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DENOISING ULTRASONIC SIGNALS USING WAVELET TRANSFORM PROCESSING

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Abstract

Wavelet processing offers great flexibility and is a well established technique for removing noise from signals. The usual discrimination between signal and noise consists of a thresholding and/or pruning of the coefficients in the transformed wavelet domain. In this work, decomposition level dependent thresholds have been used to denoise ultrasonic signals. Thresholds for each decomposition level are estimated from their wavelet coefficients utilizing Universal, Minimax and SURE threshold selection rules. Discrete wavelet transform (DWT) and translation-invariant wavelet transforms are applied. Two different undecimated wavelet transform (UWT) processors, which we have specifically developed for noise reduction purposes, have been used. The efficiency in noise reduction, for single echo detection, is evaluated by means of the signal-to-noise ratio (SNR) enhancement. Results of processing synthetic and experimental ultrasonic pulse-echo traces are shown.

INTRODUCTION

Different digital signal processing techniques have been used for denoising pulse-echo traces in ultrasonic imaging / detection applications. A particular type of noise, which is usually called grain noise or structural noise, plays an important role in ultrasonic signal detection applications. This type of noise is originated from the addition of multiple ultrasonic echoes produced by randomly located scatters (grain boundaries) inside the inspected material.

Ultrasonic grain noise has a frequency band very similar to that of the echoes issuing from the defects or discontinuities to be detected. Conventional time averaging and/or band pass filtering techniques are not useful for grain noise reduction. Specific denoising methods have been proposed for processing these ultrasonic signals, based on either spatial diversity or frequency diversity. Special techniques developed for the reduction of structural noise include Split Spectrum Processing SSP [1-3], time–frequency analysis (mainly by means of the Wigner–Ville transform) [4], and wavelet transform denoising methods [5-9].

Wavelet processing, which offers great flexibility and potential capabilities for removing noise from signals, has been used during the last years for ultrasonic grain noise reduction. In this work, discrete wavelet transform (DWT) and translation-invariant wavelet transforms are used for noise reduction of synthetic and experimental ultrasonic traces. The synthetic grain noise registers used in the work have been generated by using a frequency domain model which includes frequency dependent material attenuation and frequency dependent scattering [6]. Experimental NDT ultrasonic traces have been obtained from the inspection of a CFRP (carbon fiber reinforced plastic) composite block. The results of denoising one of these experimental NDT traces are also presented.

WAVELET TRANSFORMS

The continuous wavelet transform CWT of a signal x(t) is defined as [10]:

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t)\, \frac{1}{\sqrt{|a|}}\, \psi\!\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where $\psi(.)$ is the mother wavelet and a, b, the dilatation and translation coefficients respectively. The reconstruction formula allows to recover the signal $x(t)$ from the wavelet coefficients:

$$x(t) \;=\; \frac{1}{C_\psi} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} CWT_x(a,b)\, \frac{1}{\sqrt{|a|}}\, \psi\!\left(\frac{t-b}{a}\right) \frac{da\,db}{a^2} \qquad (2)$$

being $$C_\psi = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega \;<\; \infty \qquad (3)$$

This transform is highly redundant, since it maps a one-dimensional signal into a two-dimensional representation. The discretization of the parameters a and b still allow the reconstruction and provides less redundant representations that can be implemented using fast digital filter bank algorithms. The discrete wavelet transform (DWT) obtained by the algorithm of Mallat [10] corresponds to the dyadic discretization:

$$CWT_x(2^j, 2^j n) = \int_{-\infty}^{\infty} x(t)\, \frac{1}{\sqrt{2^j}}\, \psi\!\left(\frac{t}{2^j} - n\right) dt \qquad j,n \in Z \qquad (4)$$

This expression (4) shows an orthogonal, non-redundant transform. The Introduction of redundancy produces less efficient signal representations but it can be useful in some applications, for example in de-noising [11-13]. The undecimated wavelet transform (UWT) is a redundant wavelet obtained avoiding the coefficient decimation performed in the DWT. Two implementation methods are addressed in this paper. The first is the called the *à trous* algorithm [10] that is essentially the same algorithm as Mallat's, but removing downsampling and upsampling in the filter responses instead. An alternative method to obtain these redundant coefficients consists of applying the Mallat algorithm to circularly-shifted versions of the input sequence. For the redundant wavelet representations, the inverse operator is not unique and this allows different approaches to reconstruction that can be useful for different purposes. From the point of view of the *à trous* algorithm, reconstruction can be achieved with the dual filter bank [10]. On the other hand, for the circular-shifting implementation, an independent, orthogonal reconstruction can be done for each circular shift.

