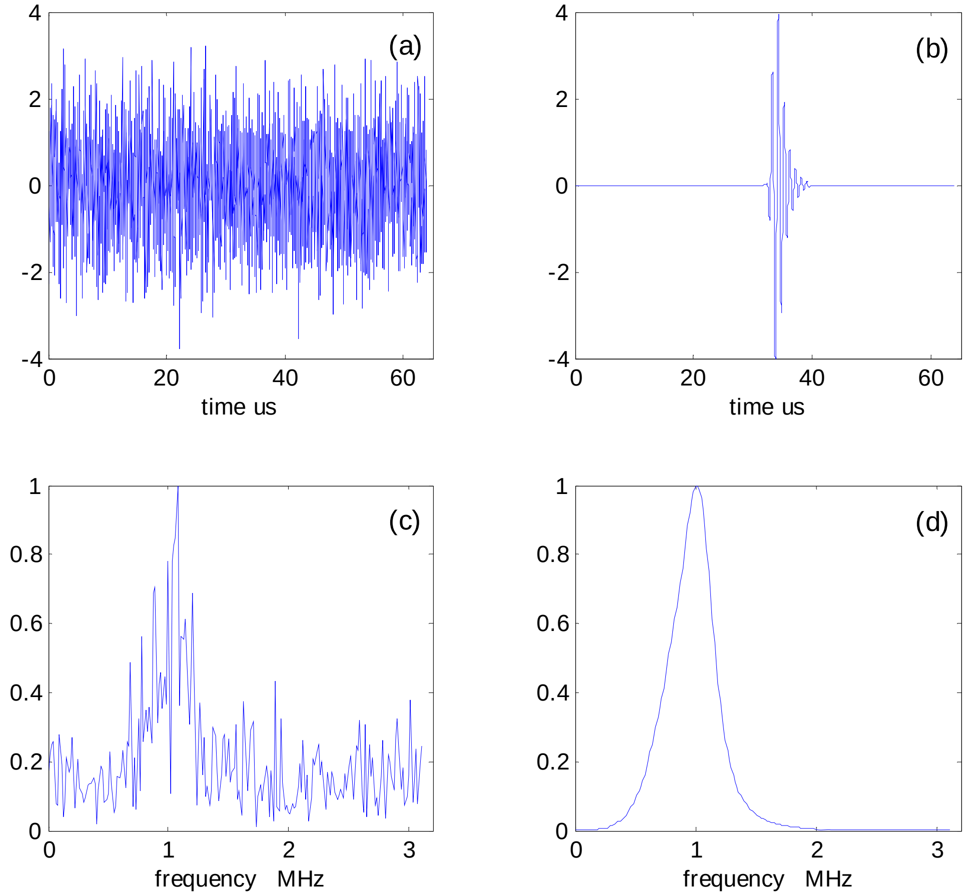

Figure 2. Synthetic noise register (a), clean ultrasonic echo (b), and their frequency spectrums (c) and (d).

synthetic noise registers, and therefore we know the location and length of the incrusted echo-signal.

5. Discussion of Results

Each set of 500 synthetic ultrasonic traces, characterized by the factor F, has been de-noised by using DWT processing. In this work, several processing options have been fixed: Multilevel threshold selection [10]; Highest decomposition level: 7; Border treatment: zero padding. The efficiency in noise reduction has been evaluated by means of the SNR of the input and processed ultrasonic traces. In particular, the SNR mean value and standard deviation of the different sets of processed traces have been computed for the following processing options: Soft and Hard thresholding; Universal, Minimax and SURE threshold selection rules; and four different mother wavelets from the Daubechies family [16] with increasing filter length: db1, db6, db12 and db24.

