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Wavelet Analysis and De-noising of Signal

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Abstract: Ultrasonic non-destructive testing process is one of the promising techniques in the field of structural analysis of materials especially metals. Ultrasonic testing involves different noises that hamper the detection of defects and their characteristics. Several signal processing techniques for de-noising and weld defect detection such as slag, porosity, LF, LP, etc., have been proposed of which Discrete Wavelet Transform is more popular. One important aspect of DWT is the choice of the mother wavelet. This study presents a comparative study of the performance in de-noising using different mother wavelets.

Keywords: Decomposition, DWT, mother wavelet, SNR, threshold

INTRODUCTION

Ultrasonic non-destructive testing for detection of defects in a material poses several constraints due to various reasons like system noise and material noise etc. These noises have significant amplitudes in many cases thereby decreasing the quality of the signal. At times they even submerge the defect echo and deteriorate the shape of the defect echo. This completely disables the detection of defect and hampers the characterization of the defect.

Ultrasonic echo signals obtained from the weldments containing large amount of noise requires de-noising. Several signal processing techniques such as Split Spectrum processing, Hilbert transform, Correlation technique have been proposed in the past. Conventional filtering method fails in de-noising because signals are non-stationary and the noise spectrum overlaps with that of the defect signal spectrum which upon filtering may lead to loss of signal information as well. In this study Discrete Wavelet Transform is used and signals are decomposed into corresponding high and low frequency components. Considering the high frequency components as material noise and other unwanted noise, they are thresholded and the coefficients are used to reconstruct the signal to obtain de-noised signal.

WAVELT ANALYSIS

Wavelet transform: Wavelet is a simple wave i.e., a simple oscillatory function of finite duration. Fourier transform decomposes the signal into sines and cosines, i.e., the merit functions localized in Fourier space. The wavelet transform is a transform uses functions that are localized in both the real and Fourier space. That is Wavelet transform is an infinite set of various transforms, depending on the merit function used for its computation. The equation of the wavelet transform is expressed as:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\psi^*_{(a,b)}(x)dx \qquad (1)$$

Both time and frequency information can be obtained simultaneously through the wavelet transform. Wavelet Transform is used for cleaning signals and images i.e., reducing unwanted noise and blurring.

Wavelet transforms types: Basically it is divided into two types. One type of the WT is easily reversible (Invertible). That is Original signal can be recovered after it has been transformed. Example: Image compression and cleaning. Here WT of image is computed; wavelet representation is changed appropriately; then WT is reversed to obtain new image. Second type of WT is designed for Signal analysis. Example: Identification of welding defects. In this case, a modified form of original signal is not needed. So WT need not be reversed. But this process needs lot of computation time.

Based on orthogonality, WT can be categorized into two. One is Continuous Wavelet Transform or Non-Redundant WT and the second one is Discrete Wavelet Transform or Redundant WT.

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Continuous wavelet transform: Non-orthogonal wavelets are used to develop CWT. CWT returns an array 1D larger than input data. It mainly provides a theoretical direction for Ultrasonic applications (Abbate *et al*., 1994, 1997; Bechou *et al*., 2003; Song and Que, 2006), whereas the discrete wavelet transform is feasible for practical Ultrasonic systems because of its fast calculation time and thus is preferable (Kaya *et al*., 1994; Donoho, 1995; Legendre *et al*., 2000; Pardo *et al*., 2006; Molavi *et al*., 2007; Qi *et al*., 2009).

Discrete wavelet transform: DWT returns a data vector of the same length as the input is. It decomposes into a set of wavelets i.e., functions that are orthogonal to its translations and scaling. Hence one can decomposes such a signal to a same or lower number of the wavelet coefficient spectrum as is the number of signal data points. Such a wavelet spectrum is good for signal processing and compression.

Wavelet analysis: Wavelet analysis gives a time-scale region unlike the Fourier and short term Fourier which give a time-frequency and frequency-amplitude analysis respectively. The major advantage of wavelets is the ability to perform local analysis over a particular region of interest. Both Continuous and Discrete wavelet transforms exist and the main difference between them is the scale of operation. It operates over a large scale from extending from the actual signal up to some maximum determined scale. The continuity also extended to the shifting of the mother wavelet over the entire working range.

A very practical filtering algorithm popularly known as Mallat algorithm was developed by Mallat (1989). It yields a fast wavelet transform which, when a signal is passed through it, yields wavelet coefficients at a much faster rate. In DWT the echo signal is passed through complementary filters whose output consists of a low frequency component and a high-frequency component. They are popularly named as approximations and details. A single level decomposition gives two components and similar decomposition can be applied to multiple stages. With each level of decomposition output of the low pass filter contains more of the original signal content free from high frequency components nothing but noise in the signal.

EXPERIMENTAL RESULTS

In order to appreciate the performance of wavelets in denoising of signals, real-time Ultrasonic signals were used. A flat surface material with defects in it was subjected to ultrasonic signal and the corresponding echo was captured. All the 330 signals were taken from AISI steel plates having dimension 260/260/25 mm. The discrete values of the echo were imported and analyzed.