In this work, the Discrete wavelet transform DWT and two UWT implementation schemes, *à trous* (UWT1) and circular-shifting (UWT2), have been applied to the problem of ultrasonic grain noise reduction by wavelet thresholding.

PROCESSING ULTRASONIC TRACES

Processing ultrasonic traces in the transformed wavelet domain is originated from the idea that only a few (high value) wavelet coefficients contribute to the signal while most of the (low value) coefficients correspond to the noise. The discrimination between the signal and noise coefficients usually consists of a thresholding and/or pruning of the wavelet domain coefficients. Therefore, in its simplest version, wavelet denoising procedures 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 denoised signal by the inverse transform.

The more significant processing parameters conditioning the overall denoising performance of a wavelet signal processor can be summarized as follows: a) Type of wavelet transform; b) Type of mother wavelet; c) Highest decomposition level; d) Type of border treatment; e) Threshold selection; f) Type of thresholding and/or pruning of the coefficients in the transformed domain.

We present, in this work, the results of a study in which several parameters have been fixed, varying only the type of wavelet transform (*DWT, UWT*), and the threshold selection rule (*Universal, Minimax and SURE* [14-16]). The following parameters have been fixed: Mother wavelet: *db6* [17]; Highest decomposition level: *7*; Border treatment: *zero padding*; *No pruning*; *Soft thresholding* [14-16]; *Multilevel threshold selection* [18]. The efficiency in noise reduction is evaluated by means of the signal-to-noise ratio SNR of the input and processed ultrasonic traces.

Synthetic noise registers are frequently used for the evaluation of signal processing algorithms. In this paper we use a previously developed structural noise model [6]. In this model, single scattering, frequency dependent material attenuation, frequency dependent scattering, and a Gaussian distribution of the scatters are assumed. The flaw echo is modelled as a reflection arriving at a fixed time, by means of the delayed delta function. The amplitude is fixed by means of a weighting factor in order to control the input SNR.

In this study, the SNR of the initial and processed traces is calculated by means of the following expression:

$$\mathrm{SNR} = 10 \cdot \log\left(\sum_{i=1}^{Nts} \left(ts_i^2 / Nts \right) \Bigg/ \sum_{i=1}^{Ntn} \left(tn_i^2 / Ntn \right) \right) \tag{5}$$

where ts_i are the amplitudes of the trace points located in a time window around the zone were 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 we are using synthetic noise registers, and therefore we know the location and length of the incrusted echo-signal.

RESULTS

There are several parameters which can be adjusted in the grain noise generator. In this work we have used the following values: number of points in the trace: 4096; attenuation $\alpha_0 = 1.8\ 10^{-26}$; instrumental white Gaussian noise N(0,1) with normalized amplitude; sampling frequency = 64 MHz; number of noise registers: 500.

Several sets of 500 synthetic traces have been generated by adding a clean echographic signal in the central position of the noise registers. The amplitude, A , of the inserted signal is determined by means of a factor $F = A/\sigma_t$, where σ_t is an estimation of the standard deviation of the trace. Thus the initial SNR is varied by means of the factor F. In this work we use F = 2, 2.5, 2.75, 3, 3.25, 3.5, 3.75, 4, and 5.

Figure 1.a shows, as an example, one of the 500 synthetic ultrasonic traces generated with amplitude determined by F=2.75. The results after the denoising procedure, using SURE threshold selection rule, are shown in figure 1.b, 1.c and 1.d for the DWT, UWT1 and UWT2 processors respectively. The initial SNRin of the trace is 3.70 dB, and the final SNRout are 7.28, 9.91 and 10.00 dB for DWT, UWT1 and UWT2, respectively.

