Compressive sampling for time critical microwave imaging applications

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Across all biomedical imaging applications, there is a growing emphasis placed on reducing data acquisition and imaging times. This research explores the use of a technique, known as compressive sampling or compressed sensing (CS), as an efficient technique to minimise the data acquisition time for time critical microwave imaging (MWI) applications. Where a signal exhibits sparsity in the time domain, the proposed CS implementation allows for sub-sampling acquisition in the frequency domain and consequently shorter imaging times, albeit at the expense of a slight degradation in reconstruction quality of the signals as the compression increases. This Letter focuses on ultra wideband (UWB) radar MWI applications where reducing acquisition is of critical importance therefore a slight degradation in reconstruction quality may be acceptable. The analysis demonstrates the effectiveness and suitability of CS with UWB applications.

1. Introduction: Ultra wideband (UWB) radar is one of the most promising techniques for biomedical imaging. UWB radar imaging and monitoring is based on the detection of reflected UWB signals from tissue boundaries within the human body. These boundaries reflect UWB signals owing to the significant difference in dielectric properties between the various constituent tissues at microwave frequencies. The wide frequency spectrum of the UWB signals means they are relatively robust to interference, while also allowing for very fine spatial resolution. Furthermore, the technology uses low-power non-ionising radiation which ensures the method is safe and a low-cost modality. This technology has been successfully implemented for applications of monitoring the heart [1] and respiration [2], and breast cancer detection [3, 4].

Among these applications, there is a need for the acquisition time of the signals to be efficiently reduced. Methods to reduce the imaging time, and correspondingly the chances for movement-related artifacts, are constantly being investigated. Therefore, proposed is a method to minimise the UWB data acquisition time for UWB radar applications through the use of a technique known either as compressive sampling or compressed sensing (CS). This particular compression algorithm was chosen because CS is a signal compression technique that can perform compression *during* the sampling stage, directly reducing the time for acquisition. Here, CS operates on the assumption that UWB signals are sufficiently sparse in the time domain, enabling reconstruction despite sub-sampling in the frequency domain and, consequently, significantly shortening the data acquisition/imaging time. This approach, allowing fewer frequency points to be sampled, is described in greater detail in Section 5. To demonstrate the potential of CS in UWB applications, the effects of compression on breast cancer detection is used as a sample application. In monostatic breast cancer detection systems, long scan times can prove problematic owing to the sequential nature of the antennas during signal acquisition. Previous studies have shown the longer the scanning process takes, the more likely that patient movement occurs, introducing unwanted artifacts in the resultant image [5]. Therefore CS has great potential with these particular applications. Size classification of different tumours in breast models is analysed at different compression rates and used to quantify the effectiveness of CS in reducing the scanning time.

The remainder of the Letter is structured as follows: a background on CS and the methodology underlying it is given in

Section 2. Section 3 presents the finite difference time domain (FDTD) modelling used to generate representative backscattered signals to test our hypothesis and gives a brief background to tumour classification using UWB/microwave imaging (MWI). Section 4 describes the feature extraction and classifier used to differentiate between tumours of different sizes, while Section 5 considers the effects of CS on the performance of the tumour classifiers. Finally, Section 6 concludes the paper and outlines the potential future work with CS in this area.

2. Compressive sampling

2.1. Compressive sampling background: CS is an emerging technique for signal compression with potential benefits in areas such as biomedical signal processing. The method of CS reduces the number of samples needed to reconstruct a signal by exploiting the sparseness of a signal in a particular domain. CS allows sub-Nyquist rate acquisition of signals, while avoiding the traditional issue of aliasing and allowing for effective compression of signals during the sampling process. The Nyquist theorem states that, when sampling a signal, the sampling rate must be at least twice the bandwidth of that signal; that is, the Nyquist rate. The conventional approach to sampling a waveform, and compressing it, takes the following steps: firstly, the signal is sampled at the Nyquist rate. Then the signal is compressed using methods such as wavelet or Fourier transforms before retaining the relevant coefficients and discarding those which are deemed unnecessary. The signal is then decompressed and a version of the original signal is recovered. Problems arise if the signal being measured has a very wide bandwidth, as this would require a very high sampling rate. It can also be considered an inefficient process if a substantial number of samples recorded are then seen to be unnecessary and, as a result, are discarded during compression.