Decomposition of the signal: Initially the signal S Fig. 1 is decomposed to one level and the corresponding approximations and details were obtained as shown in Fig. 2. The decomposition is given by:

$$S = cA + cD$$

where, cA = approximations and cD = details.

It is observed that with decomposition the low-frequency components that are essentially actual signals are separated from the corresponding high-frequency components which are nothing but noise. With multilevel decomposition still more high-frequency components are separated. The signal S was then subjected to multilevel decomposition with levels 3, 4, 5, 6, etc., and the corresponding approximations and details were analyzed.

The hierarchy of 3-level wavelet decomposition is given in the Fig. 3. In multilevel decomposition S is given by:

$S = cA_3 + cD_3 + cD_2 + cD_1$ for a 3 level decomposition.

In general, for n-level decomposition:

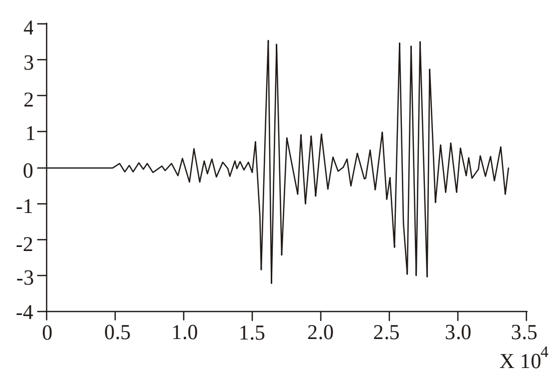


Fig. 1: Original signal with noise

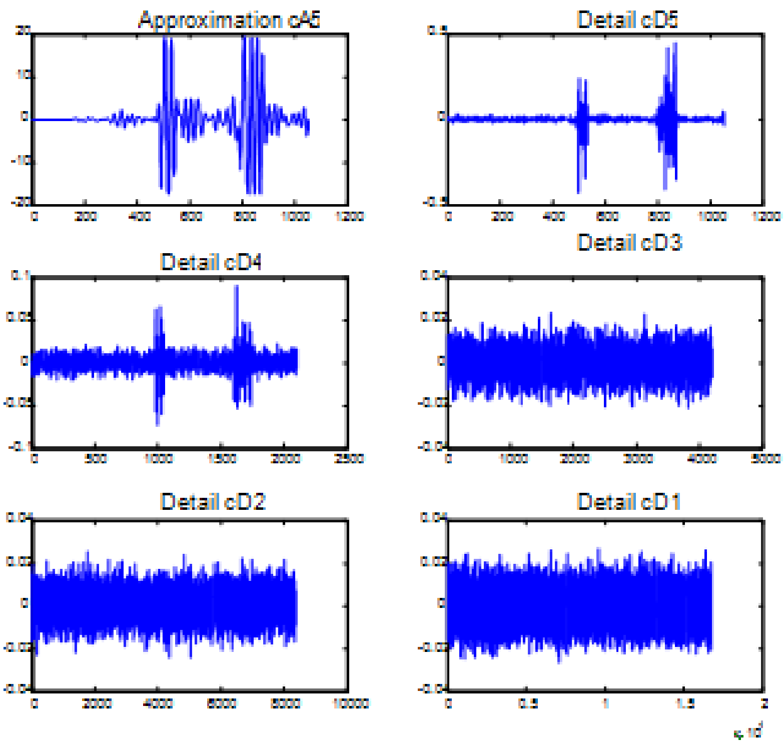


Fig. 2: Five level decomposition of signal using db5 wavelet showing the approximation cA5 and details cD_5-cD_1

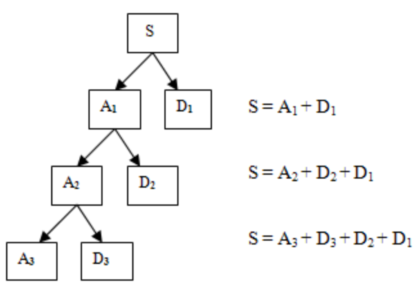


Fig. 3: Three level wavelet decomposition

$$S = cA_n + cD_n + cD_{n-1} + cD_{n-2} \ldots\ldots + cD_1$$

where, cAn is n level approximation:

