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Performance Evaluation of 3D Compression for Ultrasonic Nondestructive Testing Applications

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***Abstract-* Ultrasonic imaging and nondestructive testing applications require large volumes of data. Therefore, it is essential to compress data for storage and transmission without degrading the signal quality or inadvertently damaging desirable signal features. In this study, the ultrasonic signal compression and signal reconstruction is implemented using discrete wavelet transform (DWT), and direct signal decimation and reconstruction by interpolation when sampling rate exceeds several folds above the Nyquist rate. The objective of this study is to design 1D and 3D compressions and evaluate the degree of compression of ultrasonic data as a function of data integrity. The compression performance is evaluated by calculating the PSNR (peak SNR) and the correlation between the original and reconstructed signals with respect to compression ratio. The performance of the 3D compression algorithm used in this study offers an overall 3D compression ratio of 95% with a PSNR of 27dB indicating high signal fidelity.**

I. Introduction

One of the major challenges in ultrasonic signal processing application is the large volumes of data to be processed. The requirement of real-time processing of compute–intensive signal processing algorithms further increases the implementation challenges. Since the processed data may need to be transmitted to remote locations for expert analysis, diagnosis and archiving via low bandwidth communication channels, the data transmission time has to be reduced. Therefore, the ultrasonic signal has to be compressed as much as possible without degrading the signal reconstruction quality.

For detecting small and transient features within the signal and getting a high time resolution, it is a general practice to sample the signals at much higher rate than Nyquist rate. This oversampling ensures a high signal-to-noise ratio (SNR). However, oversampling generates huge amount of data with redundant information. This will create storage problem and cause a large delay and/or bandwidth requirement in transmitting the data. Consequently, the signal needs to be compressed without sacrificing signal fidelity.

One of the most common and classical methods for compression is Discrete Wavelet Transform (DWT), which is used for ultrasonic compression applications due to its high energy compaction properties [1]. By carefully selecting the most suitable wavelet kernel, maximum compression can be achieved using DWT. Another efficient method for compression is by decimation where the redundant information is removed, and this may cause degradation of time resolution. However, the decimated signal may need to be interpolated when certain signal features with fine time resolution are required. In this study, the shift-property of Fourier transform is used to recover the decimated samples and to reconstruct (i.e., interpolate) the signal.

Furthermore, 3D compression of ultrasonic data is performed using DWT. The compression is applied to 3D block of data through successive 1D compression on each of the 3 directions (x, y and z). The similarity between neighboring A-scans indicates high data correlation, and this promotes the possibility of high compression ratio with high signal fidelity.

This paper is organized as follows. Section II explains the DWT for 1D compression of ultrasonic signals. Section III provides an alternate compression method by using decimation and time-shift interpolation. Section IV describes the experimental setup for 3D ultrasonic data acquisition and the compression of the acquired 3D data using DWT. The performance analysis of 3D compression is also discussed in this section. Section V concludes this paper.

II. DWT Based Compression

DWT is performed by transforming and decomposing the signal into lowpass and highpass coefficients. Maximum compression can be achieved if more coefficients can be identified with very little energy which can be eliminated. Wavelet packet decomposition [2] is used in our experiment, where apart from further decomposing the lowpass (L) components, selected highpass (H) components with high energy distribution are also decomposed. This approach improves the data compaction and leads to a higher compression ratio.

The best compaction can be achieved by properly choosing the right wavelet kernel to decompose the ultrasonic signal. The kernel must be chosen such that most of the wavelet coefficients are small, which can be approximated to zero without affecting signal quality. This scenario depends on the regularity, number of vanishing moments of the scaling function of the wavelet kernel and the support size (i.e., time-width) of the kernel [3], [4].

Good regularity provides better frequency localization of the wavelet transform. Higher number of vanishing moments yields lesser number of non-zero coefficients, thus a higher compression of the signal can be achieved [3], [5]. Support is defined as the size of the interval over which the wavelet function is non-zero. A compact support will speed up the decomposition and reconstruction processes [6]. Four orthogonal and compactly supported wavelets namely Haar, Daubechis, Symmlets and Coiflets are studied here to choose the best wavelet kernel for compressing the ultrasonic data.