The CS paradigm allows for the collection of up to N samples of a signal X by acquiring only M measurements of data representing that signal X , whereby $M \ll N$. Therefore, the overhead from signal acquisition and or transmission of signals, is reduced. However, there is a trade-off which occurs at the cost of an increase in the complexity of the computational reconstruction. To recover the N samples of data from the original signal with only M samples of data available, CS requires the solution of a convex optimisation

problem. It has been shown that such a problem can be solved by using an L1-norm optimisation solution [6].

Interest in CS has grown since a number of seminal publications show that a small number of linear projections of a sparse signal can be enough for a good quality reconstruction of the complete original signal [6–8]. CS is based on two important assumptions about the signal which must be met: sparsity and incoherence. It is critical to CS that the signal being acquired is sparse in at least one domain; that is, the majority of entries in the signal are zero. In general, the more sparse the signal being measured, the more CS exploits the signal characteristics and the better the reconstruction results that are achieved. The incoherence assumption is that a basis function should exist which represents the signal sparsely, while the signal is also non-sparse in the domain in which it is acquired.

2.2. Compressive sampling implementation: The first step in the CS method involves correlating the sparse data X , consisting of N samples with a matrix Φ of row size M , shown in (1). The matrix Φ has components which are known to be independently identically distributed. These random vectors are commonly generated using methods such as Gaussian or Bernoulli distributions

$$Y = \Phi X \quad (1)$$

This linear transformation is generally the only step in the acquisition stage of the CS algorithm, which ensures it is an ideal algorithm for applications that require a low complexity acquisition of signals. The random matrix Φ is known as a sensing or measurement matrix. Note that a version of the sensing matrix must be available at the decoding stage to enable reconstruction. The data Y , of length M , is acquired instead of X , as a representation of the signal X . The next step is based on the assumption that X is sparse in at least one domain and also that there exists a sparsifying matrix or sampling basis Ψ which is incoherent with Φ . If X is not sufficiently sparse in its acquired domain, then an effective input vector X' is defined (2), where X' is a sparse signal in the basis Ψ . If X is sparse in the domain it is acquired in, then Ψ is simply an identity matrix

$$X = \Psi X' \quad (2)$$

The sampling basis Ψ can be designed or selected to ensure it is optimised for a particular type of signal X . The fixed basis Ψ is highly likely to be incoherent with a random matrix Φ . The equation for Y can now be expressed as follows:

$$Y = \Phi \Psi X' \quad (3)$$

The equation to solve for X' is of the form of the classic linear algebra problem $Ax=B$, where x is unknown. Since the set of equations consists of N unknowns in M equations, it can be a computationally expensive system to solve or approximate for real world signals. The problem can be solved using an L1-norm minimisation. It has been proven that the solution of this minimisation operation will correspond to the correct reconstructed X , provided the sparsity and incoherence constraints are upheld [6–8]. Thus, the minimisation can be implemented as in (4). The original X can then be solved from (2)

$$\text{Min} \|X'\|_1 \text{ subject to } Y = \Phi \Psi X' \quad (4)$$

There are two important conditions which must be satisfied when utilising this convex L1-norm method for reconstruction, to ensure the reconstruction is accurate. The first condition is that $M > K \log(N/K)$, where K is the number of non-zero entries in the

signal X (a measure of its sparsity) and N is the complete length of the signal X . The second condition states that the sensing matrix should satisfy the restricted isometric property (RIP) defined below

$$(1 - \delta_k) \|X'\|_2 \leq \|\Phi \Psi X'\|_2 \leq (1 + \delta_k) \|X'\|_2 \quad (5)$$

where δ_k must be smaller than 1, and the smaller the value of δ_k , the higher the probability of an exact reconstruction.

In practice, the RIP is difficult to verify and can be accommodated by measuring the coherence between the sensing matrix and the sparsity basis. The coherence μ between the two is defined in (6) [9]

$$\mu(\Phi, \Psi) = \sqrt{n} \cdot \max |(\Phi_k, \Psi_j)| \quad (6)$$

Ideally the coherence will be small; that is, the two are incoherent, as the value for μ is effectively proportional to the number of measurements required when sampling.