Figures 3.a – 3.d show the results of processing the different sets of synthetic ultrasonic traces, with increasing values of the input SNR and db12 as mother wavelet. In particular, the mean value and the standard deviation of the SNR are presented for each set of processed traces (SNRoutput) as a function of the factor F. Results are shown for both

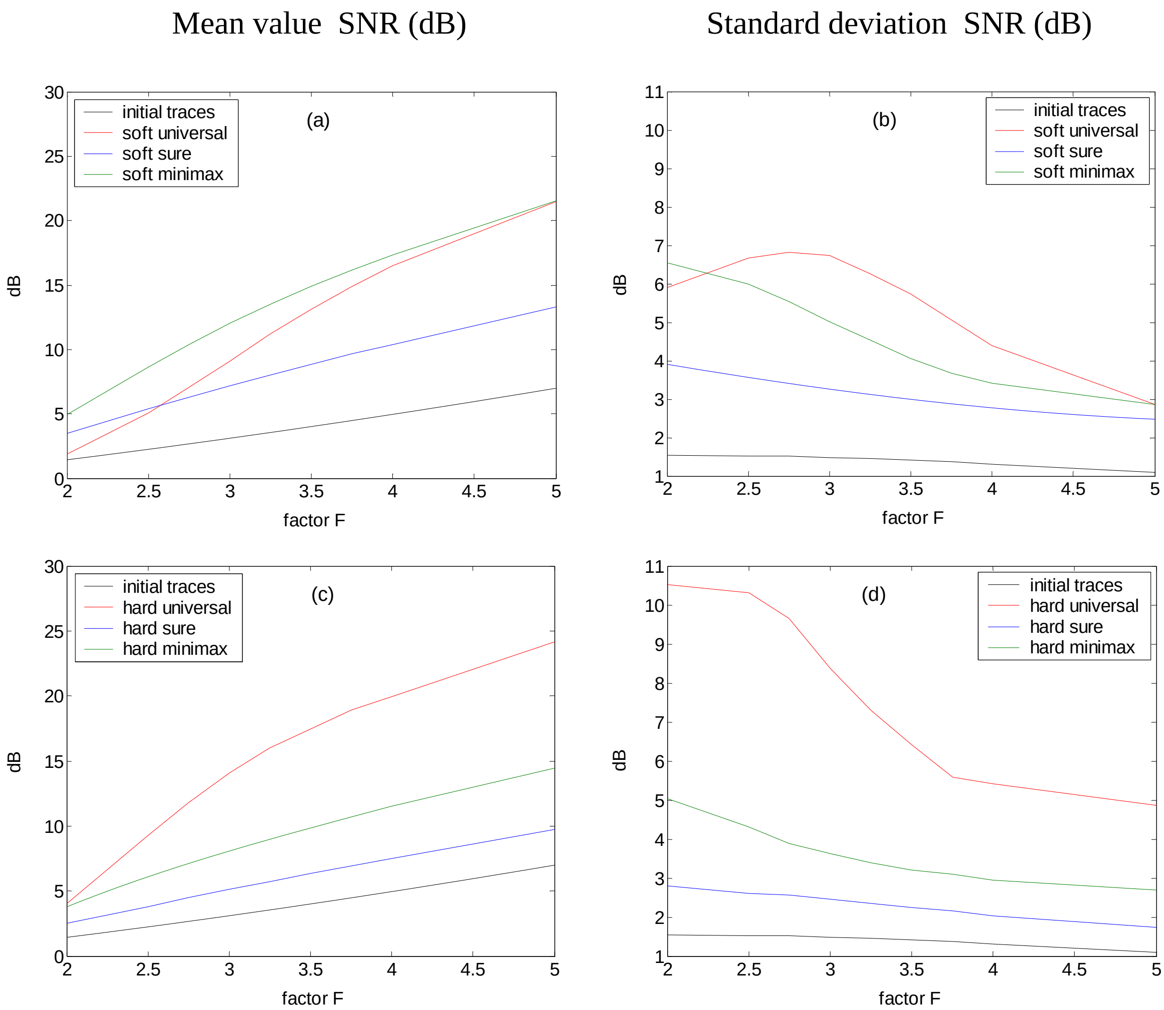

Figure 3. Mean value (a) (c) and standard deviation (b) (d) of the SNR as a function of F, for the initial and processed ultrasonic traces, with soft (a) (b) and hard (c) (d) thresholding procedures, and Universal, SURE and Minimax threshold selection rules.

soft and hard thresholding, as well as for the different threshold selection rules studied in this work. The initial SNR (SNRinput) is also shown as a function of the factor F. It can be observed how the best results in terms of SNR are obtained with Universal threshold selection rule and hard thresholding. This is in agreement with some results presented in our previous work [6]. Nevertheless it should be noticed that the standard deviation of each set of traces is notably higher than those corresponding to other processing options, indicating a high dispersion in the results. Minimax threshold selection rule with soft thresholding presents the best SNR and the standard deviation attains an intermediate value between Universal and SURE. The worst performance in terms of SNR corresponds to SURE threshold selection rule, but it presents the best behaviour in terms of standard deviation. It should be noticed that SURE with soft thresholding performs better than with hard thresholding, which could be explained since it is a data-adaptive threshold developed for soft procedures. A somewhat similar behaviour has been observed for the ultrasonic traces de-noised using other mother wavelets with different filter length (Daubechies db1, db6, db12 and db24 [16]). Nevertheless, all these results are not shown for space limitations, but they will be presented in an extended version of this work.

