15th International Symposium on Computer Methods in Biomechanics and Biomedical Engineering
and
3rd Conference on Imaging and Visualization
CMBBE 2018
P. R. Fernandes and J. M. Tavares (Editors)

COMPRESSED SENSING APPLIED TO ULTRASOUND IMAGE RF RAW DATA: EVALUATION OF IMAGE RECONSTRUCTION

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Keywords: Compressed Sensing, Ultrasound imaging, RF raw data.

Abstract: *In the last few years, compressed sensing (CS) has attracted attention from different research areas, like biomedical image processing, radar technology and seismology. Compressed sensing has found different applications in ultrasound imaging, like 3D imaging, ultrasound computed tomography and in the standard B-Mode imaging. In this work, we evaluate the application of CS to the ultrasound received RF raw-data (pre-beamforming RF signal) of each individual channel. Thus, instead of applying CS techniques to the matrix of N channels altogether, we apply it to each n_{th} vector of the matrix (each RF A-line). Prior reported works, to the best of our knowledge, only evaluate the error in each individual vector, not the quality degradation in the resulting reconstructed imaging. In this work, we used the Structural Similarity Index – SSIM to compare the original image to the image built with the data recovered with the lower sampled-rate data. We used Field II cyst phantom example as data input with sampling frequency of 35 MHz (a value close to the sampling frequency of real ultrasound imaging systems) and a transducer with center frequency of 3.5 MHz. Then we undersampled the signal of each channel using a random matrix with normal distribution, recovered the data of each channel using optimization methods and built the B-Mode imaging following the example script provided by Field II. During this evaluation, we used DFT and DCT transforms as representation bases and l1-MAGIC MATLAB® toolbox to recover the data. We performed simulations with vectors with lengths equivalent to those we would obtain when using sampling frequencies of 28, 21, 14, 7 and 3.5 MHz and compared the reconstructed images with the reference image (35 MHz sampled data). The best results (higher SSIM) were achieved using DCT transform. We have obtained images visually similar to the original image when their reconstruction uses signals at sampling frequencies above or equal to 14 MHz. These images have a SSIM greater than 0.85.*

1 INTRODUCTION

Compressed sensing (CS) is a signal processing technique that allows us, under certain circumstances, to sample a signal in a frequency below the Shannon-Nyquist frequency and recover the full information present in the original signal.

One of the main applications of CS is in image processing, including medical imaging, where we can find previous works in magnetic resonance [1] and ultrasound imaging such as in 3D ultrasound [2], ultrasound computed tomography [3], B-Mode imaging [4, 5] and others.

In this work, we present the use of compressed sensing in each of the n_{th} A-lines that compound a B-Mode image and compare the images obtained using undersampled data with a reference image obtained by the usual oversampling method using the Structural Similarity Index – SSIM, differing from previous reported works [4-7].

2 METHODOLOGY

This work consists only of simulations carried out in MATLAB® (Mathworks Inc.). As depicted in Figure 1, the first step is to generate ultrasonic RF data. For this task, we chose the ultrasound simulation toolbox Field II [8, 9] and used the cyst phantom example provided by Field II as numerical phantom used in our simulations.

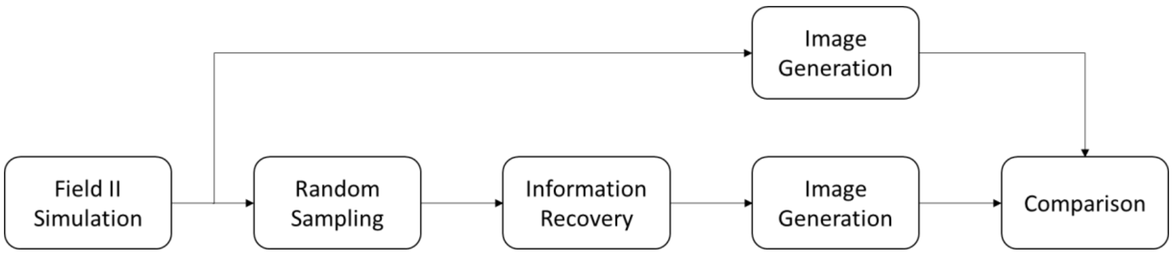


Figure 1: Block diagram of the processing operation.

