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Ultrasonic Signal Compression Using Wavelet Packet Decomposition and Adaptive Thresholding

Erdal Oruklu, Namitha Jayakumar and Jafar Saniie
Department of Electrical and Computer Engineering
Illinois Institute of Technology
Chicago, Illinois, USA

Abstract - **We introduce a systematic design flow consisting of two main stages for ultrasonic signal compression. The first stage of the algorithm is concerned with finding the maximum energy compaction. This is accomplished by finding an optimal subband decomposition tree structure for a particular combination of a wavelet kernel and the experimental input data. The second stage of the algorithm is concerned with the coefficient reduction using thresholding techniques. In addition to global thresholding, an adaptive thresholding is applied locally to each subband. The iterative nature of the algorithm ensures that the scales (subbands) that retain most of the total signal energy are preserved while the coefficients in other scales (mostly higher detail scales) are eradicated aggressively. The performance of the compression algorithm has been quantified with experimental data and shown to offer significant resilience to different experimental data sets.**

Keywords- ultrasound; compression; wavelets; adaptive thresholding; packet decomposition

I. INTRODUCTION

Data compression is indispensable to applications involving acquisition, storage, and processing of large volumes of ultrasonic data, as well as transmission over communication channels with limited bandwidth. Apart from high compression ratios, such applications also require that the reconstructed signal be as close to the original signal as possible, thereby resulting in very small reconstruction errors. The compression techniques also provide denoising, thereby enhancing signal-to-noise ratios while achieving good compression ratios. Denoising is beneficial for certain ultrasonic imaging and nondestructive evaluation (NDE) applications in which the received signal is buried in noise.

It has been shown that the application of established compression methods and standards such as Joint Photographic Experts Group (JPEG), Set Partitioning in Hierarchical Trees (SPIHT) [1], and JPEG2000 [2] yield sub-optimal results in the case of ultrasonic signal compression. These methods have been designed primarily for 2D images and do not perform well for ultrasonic RF signals. In order to address this shortcoming, ultrasonic RF signal can be analyzed directly using transform coding techniques [3,4]. Studies have been conducted using transform coding techniques such as Discrete Cosine Transform (DCT), Walsh Hadamard Transform (WHT) and Discrete Wavelet Transform (DWT) with respect to their compression and denoising properties for ultrasonic signal compression [5]. DWT provides a representation of the signal in terms of different frequency bands and is proven to achieve good compression ratios due to excellent energy compaction and time localization properties of the wavelet kernel. The design of optimum wavelet kernel to aid in better energy compaction is explained in [6]. An adaptive thresholding function was developed and applied to DWT, DCT and WHT of ultrasonic signals to improve the signal-to-noise ratio [7]. DWT in conjunction with hard thresholding techniques can provide efficient compression without significantly degrading the reconstructed signal fidelity. When thresholding is applied, the transform coefficients in frequency bands which contain a significant portion of signal energy are retained while others are discarded, thereby resulting in lesser number of coefficients.

In this study, our objective is to find optimal wavelet tree structures for experimental ultrasonic data, resulting in separation of high energy and low energy subbands. Next, several adaptive thresholding techniques are presented to discriminate the low energy subband coefficients. Multiple wavelet kernels are analyzed for ultrasonic data compression, providing choice between filter complexity and compression performance. Furthermore, the proposed compression techniques are evaluated with experimental and simulated ultrasonic data that contain broadband/narrowband, overlapping/non-overlapping echoes.

II. ULTRASONIC SIGNAL COMPRESSION USING DWT

DWT coding has good fitting properties in both the time and frequency domains. The wavelet transform splits the input signal into low-pass (approximation) and high-pass (detail) coefficients. Each set of coefficients are then downsampled by a factor of two. Hence, the wavelet kernel is shifted and dilated for correlating it with the input signal for calculating the DWT [8]. For time-frequency representation, the low-pass coefficients are repeatedly split to obtain the DWT at a particular decomposition level. Each decomposition stage splits the frequency bands into smaller subbands with different frequency characteristics. Figure 1 shows the filter banks and their corresponding outputs at each stage of filtering. At the first stage of the decomposition, A1 represents the frequency band containing the approximation coefficients and D1 represents the frequency band containing detail coefficients.