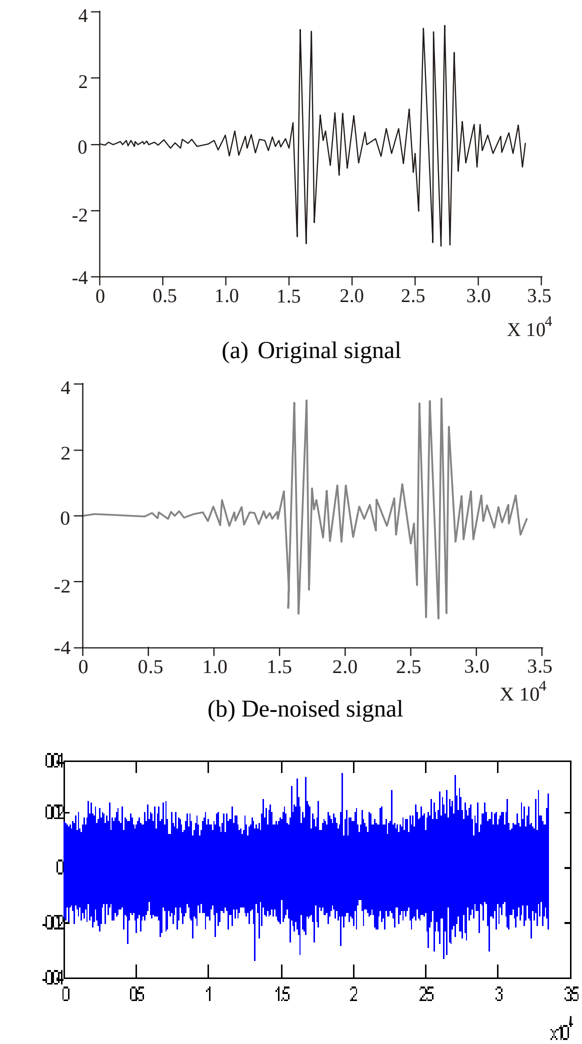
cD_n, cD_{n-1},…, cD_1 are corresponding details.

From the Fig. 2, we can observe that most of the high frequency components are separated from the signal in the first detail cD1 itself. Details obtained in the consecutive levels further separates the noise components from the signal thus leaving the echo free from noise. The signal which has been reduced in the number of samples can be up sampled or interpolated to get back the original length. The approximation which is noise and glich free is now suitable for target detection.

Table 1:SNR values before and after de-noising of different signals (db4)

Different signals	SNR before de-noising	SNR after de-noising
2-SL-03-C	9.3719	22.513
2-SL-04	8.6332	23.184
2-SL-04-C	9.8518	26.830
2-SL-03	9.4006	23.668
2-SL-02	9.4456	23.677
2-SL-02-C	9.4241	23.185
2-SL-01-C	9.3209	23.063
2-SL-01	9.3353	24.359

De-noising of the signal: We have seen that the detail cD1 consists of the high frequency components of the echo signal. We can manipulate this detail values by limiting the amplitudes of the noise. Marginalisation of the detail should be done carefully as this it may consist of high frequency components which are an integral part of the actual signal. So choice of thresholding value is an important aspect for denoising without the loss of any useful data. The thresholded cD1 is used to construct back the original signal taking into account other details and approximation values. The input i.e., original signal and the corresponding de-noised signal are as shown in the Fig. 4.



(a) Original signal

(b) De-noised signal

(c) After de- nosing, noise in (a)

Fig. 4: Original signal, de-noised signal and noise

Table 1 shows the SNR values of the signal before and after de-noising using db4. Table 2 shows the SNR improvement for different mother wavelets.

CONCLUSION

In this study, real ultrasonic signals have been used for de-noising using DWT. Since, DWT enables us to separate the original ultrasonic signal into low-frequency components and high-frequency noise components. The process of decomposition can be extended to multiple levels there by increasing the signal quality. Choice of mother wavelet and threshold values plays an important role in analyzing and denoising of the signal. Improvement in the quality of the signal is assured using wavelet technique. From the

Table 2: SNR values for a particular signal with different mother wavelets and decomposition levels

Mother Wavelet	Input SNR (5-level)	Output SNR (5-level)	Input SNR (4-level)	Output SNR (4-level)
haar	7.6981	17.009	7.6985	17.009
db2	9.8172	21.899	9.8173	21.760
db3	9.8475	23.431	9.8475	23.828
db4	9.8518	26.830	9.8518	27.469
db5	9.8507	25.730	9.8507	25.952
db6	9.8524	24.621	9.8524	24.513
db7	9.8520	24.099	9.8520	25.169
db8	9.8521	25.115	9.8522	25.081
db9	9.8524	25.094	9.8525	24.979
db10	9.8518	25.222	9.8518	26.300
coif1	9.8180	20.823	9.8181	21.299
coif2	9.8510	23.953	9.8510	24.408
coif3	9.8505	25.623	9.8505	26.797
coif4	9.8512	25.828	9.8512	26.993
coif5	9.8509	27.288	9.8509	27.082
sym2	9.3345	26.3705	9.3155	25.7771
sym3	9.3371	22.8120	9.3345	25.3933

tabulation, it is concluded that for “db4’’ and “coif5” the improvement in SNR is more compared to other mother wavelets.

ABBREVIATIONS

SNR : Signal to Noise Ratio
Haar : Haar wavelet
db4, d2,… : Daubechies wavelet
coif1, coif2, : Coiflets wavelet
sym2,… : Symlets wavelet

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