The simulations in Field II were carried out using a linear transducer with central frequency of 3.5 MHz and a sampling frequency of 35 MHz, a value that is in the range of sampling frequencies used in medical ultrasound systems. This simulation led to 50 A-lines, but not all lines had the same number of points. Considering this and to shorten the simulation time, we cropped the heads and tails of the lines, while preserving the information contained in the signals, thus resulting in 50 A-lines of 2751 points each.

Based on the Shannon-Nyquist theorem, the minimum sampling frequency for these signals is 7 MHz, so we name the simulated data obtained at 35 MHz as oversampled data and the image obtained with these signals as the reference image.

The next step is to undersample the oversampled data. In the compressed sensing framework, the digital data acquired would be this undersampled data, so it would not be necessary to realize this step. The undersampling operation was obtained by multiplying each A-line by a random matrix with normal distribution, named Φ.

The Φ matrix is a wide matrix, i.e., has more columns than lines. The number of columns was always equal to the number of points of the lines, 2751, while the number of lines varies. We used five different number of lines, corresponding to the number of points that we would obtain using sampling frequencies of 3.5, 7, 14, 21 and 28 MHz. The corresponding number of lines in the Φ matrix is 275, 550, 1100, 1650 and 2200.

Equation 1 gives the undersampled vector *y*, where *x* is one A-line:

$$y = \Phi x \tag{1}$$

One of the conditions that must be met in order to use the compressed sensing technique is that the sampled signal must be sparse in a certain domain. A typical ultrasound signal is not sparse in the time domain. At this point, we used two different transforms in order to obtain a sparser representation of the A-lines: the Discrete Fourier Transform – DFT and the Discrete Cosine Transform – DCT. Thus, considering *s* the sparse representation of *x* in the domain Ψ, we have:

$$x = \Psi s \tag{2}$$

The process of information recovery consists of finding the sparse vector *s* with the smallest l1-norm. This is shown in Equation 3:

$$min||s||_{l1,} \text{ with } y = \Phi\Psi s \tag{3}$$

This problem is solved using the l1-MAGIC toolbox [10] for MATLAB®.

The final phases are to generate the ultrasound undersampled images and compared them to the reference image. The image generation used the classical ultrasound imaging processing flow: envelope detection, logarithmic compression and scan conversion. The comparison between the pairs of images uses the Structural Similarity Index – SSIM [11].

3 RESULTS

Our objective in this work was to evaluate two different representation basis for use of compressed sensing in B-Mode ultrasound imaging and compare the resulting images with a reference image constructed with typical oversampled data.

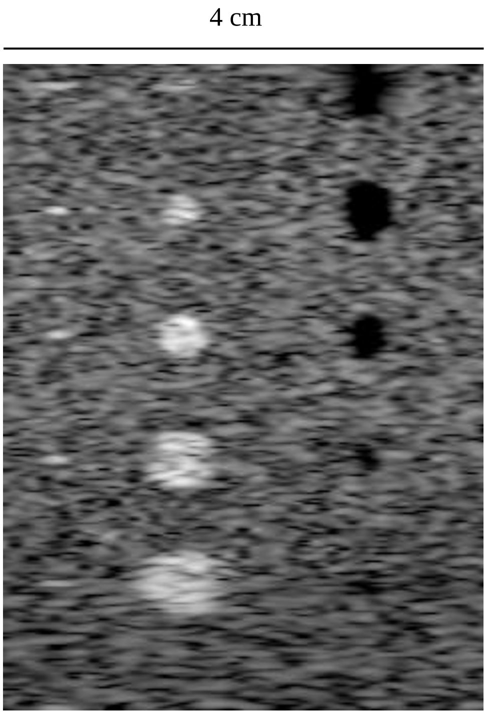
In Table 1, we present the values of SSIM when comparing the images reconstructed with data recovered using compressed sensing technique to the reference image. As can easily be seem, the representation using DCT gave a better result than DFT as representation basis.

f_{eq} (MHz)	DCT	DFT
3.5	0.12	0.06
7	0.33	0.06
14	0.87	0.08
21	0.99	0.06
28	0.99	0.07