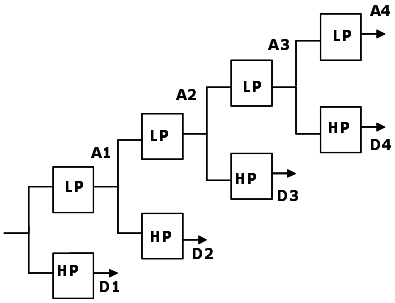

Figure 1. DWT with 4-level decomposition

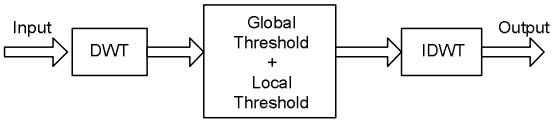

Figure 2. Ultrasonic signal compression

Figure 2 represents the ultrasonic signal compression algorithm. The experimental ultrasonic RF signals are first decomposed using DWT, which provide a more compact representation of the corresponding signals. This is followed by thresholding the transform values in order to eliminate insignificant transform coefficients. Both global and local thresholding are used to discard insignificant coefficients. This reduces the number of data points in the transform, thereby resulting in compression. Inverse DWT is then applied to get the reconstructed signal. The quality of the reconstructed signal is measured in terms of the means square error, which shows the differences in amplitudes of the original and reconstructed signals. Depending on the application, there's a trade-off between the amount of compression that can be achieved and the amount of reconstruction error that can be tolerated, which in turn governs the quality of the reconstructed signal.

A. *Experimental and Simulated Ultrasonic Signals*

To study the DWT decomposition of ultrasonic data, a set of ultrasonic echo signals were generated and simulated in Matlab. These signals form the basic components of complex ultrasonic signals encountered during the acquisition of experimental ultrasonic data. All simulated signals were centered at 5 MHz and sampled at 100 MHz. 2048 samples of the resulting echo signal have been utilized. The simulated signals include single broadband echo, single narrowband echo, two non-overlapping broadband echoes, two non-overlapping narrowband echoes, two broadband echoes with 40% overlap, and two narrowband echoes with 40% overlap. This study also utilizes experimental ultrasonic data acquired using a 5 MHz transducer, from a steel source with a flat bottom hole, at a sampling rate of 100 MHz.

B. *Identifying the Wavelet Kernel and Decomposition Levels*

The DWT decomposition of the given set of simulated ultrasonic echo signals has been studied by employing different families of wavelets. The objective is to determine the most suitable wavelet kernel for a given signal in terms of maximum energy compaction within a subband. This depends on the extent of similarity of the wavelet kernels with the ultrasonic signals. The different families of wavelets examined are Daubechies (D4, D6, D8, and D10), Symlet (5,6,7, and 8); Coiflet (2,3,4, and 5) and Haar. The simulated echo signals were transformed using a 4-level DWT decomposition, obtained by successively splitting the approximation level at each stage, which results in four detail levels and one approximation level. The number of decomposition levels strictly depends on the nature of the signal, which governs the distribution of energy across the frequency bands. The reason for limiting the number of levels to four was due to the fact that signal energy was concentrated in the D3 and D4 wavelet scales and not in the A1 wavelet scale.

The energy of the signal in a particular subband of the wavelet decomposition is determined as the sum of the squares of the amplitudes of the transform coefficients lying in that energy band. The optimal wavelet kernel from each wavelet family is chosen such that 85%-90% of the total energy is packed into a minimum number of subbands. This means that only those significant frequency bands have to be retained while the coefficients in the remaining frequency bands can be discarded without degrading the quality of the reconstructed signal. By observing the subband energy distribution of the 4-level DWT, it is determined that, within each family, the wavelet kernels with higher number of filter taps provided more energy compactness. Daubechies-10, Symlet-6/8 and Coiflet-5 consistently performed better than the other kernels within their family. Experimental ultrasonic data analysis also confirmed the simulated ultrasonic signal findings.

