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COMPRESSION FOR ULTRASONIC PHASED ARRAY IMAGING: COMPRESSIVE SENSING AND WAVELET THRESHOLDING

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ABSTRACT

Compressive Sensing and Wavelet Thresholding are techniques that can allow data to be represented with much fewer values that the Nyquist sampling criterion would suggest. This paper explores using these techniques to affect lossy compression on phased array ultrasound data while retaining the ability to detect defects once imaged.

Keywords: Compressive Sensing, Wavelet Thresholding, Discrete Wavelet Transform, Phased Array Imaging

1. INTRODUCTION

Advances in ultrasonic phased array imaging algorithms are allowing for more and more accurate defect characterization but the associated increase in transducer number requires large amounts of data to be stored. Coupled with the high sampling rate needed to satisfy the Nyquist sampling criterion for high frequency sound one can quickly run into data storage issues. This is especially true in applications such as inline pipe inspection and structural health monitoring where hours' or even days' worth of recorded data need be stored on a relatively small device.

This paper compares two compression methods: Wavelet Thresholding (WT) and Compressive Sensing (CS) that both rely on sparse representations. Their ability to provide lossy compression of ultrasonic phased array data is explored by comparing the resulting images using two common algorithms: Plane Wave Imaging (PWI) and the Total Focussing Method (TFM). Images are assessed using Normalized Cross-Correlation (NCC) and Signal to Noise Ratio (SNR). The impact of multiple defects is considered as well as the trade-offs in compression and decompression computational complexity.

The results describe the ways these two compression methods affect defect detection and their relative advantages and disadvantages. Both methods show promise in achieving large amounts of compression but CS is able to better minimize computation during compression while WT is shown to outperform its reconstruction accuracy in terms of both SNR and NCC.

2. MATERIALS AND METHODS

The compression and decompression methodology used here is displayed in Fig. 1. Both CS and WT rely on data to be sparsely represented, achieved in this case with the Discrete Wavelet Transform (DWT). Simulation has been used to create data with varying numbers of artifacts after validating it against representative experimental results.

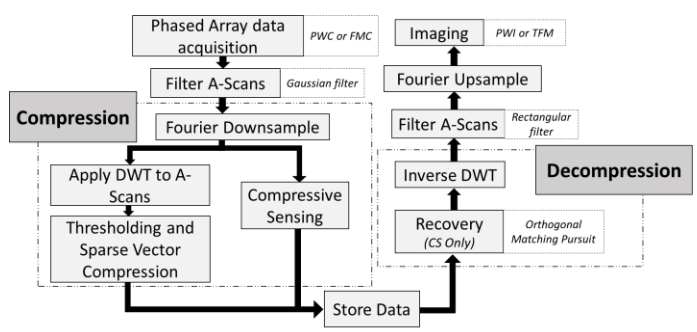

FIGURE 1: FLOW CHART DESCRIBING COMPRESSION AND RECOVERY STAGES.

2.1 Compressive Sensing

The general CS model is based around recovering an N length signal X from M ($M < N$) random measurements. This signal must have a suitably sparse representation

$$X = \psi F \tag{1}$$

given by the S sparse vector F and described using the $N \times K$ dictionary ψ.

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Compression is achieved by linear measurements taken from X

$$Y = \phi X \tag{2}$$

where ϕ is an $M \times N$ sensing matrix. Given that X is sparse there is only one more condition needed for satisfactory recovery of X (providing Y and ϕ are available). This is called the Restricted Isometry Property (RIP) and requires that a constant δ_S $(0 < \delta_S < 1)$ exists such that

$$\sqrt{1-\delta_S} \leq \frac{\|\phi\psi F\|_2}{\|F\|_2} \leq \sqrt{1+\delta_S} \tag{3}$$

meaning that $\phi\psi$ preserves the ℓ_2 norm of all S-sparse vectors.

Throughout this paper ϕ is produced by drawing values from a Gaussian distribution, modelling analogue random sensing whilst also guaranteeing satisfaction of the RIP [1,2].