3. Tumour classification and FDTD modelling

3.1. Gaussian random sphere tumour models: For this study, the potential of CS in UWB applications is investigated by focusing on the size classification of early-stage tumours. Size has been shown to be crucial when looking at the development of a tumour over a period of time and may indicate malignancy when the tumour reaches a higher volume [10].

The tumours are modelled in the following way using the Gaussian random sphere (GRS) method: the shape of the GRS is determined by the radius vector, $r = r(\theta, \psi)$, described in spherical coordinates (r, θ, ψ) , by the spherical harmonics series for the log radius $s = s(\theta, \psi)$

$$r(\theta, \psi) = \alpha \exp \left[s(\theta, \psi) - \frac{\beta^2}{2} \right] \quad (7)$$

$$s(\theta, \psi) = \sum_{l=0}^{\infty} \sum_{m=-l}^l [s_{lm} Y_{lm}] \quad (8)$$

where α is the mean radius and β is the standard deviation of the logradius, s_{lm} are the spherical harmonic coefficients and Y_{lm} are the orthonormal spherical harmonics.

The database of tumours used in this study includes four different shapes of tumours, of four different sizes. The four different types of tumours are spiculated, microlobulated, macrolobulated and a smooth GRS, in which the first two represent malignant tumours and the others represent benign tumours. Microlobulated, macrolobulated and a smooth GRS are obtained by varying the correlation angle of GRS from low to high. Furthermore, spiculated GRS are obtained by adding three, five or ten spicules to smooth GRS. The average radius of all types of spheres take discrete values: 2.5, 5, 7.5 or 10 mm. Between all sizes and shapes, the number of tumour models developed was 480. Samples of the tumours illustrating the variations in the size and the type created are shown in Fig. 1.

3.2. FDTD breast model: The tumour GRS models are placed in a three-dimensional (3D) FDTD model. The FDTD model has a 0.5 mm cubic grid resolution and the backscattered signals were generated through a total-field/scattered-field (TF/SF) structure [11], in which the tumours and fibroglandular tissue are completely embedded in the TF. Each FDTD model is compliant with the breast phantoms in the UWCEM repository at the University of Wisconsin, Madison [12]. The intensity of each voxel in the magnetic resonance image is estimated and mapped to appropriate dielectric properties in the resultant FDTD model [13].

Figure 1 Samples of tumours illustrating variations in size and type
a Smooth tumour of radius size 5 mm
b Smooth tumour of radius size 10 mm
c Five spicules on tumour of radius size 5 mm

Dimensions within the 3D region of the breast are described according to each axis. The x-axis signifies the depth of the breast, with 0 cm indicating the anterior position, and y and z represent the span and breadth of the breast, respectively, with 0 cm centred at the midpoint of each. The overall FDTD grid size excluding the uniaxial perfectly matched layer (UPML) is approximately 25.9 million cubic cells, the grid resolution (dx, dy and dz) is 0.5 mm for each axis and the time step Δt is defined as $\Delta x/2c$, where c is the speed of light in vacuum. The FDTD grid is terminated on each side by a UPML of 6 mm to minimise edge reflections.

The SF is modelled within a cuboid region, the X dimension of the TF is 137.5 mm, while the square base area measures 153.5 mm along both y and z-axes. The TF is modelled within a cubic region with 40 and 50 mm axes for the homogeneous and heterogeneous breast phantoms, respectively.

Four pulsed plane waves are transmitted towards the target, each at an angle of 0° and 90° from the x - z and x - y planes. Co-polarised scattered electric fields are observed at one of four positions (0, 0, -74), (0, 0, 74), (-74, 0, 0) or (74, 0, 0) mm depending on the direction of the plane wave. The incident pulse is a modulated Gaussian pulse with centre frequency at 6 GHz where the $1/e$ full temporal width of the Gaussian envelope was 160 ps. For two transmitters, the pulse is linearly polarised in the x - y plane and transmitted in the z -direction, and for the remaining transmitters, the pulse is polarised in the y - z plane and transmitted in the x -direction. The acquired backscattered recorded signals are downsampled from 1200 to 75 GHz.