C. *Wavelet Tree Decomposition Structure*

The standard DWT decomposition is extended to wavelet packet decomposition [8] in order to recognize and detect additional subbands which carry insignificant signal energy and can be mostly discarded. In contrast to standard DWT, wavelet packet decomposition allows for detail subbands to be split as well. Wavelet packet decomposition levels are determined by observing the energy concentration in each of the subbands at a given level of decomposition. Those subbands which carry a significant percentage of the total signal energy are further split into high-pass (detail) and low-pass (approximation) transform coefficients. If both of the new frequency bands carry comparable (even) percentages of the total energy, this level of decomposition is not necessary. However, when one of the two new frequency subbands dominates (packs significant portion of the energy), the transform coefficients corresponding to the insignificant frequency subband can be discarded without significantly altering the total energy of the transform. This enables major reduction of transform coefficients during the thresholding operation. Figure 3 shows the wavelet packet decomposition tree structure that is used for both simulated and experimental ultrasonic data compression.

III. THRESHOLDING METHODS

Compression of ultrasonic signals is achieved by applying thresholding techniques to the DWT coefficients of the original signal. Hard thresholding is used in which all transform coefficients greater than a specified threshold T are retained while those lesser than T are set to zero. Two stages of thresholding are proposed; a global thresholding stage and a local adaptive thresholding stage.

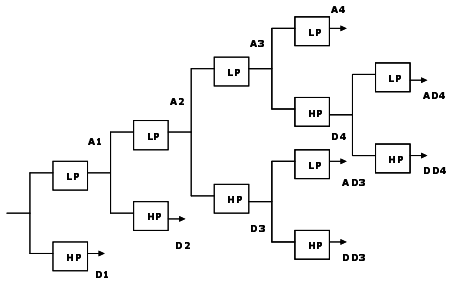

Figure 3. Wavelet Packet Decomposition Tree

A. Global Thresholding

The first stage, global thresholding, is used to denoise the signal and reduce coefficients based on the signal properties such as signal bandwidth, sampling rate and decomposition method. As discussed in Section II-A, the transducer frequency as well as the center frequency of the simulated signals are 5 MHz and the sampling frequency is 100MHz. The sampling frequency and the bandwidth of the ultrasonic signals directly affect the thresholding operation. Due to oversampling of signals, certain frequency bands have no information content and their corresponding transform coefficients have negligible magnitudes. For a broadband echo, the bandwidth is about the same as the center frequency and for a narrowband echo, it is about 60% of the center frequency. This is the 3dB bandwidth which is bounded by the upper and lower frequencies at which the power falls by 3dB of the peak power. It should be noted that for 5 MHz center frequency, the information content in the signal will not extend beyond a range of 10 MHz. Since the center frequency governs the bandwidth of the ultrasonic signals as well as the frequency span of the signals, significant signal energy will not lie beyond a range of 10 MHz. Since none of the simulated signals were corrupted by noise, it has been found out that the DWT coefficients between n=512 and n=2048 (which correspond to subbands D1 and D2 and the frequency range from 12.5 MHz to 50 MHz) carry negligible signal energy. Discarding these coefficients does not result in significant degradation of reconstructed signal quality. Thus, the signal can be represented by only 512 (75% reduction) coefficients in the transform domain before even applying any adaptive local thresholding techniques. This is equivalent to global thresholding of the DWT to remove contributions of noise leading to an improvement in signal-to-noise ratio.

B. Adaptive Local Thresholding

In the second thresholding stage, an adaptive local thresholding technique is adopted in order to be more selective in discriminating the approximation and detail coefficients in the lower frequency bands of the DWT. Four different adaptive thresholding techniques are proposed and studied for ultrasonic compression:

1) Coarse thresholding:

A single global threshold is used which is derived from total signal energy distribution in the corresponding DWT. The threshold value is uniform and it is applied to all the subbands. This thresholding is called coarse thresholding and it results in zeroing of those transform coefficients associated with minimum signal energy.