Recovery is achieved by solving

$$min\|F\|_0 \;\; subject\ to\ \|\phi\bar{X} - Y\|_2 < \varepsilon \tag{4}$$

for $\bar{x}$, where ε (often assumed to be negligible) is a function of the amount of noise and/or deviation from exact sparsity in X. Finding the true minimum for Eq. 4 is NP-hard but when $\phi\psi$ satisfies the RIP it can be approximated accurately by

$$min\|F\|_1 \;\; subject\ to\ \|\phi\bar{X} - Y\|_2 < \varepsilon \qquad (4)$$

which is a solvable convex problem. In this paper Orthogonal Matching Pursuit (OMP) is used to find the solution to Eq. 4. OMP is an iterative 'greedy' algorithm that sequentially estimates the S largest values in X while attempting to obtain the fastest reduction in residual error, $\|\phi\bar{X} - Y\|_2$ [3].

2.2 Wavelet Thresholding

Thresholding of data can be done in both soft and hard regimes [4,5]. In this paper only hard thresholding is considered as it gives a direct comparison to the $\frac{M}{N}$ compression via CS. This involves setting all DWT co-efficients below the largest M values to zero for each A-Scan. The resulting sparse matrix is represented efficiently using Compressed Sparse Column or Row (CSC or CSR) storage. [6]

2.3 Simulating Data

A simulation of the linear acoustic response from point scatterers has been used in this paper [7]. The simulation assumes the response at receiver i from transmitter j due to any given point scatterer can be calculated as

$$f_{ij}(t) = f_0(t-\tau)\frac{1}{\sqrt{R_T R_R}} D_T D_R K_T K_R V \tag{5}$$

where f_0 is the pulse input at time τ, delayed by t time, R_T, R_R are the distances from the transmit and receiver elements to the reflector, D_T, D_R are the directivity of the transmit and receive elements, K_T, K_R factors for coupling of transducer to medium movement [8] and V is the scattering coefficient (assumed angle and frequency independent). Directivity and coupling factors are functions of transmit/receive angle and angular frequency.

Satisfactory agreement with the response from a single 1mm side drilled hole has been found and the simulated set up used for CS and WT comparison is shown in Fig. 2.

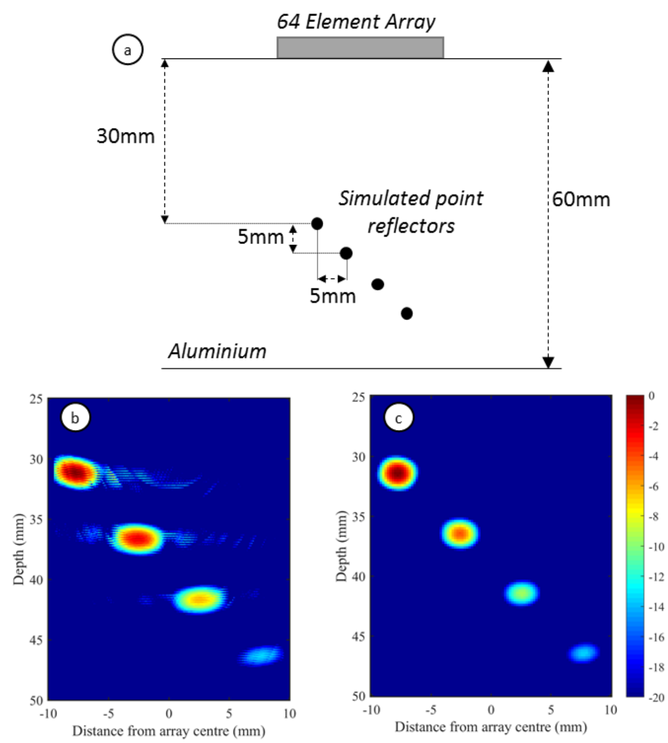

FIGURE 2: (a) SET UP FOR SIMULATED DATA AND RESULTING UNCOMPRESSED (b) PWI AND (c) TFM OVER A 20dB RANGE.