To examine the effects of dielectric heterogeneity, two sets of heterogeneous breast models were created. Portions of

fibroglandular tissue, extracted from the UWCEM breast phantom repository (phantom ID 071904), are introduced into the FDTD model. The first heterogeneous model consists of a breast model with a cluster of fibroglandular breast tissue in a fixed location independent of the tumour location and the second model consists of a breast model with a cluster of fibroglandular breast tissue, in a fixed location which possibly overlaps the tumour. Examples of the heterogeneous breast models are shown in Fig. 2. For the first model, the portion of fibroglandular breast tissue is located within the cubic TF region close to one of its vertices. In the second model, the same block of fibroglandular breast tissue is also located within the TF region, at a distance of $\sqrt[3]{5}$ from one vertex of the cubic TF region, that is, the block is moved 5 mm in each of the x, y and z-axes towards the centre of the TF region.

The dispersive properties of breast tissue are incorporated into the FDTD model using a single-pole Debye model [14]. The dielectric properties for the variations of adipose and fibroglandular tissues are based on the results described by [13], while the Debye parameters for malignant tissue are taken from [15]. The breast is surrounded by a synthetic material matching the dielectric properties of adipose tissue.

3.3. Tumour classification using MWI: Although most studies addressing MWI techniques for breast cancer have examined their potential in detecting the tumour response, a number of studies have also examined the use of microwave signals for tumour classification in terms of its size and/or shape [3, 11, 16–18]. In particular, Chen *et al.* [16] studied the effect of the morphology

Figure 2 Heterogeneous models

a Fibroglandular tissue (black) in a fixed location independent of the tumour (blue)

b Fibroglandular tissue (black) in a fixed location possibly overlapping the tumour (blue)

of different tumour masses on the late-time response of the microwave signature in 2D imaging simulations, while Teo *et al.* [19] studied the effect on the early-time response. Both built tumour models by using a polygonal approximation and then looked at classification between oval/macrolobulated and microlobulated/spiculated shaped tumours embedded in both homogeneous and heterogeneous breast phantom scenarios.

Davis *et al.* [11] created a tumour database using GRS models which comprised tumour models of four different sizes and three different shapes (smooth, microlobulated and spiculated). They proposed a classification system which comprised different feature extraction methods (FEMs): principal component analysis (PCA) and local discriminant bases; and a classification algorithm: linear discriminant analysis (LDA). The tumour models were classified in a homogeneous breast phantom, but different levels of white Gaussian noise were added to the simulations.

Later, Conceicao *et al.* [3, 17] created a large GRS-based tumour database comprising 480 models of four different sizes and four different shapes (macrolobulated shapes were added). Three FEMs were tested: PCA, independent component analysis and discrete wavelet transform. Further classification algorithms were tested, including LDA, quadratic discriminant analysis, machine learning classifiers such as support vector machines (SVMs) [3] and self-organising maps [4]. These studies were tested in homogeneous and heterogeneous breast phantom scenarios [18].

4. Feature extraction and classification

4.1. Principal component analysis: To extract the relevant features in the backscattered signals that will reflect the size characteristics of the tumour, it is important to use a FEM such as PCA. PCA reduces the dimensionality of multivariate data and reveals

simplified structures that are often hidden in the original dataset, while also disregarding less relevant information such as noise or co-linearities in signals [20]. PCA allows for a new representation of the original data in which maximum variance is exposed, so that data may then be better discriminated. Mathematically, the basis that was used to record the original signals is changed, by means of a linear algebraic operation, into a new orthonormal basis that allows for the data to present maximal variance [20]. The resulting principal components are ordered by decreasing variance. It must be noted that PCA is non-parametric so only the data influences the principal components calculation disregarding any prior acquiring system or known labels.

4.2. Support vector machines: The breast cancer classification system presented here is based on a SVM. A SVM is a machine learning algorithm, where training vectors are mapped to a high (or infinite) dimensional feature space labelled a hyperplane. A discriminant hyperplane is chosen to correctly classify the data into two distinguishable sets. The maximum distance between the parallel supporting planes is known as the margin. SVM maximises the margin between the discriminant plane and the examples in the training set. To account for linearly inseparable cases, soft margins [21] are implemented.