2) Fine thresholding:

One local threshold per frequency band is used. This is called fine thresholding as the energy of the transform coefficients are analyzed within each subband for determining the local threshold. This local threshold value is irrelevant to other subbands.

3) Window thresholding:

Multiple local thresholds per frequency band are used where the number of local thresholds in a particular band depends on the size of the subband. The entire transform is divided into a number of non-overlapping sets and the threshold is chosen to be a specific percentage of the maximum value of the transform coefficients in each set. In choosing the number of local thresholds per wavelet scale, the following reasoning has been used. In a 4-level DWT decomposition of a 2048 point data set, the 4th level of decomposition consists of approximation and detail coefficients with 128 points each. This size, i.e. 128, is made the size of the window and used to partition the entire DWT into non-overlapping sets, each of which is assigned one local threshold. Hence, in the 3rd level, where there are 256 samples for the detail coefficients, there are two local thresholds. On the other hand, in a 5-level DWT decomposition, the window size is chosen to be the size of the smallest frequency band, corresponding to the size of both AD4 and DD4, which is equivalent to 64 points.

4) Weighted thresholding:

Local thresholding is applied using weighted thresholds; the weights assigned being inversely proportional to the percentage of total energy retained by each of the frequency bands of the DWT. This results in elimination of the coefficients from subbands that contain the smallest percentage of total energy.

IV. RESULTS

To analyze the compression performance of DWT, experimental ultrasonic signal is first decomposed using either standard 4-level DWT or 5-level wavelet packet decomposition which consists of additional splitting of only D4 and D3, resulting in subbands (AD3, DD3, AD4, and DD4). Then, each

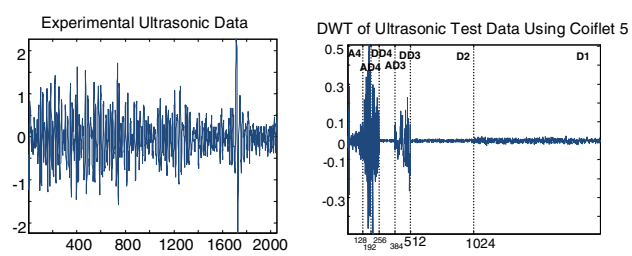

Figure 4. Experimental ultrasonic signal and the DWT coefficients

TABLE I. DWT ENERGY DISTRIBUTION PERCENTAGES FOR EXPERIMENTAL ULTRASONIC DATA AT 5MHZ

Wavelet Kernels	A4	AD4	DD4	AD3	DD3	D2	D1
Daubechies10	8.4	38.9	31.7	0.02	19.4	0.10	1.17
Symlet8	8.7	41.7	21.2	0.05	26.8	0.22	1.16
Symlet6	9.6	39.9	20.3	0.08	28.3	0.31	1.16
Coiflet5	6.5	48.7	24.2	0.03	19.0	0.14	1.18
Haar	7.9	32.5	19.1	3.35	23.2	10.21	3.49

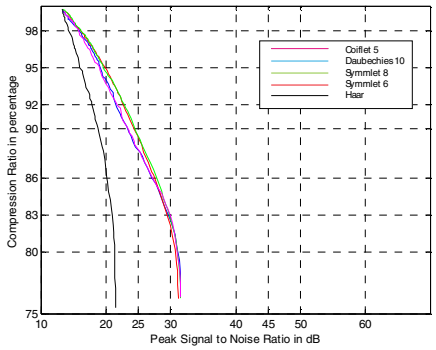

Figure 5. (a)- PSNR vs. compression ratio using *fine* thresholding

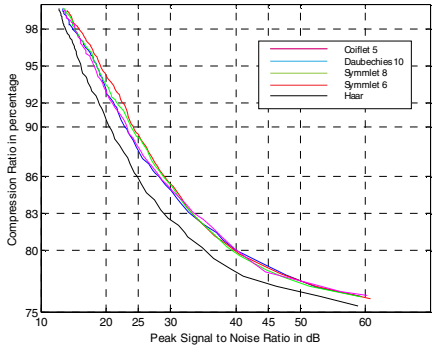

Figure 5. (b)- PSNR vs. compression ratio using *window* thresholding (window size=128)