Figure 4.a shows an experimental pulse-echo trace obtained by ultrasonic testing of a CFRP (carbon fiber reinforced plastic) composite block of 31.5 mm thickness with flat-bottom holes properly drilled. An ecographic inspection has been performed with an ultrasonic probe Panametrics 310S of 5 MHz and 6.35 mm in diameter. As an illustrative example, figures 4.b, 4.c and 4.d show the results of de-noising this echo-trace with Universal, SURE and Minimax thresholds respectively, db12 as mother wavelet and soft thresholding. It should be noticed that, in this experimental ultrasonic trace, there are 3 echoes from real reflectors, the first near the surface, the second at approximately 12.5 μs, which corresponds to a flat-bottom hole, and the third at approximately 16 μs, which corresponds to the back wall echo. The SNR values displayed in the figure are computed considering a target zone around 12.5 μs, where the flat-bottom hole echo is located.

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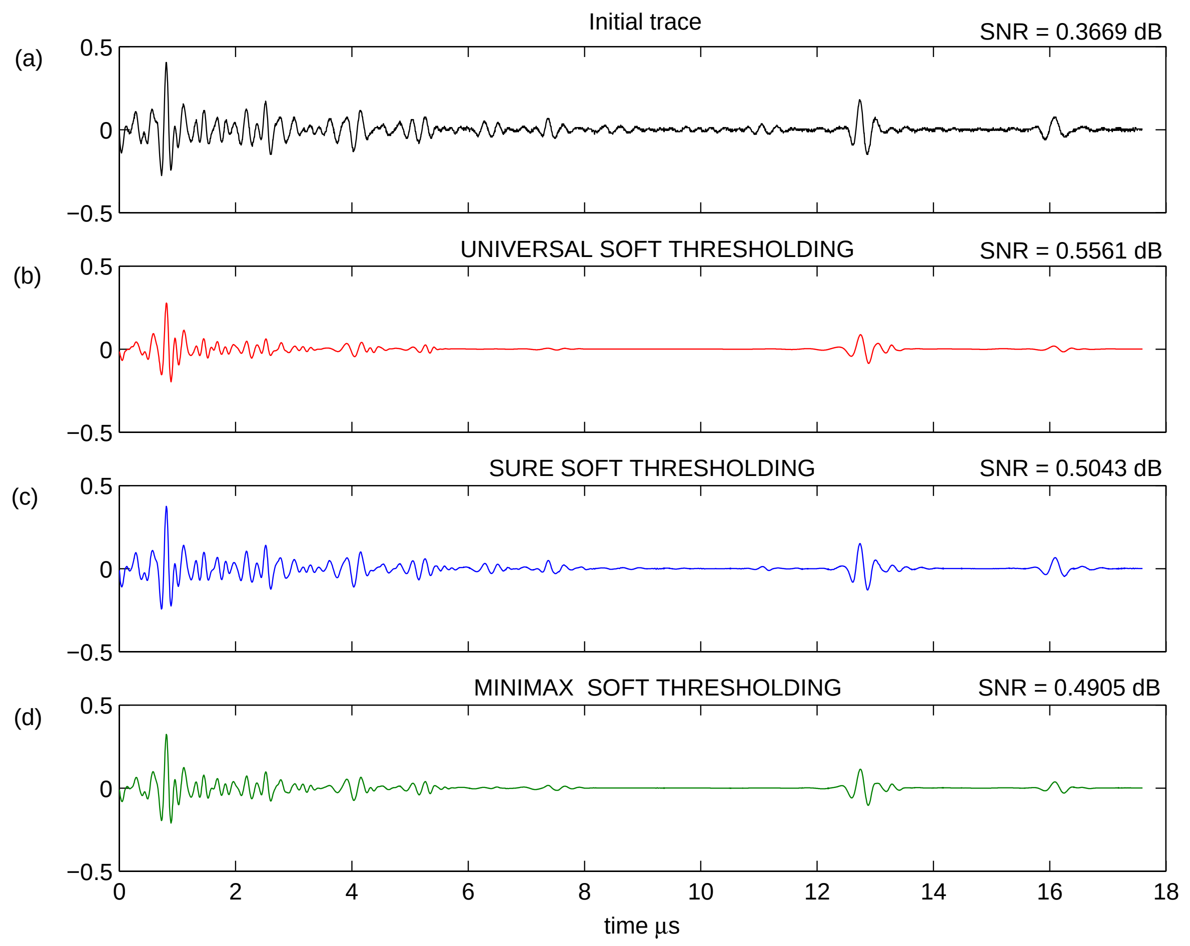