Haar wavelet has a simple 2-point filter with only one vanishing moment [5]. It is discontinuous and also offers the lowest frequency resolution [7]. Therefore, Haar kernel is not efficient in approximating smooth continuous functions such as ultrasonic signals. Daubechies (Db) kernels are orthogonal, compactly supported and continuous with a support of minimum size equal to [-p + 1, p] for any given number 'p' of vanishing moments [6]. The high similarity between the Db10 wavelet function [6] and ultrasonic echo [8] indicates that Db10 will be more suitable for decomposing ultrasonic signals. By increasing the support width, the Db kernel becomes smoother, and provides better frequency localization. Symmlet kernels are symmetric and have a minimum size support equal to [-p + 1, p] with p vanishing moments. Coiflet kernels also have 'p' vanishing moments with a minimum support size [9].

The best wavelet kernel for compressing ultrasonic signals is determined by comparing the compression performance for the four compactly supported kernels: Db10, Haar, Coif1 and Sym2. The energy distributions for various wavelet kernels are calculated and described in Table I. For evaluating the compaction performance of the kernels, several ultrasonic A-scans are analyzed and the mean value of the energies for all the decomposed components is calculated. Table I indicates that Db10 will provide the best compression without losing much of the energy, because the energy distribution in the larger sized decomposition components (H, LH) are very low compared to the other kernels. From Table I, it is clear that H, LH and LLHL do not contain any energy compared to others. Therefore, we need to preserve only LLLL (145 coefficient bins), LLLHL (82 coefficient bins), LLLHH (82 coefficient bins) and LLHH (145 coefficient bins) – a total of 454 coefficient bins. Thus we achieve *79%* compression.

Table I. Energy distribution for various wavelet kernels

Kernel	***Coefficients (Number of Bins)***						
	LLLL (145)	***LLLHL (82)***	***LLLHH (82)***	***LLHL (145)***	***LLHH (145)***	***LH (526)***	***H (1033)***
Db10	24.16	28.34	34.41	0.48	11.71	0.13	0.8
Haar	20.8	22	20	3.6	22.6	8.2	3.2
Coif1	23.4	25.8	24.8	1.4	20.8	2.5	1.1
Sym2	22.8	26.2	24.6	1.3	21	2.7	1.2

II. Compression By Decimation and Reconstruction by Time Shift Interpolation

Another efficient method to perform compression is by decimation. For practical applications, the signal is usually oversampled to avoid aliasing effect. The signal may contain unwanted frequency components such as noise, which has a much higher frequency than Nyquist frequency. Oversampling increases the fold-over frequency and these unwanted high frequency components will not be aliased into the passband of the signal. Since the signal is oversampled, there will be a significant redundant information which can be removed by performing signal decimation. Decimation is performed by periodically sampling the original signal and keeping every j^{th} sample while removing (j-1) samples in between. Signal samples that are removed through the process of decimation for compression can be recovered by interpolation method. In this study, a simple interpolation technique is used which incorporates time-shift property of Fourier transform. This method is very efficient for reconstruction of decimated/compressed ultrasonic signal. If signal s(nT) is shifted by $\Delta t < \mathrm{T}$, where T is the time period of s(nT), then

$$s(nT - \Delta t) <=> S(k\Omega)e^{-jk\Omega\Delta t} \tag{1}$$

where $S(k\Omega)$ is the discrete Fourier transform of s(nT). Equation (1) indicates that, by finding the discrete Fourier transform of the measured sequence and multiplying it by $e^{-jk\Omega\Delta t}$, the discrete Fourier transform of the intermediate points can be determined. The inverse Fourier transform of this term yields the desired interpolated points. The interpolated sequence obtained by the time-shift method contains all the information of the original sequence. For example, if the decimation factor is 5, we need to create 4 spectrums which are time-shifted by T/5, 2T/5, 3T/5 and 4T/5 relative to the original decimated spectrum. Then Inverse FFT (IFFT) is performed on these time shifted signals to convert them into time domain. Finally, these time-shifted signals are interleaved to recover the original signal. Figure 1 shows the decimation and reconstruction of an ultrasonic A-scan, with a decimation factor 5, which gives 80% compression.