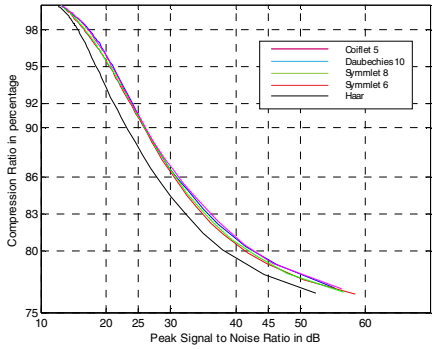

Figure 5. (c)- PSNR vs. compression ratio using *coarse* thresholding

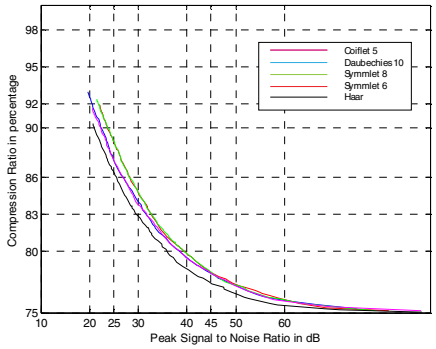

Figure 5. (d)- PSNR vs. compression ratio using *weighted* thresholding

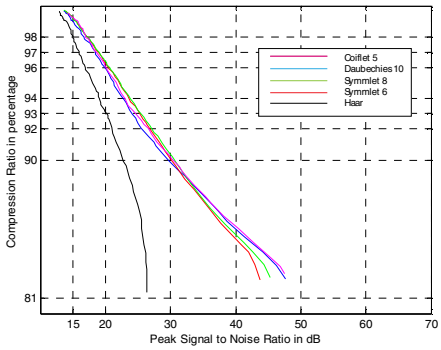

Figure 6. (a)- PSNR vs. compression ratio using *fine* thresholding

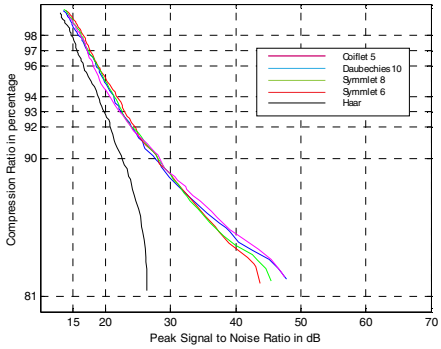

Figure 6. (b)- PSNR vs. compression ratio using *window* thresholding (window size=64)