Given a training set of sample-label pairs (x_i, y_i) , with features x , label y and $i = 1, \dots, M$, the SVMs are constructed from the following mathematical optimisation procedure

$$\begin{aligned} & \underset{\mathbf{w}, b, \xi}{\text{minimise}} && \left[\frac{1}{2} (\mathbf{w}^T \mathbf{w}) + C \sum_{i=1}^M \xi_i \right] \\ & \text{subject to} && y_i (\mathbf{w}^T \phi(\mathbf{x}_i) + b) \geq 1 - \xi_i \\ & && \xi_i \geq 0 \end{aligned} \quad (9)$$

where $\mathbf{w}$ is the decision plane orientation vector, b is the bias, ξ_i represents the margin slack variable, ϕ is the mapping function and C is the penalty parameter of the error term. To avoid overfitting and excessive computation, each training vector is mapped to an infinite dimensional feature space by means of a kernel function: $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$. A linear kernel is implemented in this study.

5. Experimental results: The database has in total 1920 UWB signals. These are equally divided into sets of 480 signals with tumours of four sizes: 2.5, 5, 7.5 and 10 mm. Each signal in the database consists of a 100 sample length time-domain signal denoted by $\mathbf{X}$. This method assumes sparsity of $\mathbf{X}$ in the time domain so the basis Ψ is an identity matrix within the framework for CS described in Section 2. To compress each signal, the following steps are taken: each time-domain signal is multiplied by a discrete Fourier transform (DFT) matrix, which for CS purposes, is the measurement matrix, Φ . This DFT matrix is an $N \times N$ matrix (where N is the signal length, 100). However, as the DFT matrix is a measurement matrix, the size of this matrix is controlled to alter the sub-sampling rate; that is, the compression rate. At sub-sampling rates, fewer rows (Fourier coefficients) are chosen at random which results in fewer frequency points being obtained. For example, at a sub-sampling rate of 20 (i.e. a compression ratio of 5, 20 out of 100 measurements chosen), the original 100 sample long signal is multiplied by 20 randomly selected rows of the DFT matrix. This yields a compressed signal with 20 measurements comprising 20 frequency points which is equivalent to initially acquiring 20 random frequency points instead of 100 (a 5-fold reduction in frequency domain data acquisition). The 20 frequency domain measurements and the DFT measurement matrix are used to reconstruct the 100 sample time-domain signal. The reconstructed signal is obtained using an L1-norm solution to solve the convex optimisation problem

which is the standard approach in CS. In this Letter, the reconstruction is performed in MATLAB using a primal–dual interior point method. To summarise, as the compression increases for such a monostatic breast cancer detection system, the antennas would effectively acquire fewer random frequency points than the 100 frequency points required for the complete signal in the database used. This reduced number of frequency points enables a quicker scan time.

Fig. 3 provides an illustration of the effects of CS on a typical UWB signal. As the number of measurements decreases (level of compression increases), the distortion becomes more evident in the signal which for classification applications will result in poorer performance. Similarly in image reconstruction, increased noise and unwanted image artefacts would be expected.

5.1. Size classification: In a clinical setting, the size of a tumour is one of the most important attributes considered when deciding on the type of therapy. For example, the size of a tumour may give evidence on the type of tumour that was detected, and also in some cases reducing the tumour may be a requirement before a surgical procedure takes place. In each test there were two classes. As the database consists of tumours of sizes 2.5, 5, 7.5 and 10 mm, three variations of tests were done classifying 2.5 mm and each of the other sizes.

The results presented in this Letter are from compressing each signal at sub-sampling rates ranging from 10 measurements (a compression ratio of 10) to 100 measurements (a compression ratio of 1) in steps of 10. Training of the classifier for each test runs done by random selection of 90% of the signals available. The remaining 10% of the signals are used as testing data to test the classifier. The testing and training datasets are changed for every test run. Results shown are based on the average classification rate

from ten tests of the classifier at each sub-sampling rate. At each sub-sampling rate shown in Fig. 4, the training data consists of signals compressed at that rate.