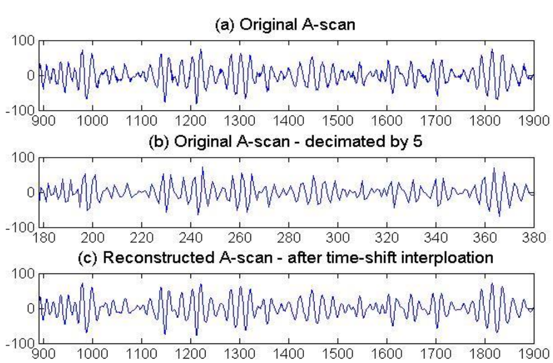

Figure 1. 80% Compression by decimation and reconstruction by time-shift interpolation

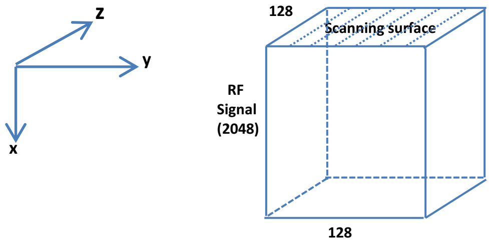

Figure 2. 3D DWT block representation

IV. Ultrasonic 3D Compression using DWT

Medical imaging applications as well as industrial NDE applications require processing of large amount of volumetric information. This information is collected by the process of 3D scanning and massive signal data acquisition. In 3D ultrasonic data compression, data sets (slices) are grouped into a 3D block of data as shown in Figure 2 and this block of data is compressed to remove the inter-slice redundancy. Figure 3 illustrates the ultrasonic 3D data acquisition setup in our laboratory to generate 3D block of data. The setup includes a water tank with two step motors mounted for scanning. A 5 MHz, 0.375 inch radius ultrasonic transducer (A3062), a pulser/receiver model 5052 PR, and an HP 54616C oscilloscope are used to acquire and display the received signal. Then the data are processed by an image analyzer and data compression unit.

A volumetric image of 128*128*2048 samples is used for the analysis of results. This experimental data was generated using a steel block specimen. A 2 inch by 2 inch surface of the steel block was used for inspection. The measurement points by looking at the top surface of the steel block are shown in Figure 4, where, the scanning in the spatial directions (y and z) is also marked. As shown in Figure 4, 128 A-scans (each A-scan is a measurement point which has 2048 samples in the x-direction) were taken per line in y-direction. A-scans were taken on 128 such lines to cover the z-direction.