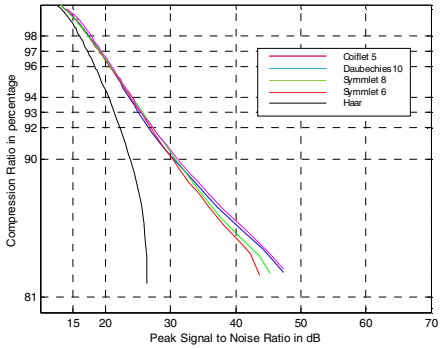

Figure 6. (c)- PSNR vs. compression ratio using *coarse* thresholding

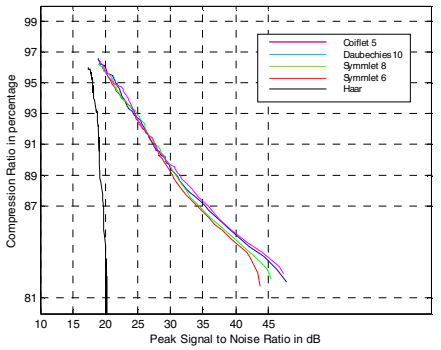

Figure 6. (d)- PSNR vs. compression ratio *weighted* thresholding

of the thresholding techniques is applied. Based on the observation of DWT of experimental ultrasonic test data, it has been seen that the DWT coefficients lying in the D1 and D2 wavelet subbands are negligible and hence these coefficients can be discarded. This global thresholding lead to the reduction in the number of DWT coefficients by 75%. Furthermore, the frequency band AD3 of the wavelet packet decomposition is also found to carry a negligible portion of the total signal energy. The coefficients of this band was entirely eliminated which led to an increase in the compression ratio from 75% to 81.25%, before the application of local adaptive thresholding.

Figure 4 and Table I shows the energy distribution per frequency band of the experimental ultrasonic data. Majority of the energy is distributed among the bands A4, AD4 and DD4 (for clarification see Figure 3). Note that this reduction of the transform coefficients is possible in the case of all wavelet kernels except Haar. This is because Haar has the worst energy compaction in terms of energy distribution per frequency band and hence, elimination of these frequency bands results in severe degradation of Peak-Signal-to-Noise-Ratio (PSNR).

In Figures 5 and 6, the compression performance is quantified using two quantities, Compression Ratio (CR) and PSNR.

The compression ratio is defined as:

$$CR = \frac{\text{Number of transform coefficients set to zero}}{\text{Total number of transform coefficients}}$$

The Peak-Signal-to-Noise-Ratio is defined as:

$$PSNR = 20 \log_{10} \frac{Max}{\sqrt{MSE}}$$

Figures 5 a) to 5 d) show plots of PSNR vs. compression ratio for 4-level standard DWT transform (75% reduced after initial global thresholding step) with four thresholding techniques. At a PSNR of 30dB, the compression ratio is around 86% for global thresholding technique. The compression ratio is worse for the other three thresholding methods. Figures 6 a) to d) show plots of PSNR vs. compression ratio for 5-level wavelet packet decomposition (81.25% reduced after initial global thresholding step) with four thresholding techniques. At around 30 dB, 90% compression is achieved in weighted, coarse and fine thresholding methods while compression ratio is less for window-based thresholding.

PSNR vs. Compression ratio performance is better for 5-level wavelet packet decomposition than the standard DWT decomposition. This is because subbands contain information related to the quality of the signal and changing thresholds emphasizes certain bands while deemphasizing the information contained in other bands.

In general, window based thresholding showed degradation in PSNR because it cuts up the signal into different disjoint subsets, thereby possibly resulting in the elimination of significant coefficients which fell into coefficient sets with higher thresholds.

It has been noted that the wavelet kernels show more or less the same performance except for Haar. If the application can tolerate high errors, then Haar is desirable due to low computational complexity.

Based on simulated signal compression results, narrowband echoes achieve higher energy compaction than broadband echoes. In the case of broadband echoes, generally two or more subbands are found to hold a majority of the signal energy whereas for narrowband echoes, about 90% of the energy is found to be concentrated in a single band, thus providing better scope for compression.

For narrowband signals (Single echo, two non overlapping echoes and two overlapping echoes), Coiflet-5 kernel is found to be the best wavelet kernel in terms of energy compaction and AD4 subband is found to be the most dominant band.

For broadband signals, best energy compaction is achieved by Coiflet-5 kernel for single echo and non-overlapping echoes, and by Daubechies-10 kernel for overlapping echoes.

V. CONCLUSION

The most suitable wavelet kernel from different wavelet families for different types of ultrasonic signals is determined by observing the corresponding DWTs for maximum energy compaction. The results also indicate that narrowband echoes attain higher energy compaction than broadband echoes. Ultrasonic test data is decomposed using two different wavelet tree structures. The corresponding DWTs have been thresholded using four different thresholding techniques and PSNR vs. compression ratio is plotted. Considerable improvement in PSNR for a given compression ratio is observed when the number of wavelet scales in the DWT increased by employing a wavelet packet tree structure. Among thresholding techniques, coarse thresholding and fine thresholding methods performed best.

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