Several ultrasonic traces were acquired from a CFRP (carbon fibre reinforced plastic) composite block, 31.5 mm thickness, in which flat-bottom holes FBH were machined. They were acquired by a digital oscilloscope Tektronix TDS 744 (2GS/s of maximum sampling rate), with data length of 5000 samples, and were transferred via GPIB to a computer for further processing. Figure 2 shows the results of processing

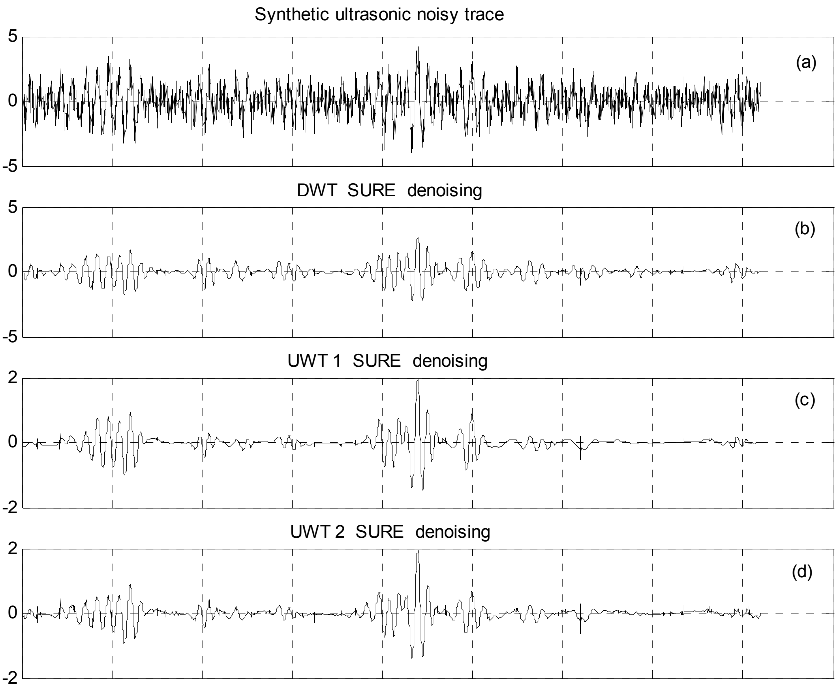

Figure 1. Synthetic ultrasonic trace with factor F = 2.75 a), and results after denoising with b) DWT c) UWT1 and d) UWT2 processors, using SURE as threshold selection rule.

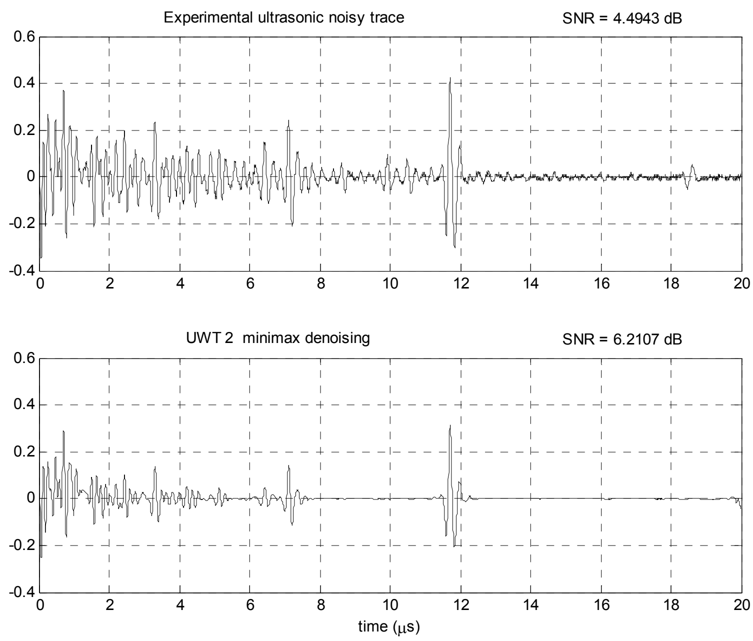

Figure 2. Experimental ultrasonic trace, before and after denoising with UWT2 processor and minimax threshold selection rule.