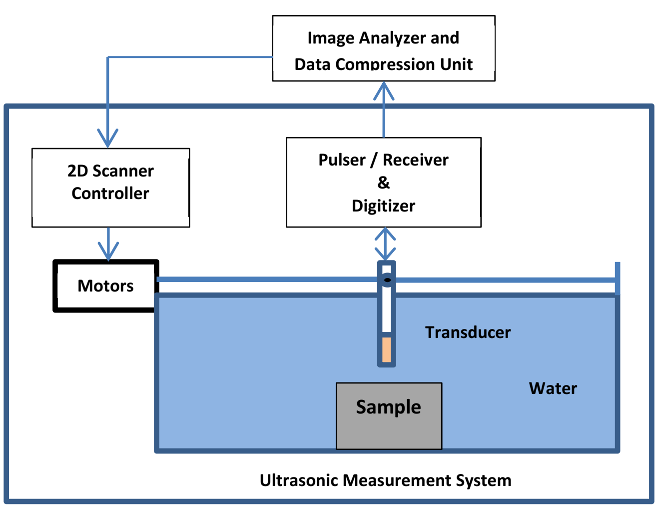

Figure 3. Ultrasound data acquisition setup

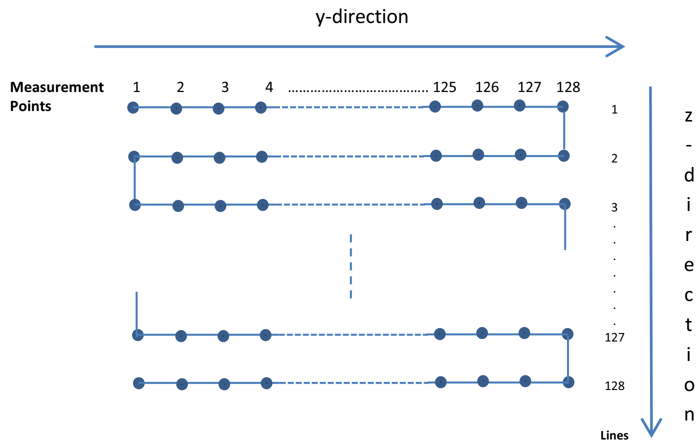

Figure 4. Scanning pattern of the transducer for 3D ultrasonic data acquisition

Figure 5 shows the position of the transducer cross-section at two consecutive measurement points which are very close to each other (0.44 mm apart) to ensure no information is missed out within the specimen under test. At the same time, the nearby measurement points will have a significant similarity, which can be capitalized on for compressing the data. The high correlation between neighboring A-scans indicates that there are some redundancies between nearby A-scans, which can be removed during the process of compression.

In this study, the 3D compression is implemented using DWT. This is performed in three successive steps. In the first step, the A-scans in the x-direction are compressed by using 1D DWT. This is followed by another 1D DWT in the y-direction. Finally, the 1D DWT is performed in the z-direction to form the 3D compressed data. Since, the signal characteristics are more predictable for the A-scans, maximum compression can be achieved in x-direction. A higher-order Daubechies wavelet kernel (Db10) is selected for compressing A-scans, due to its frequency localization property. Four-level wavelet packet decomposition is chosen in this case to compact and isolate high energy coefficients, so that the low energy coefficients can be eliminated. Since the correlation properties of lines in y and z directions are not as predictable as that in the x-direction, a simple Haar wavelet kernel is used for compression. A two-level DWT is performed in this case for reducing the computation time.

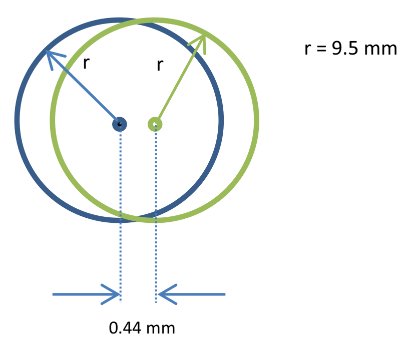

Figure 5. Transducer cross-section at two sample points

The compression performance is analyzed based on the compression ratio, PSNR of the reconstructed signal and correlation between original and reconstructed A-scans after 3D compression. In our experiments, 32 MB of data has been compressed into 1.6 MB to achieve an overall compression of 95%, with a PSNR of 27 dB for the reconstructed signal, indicating high signal fidelity. As the compression ratio is increased, the correlation between the original signal and reconstructed signal is reduced. However, our experiments show that, for a larger increase in compression ratio from 80% to 95%, the correlation reduces from 0.99 to 0.96, which is a small variation for all practical purposes. This is also true for the PSNR.

V. Conclusion

Ultrasonic medical and industrial applications require real-time processing of large volumes of data. Compressing the signal is essential to accelerate the processing performance and also to transfer the data rapidly to remote locations for expert analysis. Two methods for ultrasonic compression: Discrete Wavelet Transform (DWT) and Decimation/Interpolation are examined in this study. By selecting the right wavelet kernel and optimal decomposition structure for best compaction, maximum compression can be obtained. The decimation and interpolation techniques help in precisely detecting certain desirable features of the ultrasonic signal. Ultrasonic 3D data compression algorithm is analyzed based on the degree of compression of ultrasonic data as a function of data integrity. Our study brings out different possibilities in designing the 3D compression schemes depending on the application requirement to achieve best compression with high signal fidelity.

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