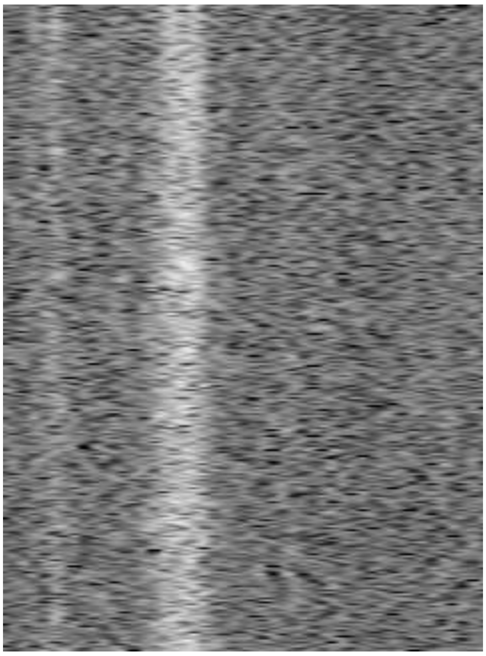
Table 1: Values of SSIM between the images using compressed sensing and the reference image.

The quality of the images obtained using DFT was very poor making it difficult to identify cysts in the phantom. We present in Figure 2 only the images obtained using DCT as representation basis.

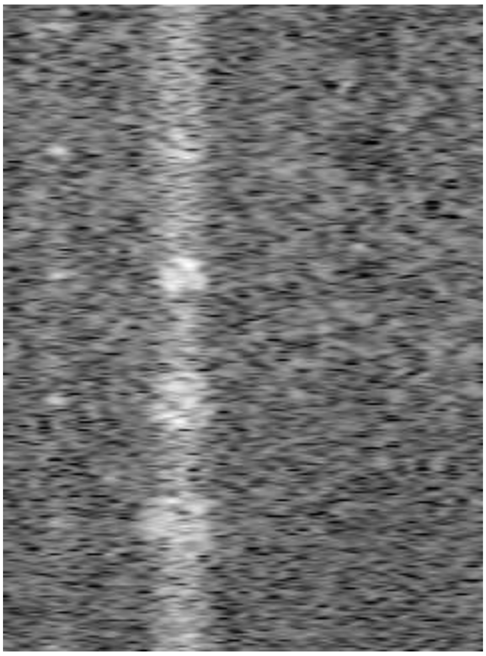
In Figure 3, we present the zoomed versions of Figure 2.a and 2.d. We can see, inside the hypoechoic cyst of Figure 3.b, that there are some small grey regions, where it should be all black like in Figure 3.a. This happens because the optimization procedure does not perform well in some parts where the A-line signal is close to zero.



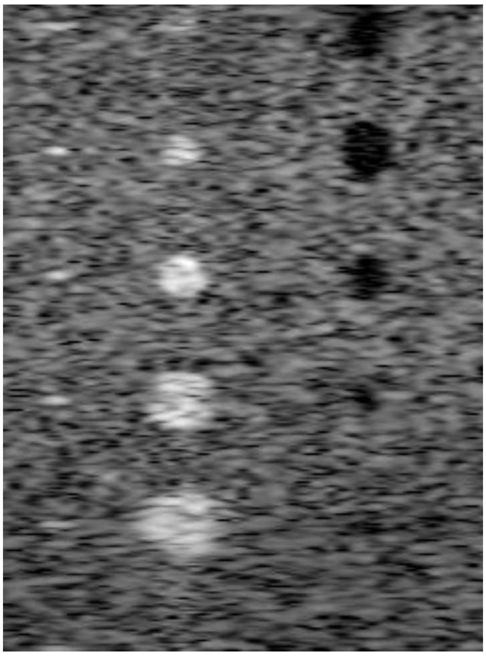
(a)