Figure 4. Experimental ultrasonic trace (a) and results of de-noising with soft thresholding and different threshold selection rules: Universal (b), SURE (c) and Minimax (d).

References

[1] V.L. Newhouse, N.M. Bilgutay, J. Saniie, E.S. Furgason, “Flaw-to-grain echo enhancement by split-spectrum processing”, Ultrasonics, 20, 59-68 (1982)

[2] P. Karpur, P.M. Shankar, J.L. Rose, V.L. Newhouse, “Split spectrum processing: optimizing the processing parameters using minimization”, Ultrasonics, 25, 204–208 (1987)

[3] J.D. Aussel, “Split spectrum processing with finite impulse response filters of constant frequency-to-bandwidth ratio”, Ultrasonics, 28, 229–240, (1990)

[4] M.A. Rodríguez, J.L. San Emeterio, J.C. Lázaro, A. Ramos, “Ultrasonic flaw detection in NDE of highly scattering materials using wavelet and Wigner-Ville transform processing”, Ultrasonics, 42, 847-851, (2004)

[5] A. Abbate, J. Koay, J. Frankel, S.C. Schroeder, P. Das, “Signal detection and noise suppression using a wavelet transform signal processor”, IEEE Trans Ultrason Ferroelectr Freq Control, 44, 14–25, (1997)

[6] J.C. Lazaro, J.L. San Emeterio, A. Ramos, J.L. Fernandez, “Influence of thresholding procedures in ultrasonic grain noise reduction using wavelets”, Ultrasonics, 40, 263-267, (2002)

[7] M. Jansen, *Noise reduction by wavelet thresholding*, (Lecture notes in statistics, Springer-Verlag, 2001)

[8] J.C. Lazaro, J.L. San Emeterio, A. Ramos, “Noise Reduction in Ultrasonic NDT using Discrete Wavelet Transform Processing”, Proc. of the IEEE2002 Ultrasonic Symposium, 756–759, (2002)

[9] E. Pardo, J.L. San Emeterio, M.A. Rodriguez, A. Ramos, “Noise Reduction in Ultrasonic NDT using Undecimated Wavelet Transforms”, Ultrasonics, Accepted (2006)

[10] I.M. Johnstone, B.W. Silverman, “Wavelet threshold estimators for data with correlated noise”, Journal of the Royal Statistical Society, 59, 319-351, (1997)

[11] S. Mallat, *A wavelet tour of signal processing,* Academic Press, (1999)

[12] D.L. Donoho, “De-noising by soft thresholding”, IEEE Transactions on Information Theory, 41, 613-627, (1995)

[13] D.L. Donoho, I.M. Johnstone, “Ideal spatial adaptation by wavelet shrinkage”, Biometrika, 81, 425-455, (1994)

[14] D.L. Donoho, I.M. Johnstone, “Adapting to unknown smoothness via wavelet shrinkage”, J. Amer. Statist. Assoc., 90, 1200-1224, (1995)

[15] D.L. Donoho, I.M. Johnstone, G. Kerkyacharian, D. Picard, “Wavelet shrinkage: Asymptotia?”, J. of the Royal Statistical Soc., Series B, Vol. 57, Nº2, pp. 301-369, 1995.

[16] I. Daubechies, “Ten Lectures on Wavelets”, CBMS-NSF Series in Applied Mathematics, 61, SIAM, Philadelphia, (1992)