3. RESULTS AND DISCUSSION

The compression performance of WT and CS has been compared by analyzing the SNR of individual defects and the maximum NCC of resulting images against an uncompressed counterpart. There are several interesting trends that can be drawn from the results and an outline of them are as follows.

Firstly, WT achieves higher NCC than CS at every compression ratio. This is perhaps intuitive as CS is attempting to reconstruct the dominant wavelet coefficients from a reduced data set whereas WT directly stores them.

Secondly, whether CS is applied to wavelet coefficients or time domain signals the result is the same. This acquisition basis independence is an advantage of CS because it means the DWT need not be implemented alongside data acquisition, where computational power is often limited. It also means that if at a later date the results are found to be sparser in a different domain this can be implemented in the recovery stage to provide more accurate reconstruction.

Finally, with respect to SNR the two methods behave quite differently. As shown in Fig. 3 both methods maintain near lossless compression for longer when fewer defects are present but the way they affect SNR beyond this point differs. WT causes sudden drops in SNR when the wavelet coefficients relating to those defects are thresholded out where as CS causes a much more gradual decrease in SNR as less information is available to the recovery process. These trends in SNR demonstrate that the dominant features in a signal will be reconstructed at the detriment of others, especially with WT. This means care must be taken to reduce any strong but unwanted artifacts, such as back wall reflections, before compressing data.

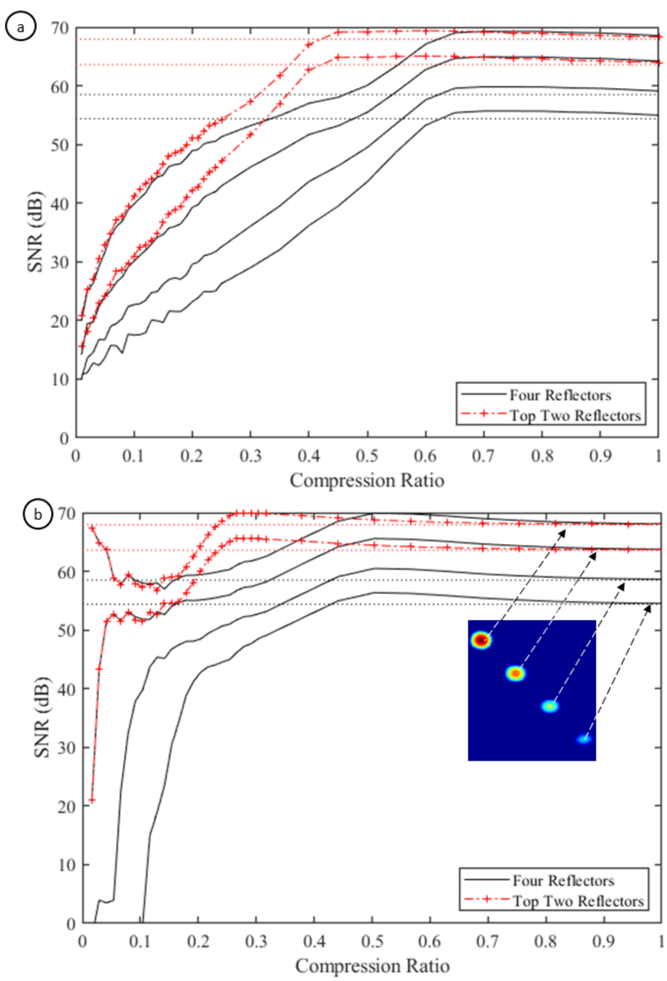

FIGURE 3: SNR FOR SIMULATIONS OF BOTH FOUR AND TWO DEFECTS IMAGED WITH TFM AFTER COMPRESSION WITH (a) CS AND (b) WT.

4. CONCLUSION

This paper has explored the usefulness of Compressive Sensing and Wavelet Thresholding as lossy compression tools for ultrasonic phased array data. At this stage WT has been found to be the more generally effective of the two but CS is able to perform extremely computationally simple compression and has more potential for adaption to a specific situation. In summary, both methods show promise in helping to reduce the amount of data phased arrays need to store in situations where data storage pressure is currently a barrier to phased array imaging.

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