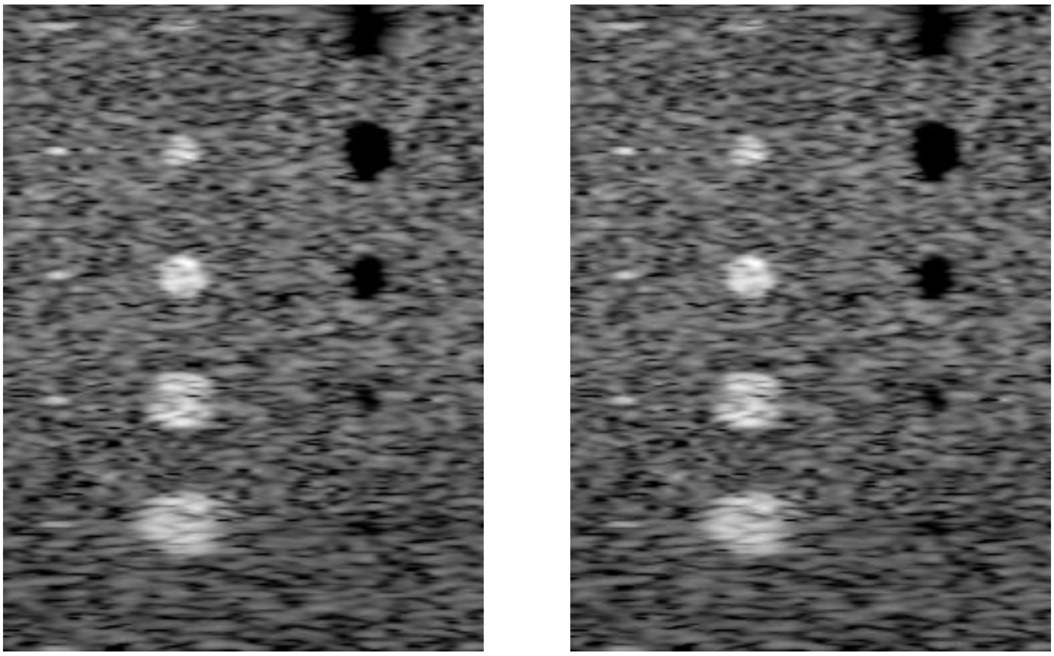
(b)



(c)

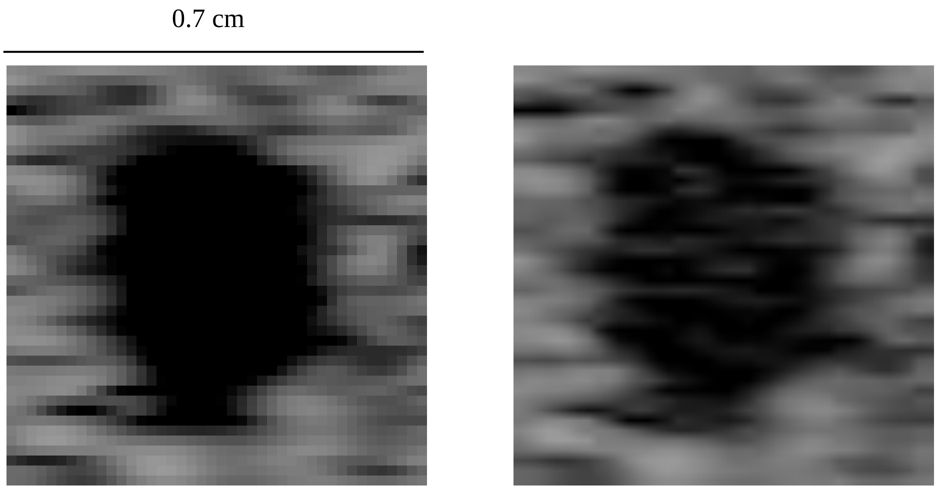


(d)



(e) (f)

Figure 2: (a) Reference image; (b) Reconstructed image with n = 275 (f_s = 3.5 MHz); (c) Reconstructed image with n = 550 (f_s = 7 MHz); (d) Reconstructed image with n = 1100 (f_s = 14 MHz); (e) Reconstructed with image n = 1650 (f_s = 21 MHz); (f) Reconstructed image with n = 2200 (f_s = 28 MHz).



(a) (b)

Figure 3: a) Zoomed version of Figure 2.a; b) Zoomed version of Figure 2.d highlighting one hypoechoic cyst.

4 CONCLUSIONS

In this work, we presented the results of the comparison of B-Mode ultrasound images generated using compressed sensing techniques with a classical oversampled image. The signal processing chain included the use of two different representation bases, DFT and DCT, and l1-MAGIC toolbox to recover the information of the original signal. We have obtained better results using DCT, however still with sampling frequencies greater than twice the transducer frequency.

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