Fig. 4a shows the classification performance along a range of sub-sampling rates. The results for classifying between 2.5 and both 7.5 and 10 mm tumours work particularly well. The 2.5 and 10 mm case does not drop below 99% classification until 40 measurements are used, and still achieves approximately 90% classification when 20 measurements are used. This suggests acquiring 20 random frequency points instead of the complete 100 is sufficient to distinguish between 2.5 and 10 mm sized tumours with an accuracy of 90%. In the 2.5 and 7.5 mm case the classification rate begins to drop at the 50 measurement point. However, at this point, the classification still achieves over 90% accuracy. Fig. 4a demonstrates that 40 measurements is the minimum required to obtain 90% accuracy for these two sizes, implying a reduction of 2.5 times in the amount of data required during acquisition.

The next focus of this study was to demonstrate the effects of performing PCA as a FEM in conjunction with the CS compression algorithm. These tests take the reconstructed time-domain signals and perform PCA on them. It is important to find the optimal number of principal components to use when training and testing the classifier. Choosing too few components can fail to represent the full variability in the signals, while choosing too many can result in additional values being used with little, if any, advantage gained. To find the optimal number of principal components for this application, the classifier was tested with principal components ranging from 5 to 100 in steps of 5. The tests were averaged out over ten runs. The optimal number of principal components for this application was found to be 20. As a result, the tests presented in this study on classification associated with PCA have 20 principal components selected. Fig. 4b shows the performance of PCA on the compressed

Figure 3 Illustration of the effects of CS on the reconstructed time-domain signals, and their magnitude spectra

Time-domain signals

a Original signal

b Original signal

c 40 measurements

Corresponding magnitude spectra signals

d 40 measurements

Figure 4 Classification of signals at sub-sampling rates for
a Size and
b Size using PCA on signals

signals. The results are similar to Fig. 4a with only discrimination between the 2.5 and 7.5 mm size cases showing an improvement in classification.

5.2. Effects of dielectric heterogeneity: The tumours tested in 5.1 were in a homogeneous media. To further test the effects of CS

Figure 5 Size classification with
a Fixed position fibroglandular tissue
b Moving fibroglandular tissue

on UWB signals, scenarios of increasing dielectric heterogeneity were introduced, as described in Section 3.2. The two scenarios are a cluster of fibroglandular breast tissue in a fixed location independent of tumour location and a cluster of fibroglandular breast tissue in a fixed location possibly overlapping the tumour. These conditions increase the difficulty of classifying tumour size.

The tests are similar to the initial size classification tests in the sense that 1920 signals are used, 4 sizes of tumour are present, testing and training is performed using 10 and 90% of signals, respectively, and the classification performance is averaged over ten runs. Fig. 5 illustrates the performance of CS in the increasing heterogeneous environments. Overall, the method is shown to be relatively robust to these changes. The case where the piece of tissue is potentially overlapping the tumour is the most difficult scenario presented and only a slight degradation of performance can be seen. In fact, in both scenarios the performance is very similar to that obtained when the tumour was in a homogeneous medium suggesting this implementation of CS is reliable in more realistic environments.

6. Conclusion and future work: This Letter has discussed the suitability of CS to time critical UWB applications. In particular, this Letter has demonstrated the effects of compression on UWB signals in size classification of tumours for breast cancer detection to reduce scan time. Previous studies have shown the time required to record signals for monostatic microwave breast imaging systems can be as long as 30 min [22]. The results of this study show that in a dielectrically homogeneous breast environment a 5-fold reduction in frequency-point sampling can be achieved whilst maintaining a size classification accuracy of 90%, between 2.5 and 10 mm sized tumours. This indicates the potential to reduce this scanning time by 80% to 6 min for this test scenario. Similarly, more than a 2-fold reduction can be obtained while maintaining classification accuracy between tumours of sizes 2.5 and 7.5 mm, reducing scanning time to 12 min. Finally, to further illustrate the potential of the technique, two additional classification scenarios are considered, where the tumour is located in two different dielectrically heterogeneous breast models, and once again no significant drop in classification performance was found.

Future work will analyse the effects of CS in other UWB applications such as respiratory and heart monitoring. In terms of breast cancer detection, further work will investigate the classification of type of tumours. A final possibility is an investigation of alternative sensing matrices or basis functions to improve sparsity in UWB signals and consequently to improve reconstruction quality with CS.

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