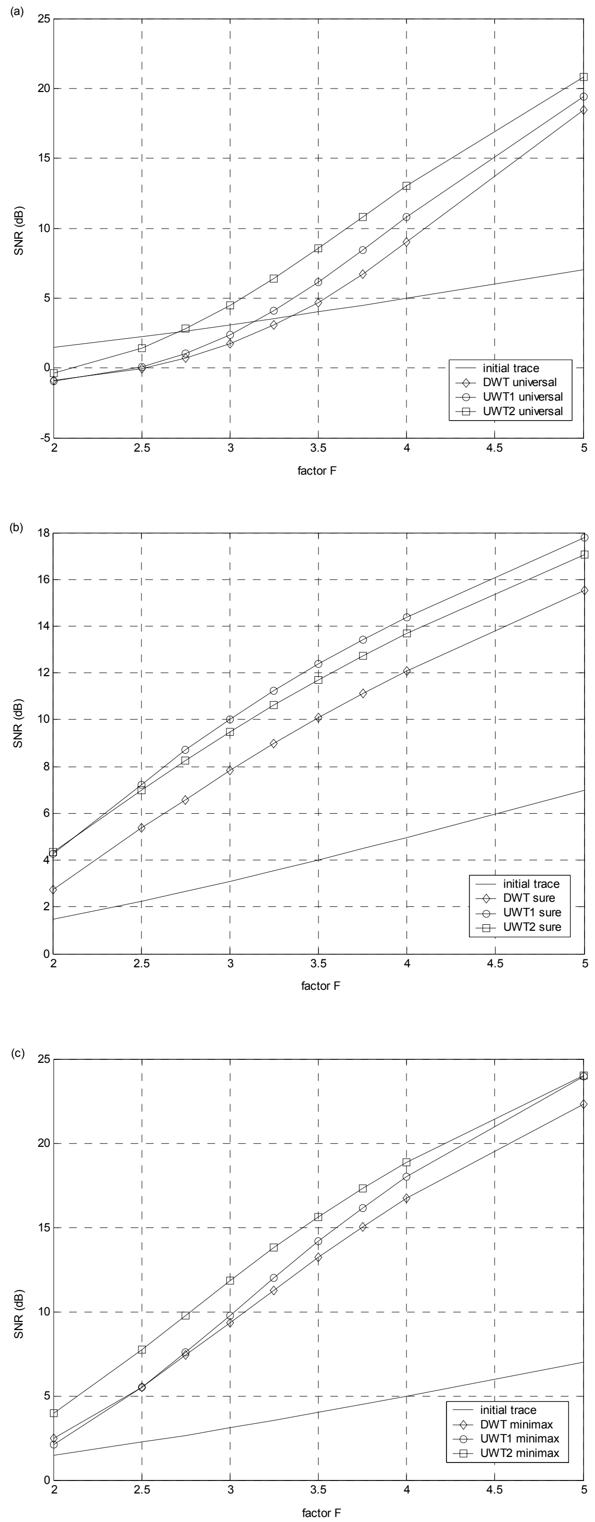

Figure 3. Signal-to-noise ratio of the initial and processed ultrasonic traces, using DWT, UWT1 and UWT2 processors, with a) universal, b) SURE and c) minimax threshold selection rules, as a function of the factor *F* related to the initial SNR.

an experimental trace by using Cycle-spinning and minimax threshold selection rule. The initial SNRin of this trace is 4.49 dB, and the final SNRout 6.20 dB.

An analysis of the SNR improvement has been performed from the results obtained by denoising the 9 sets of 500 synthetic ultrasonic traces. Each set of 500 traces was processed using the fixed parameters described previously and applying DWT, UWT1 and UWT2 wavelet transforms. For each wavelet transform, the denoising procedure was applied using a) universal; b) minimax and c) SURE threshold selection rules. The mean value in dB of each set of 500 traces (initial and denoised) was computed.

Figure 3 shows the mean value of the signal-to-noise ratio of the processed ultrasonic traces, SNR_{out}, as a function of the factor F (that controls the initial SNR_{in}). The initial values SNRin of the synthetic traces are also plotted. Figure 3.a shows the results for the universal threshold selection rule, and figures 3.b and 3.c show the corresponding results for SURE and minimax thresholds. A better performance of the shift invariant wavelet processing can be observed.

SUMMARY

Several processing parameters condition the overall de-noising performance of a wavelet signal processor (type of wavelet transform, type of mother wavelet, highest decomposition level, type of border treatment, threshold selection, thresholding and/or pruning procedures). Redundant wavelets can provide great improvements for ultrasonic grain noise reduction but with an increase in the computational cost [9]. To take advantage of all the benefits of wavelet denoising additional work is needed looking for systematically analyse the separated effects of the different parameters and the global interactions among them.

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