Accelerating MRI with Compressed Sensing

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Abstract: Even though the Compressed Sensing or Compressive Sampling (CS)[1][5] has emerged as the promising field a decade ago, the exploitation of signal sparsity has gained a lot of attention in the field of signal processing. The inherent property of many natural signals is the sparsity of the signal. If the signal contains mostly zeros and only a few non-zero elements, then the signal is said to sparse. If the signal contains only S non zero elements, then it is S-sparse. The signal can be stored only in few number of samples because of it's sparsity characteristic. The reconstruction of the signal from very few numbers of samples than the actual quantity of samples can be done through CS method. CS -- a Mathematical Framework provides a new approach for data acquisition in terms of less number of samples that violates the Niquist rate. Nyquist theorem states that signal can be reconstructed precisely and outstandingly provided that signal should be sampled at-least double of its highest frequency rate. Medical imaging method used in radiology to form pictures of the anatomy and the physiological processes of the human body in both health and disease analysis is said to be Magnetic resonance imaging (MRI)[3]. Strong magnetic fields, magnetic field gradients and radio waves are used to make images of the organs in the body. MRI, vital medicinal imaging tool has naturally a time-consuming data acquisition procedure. The considerable data acquisition period can be reduced by applying the CS to MRI for the benefit of the health care units and patients. This paper gives a brief survey on the Compressed Sensing Magnetic Resonance Imaging (CSRMI). The CS predicates that the efficient and accurate signal acquisition is said to be happened by combining the low rate sampling and the high power of computation. The 2 basic properties for enabling the CS are the transform sparsity and coded characteristics of the MRI. The wavelet transforms (WT) [4] is used along with the CS technique to provide the compression and reconstruction of MR Images. Wavelet is a mathematical function used for denoising and compression of two dimensional signals, such as images. When WT is applied on images, it produces 4 sub- bands such as low low (ll), low high (lh), high low (hl), high high (hh). The ll sub band is having a large amount of the information of the image i.e. the low frequency components of the images. The other high frequency components are rejected. The WT is applied only on ll sub band under more number of stages. So that the image gets compressed to a maximum extent. By using only ll sub band, one can reconstruct the image to the original image by using CS Method. CS has found under large number of real time applications in the field Medical Imaging, Seismic Imaging, Radars, Cameras, Analog to Information (A/I) Convertors, Communication Networks and etc because of the inbuilt sparsity of various real world signals like sound, image, video, etc.

Keywords: *Compressed Sensing, Magnetic Resonance Imaging, Sparsity, Wavelet Transforms.*

I. INTRODUCTION

MRI that uses the electromagnetic waves and the radio waves to capture the internal organs of human body. The protons in the body largely consisting of water molecules will produce the MRI images. It has long examination time to capture the details of human body. During this long duration of scanning, patient will not maintain his body steadily. He/She under goes a lot of disturbances in many ways like changing his/her position in some manner, moving by to his/her sides gently, increasing his heart beats due to new medical environment like Scanning Machine and its arrangements. By reducing he scanning period of the MRI, a better and improved expression of the scan can be obtained by lowering the patient's inconveniences. The drawbacks of the MRI techniques are overcome by a new technique namely Compressed Sensing.

Compressive Sensing[2] is a signal processing method for acquiring signals fastly and reconstructing the signal. The acquired signals are vey less compared to the Niquist rate and based on the concept of optimisation that is, the signal can be reconstructed from a very less number of samples than what the Shannon Nyquist rule says. The reconstruction can be achieved under 2 cases.1) the signal is to be sparse in some domain viz. wavelet transform and 2) the incoherence which is applied through the isometric property which is adequate for sparse signals. During the scanning, the patient undergoes long duration of scanning. The compressed sensing method reduces the scanning time by increasing the acquisition speed of the signal. So that a very less number of samples are acquired that may be less than the Nyquist rate.

The frequency domain with magnitude and phase sequence of data points in MRI are generally complex in nature. These data points will form a matrix known as k-space. The data acquisition of MRI images is influenced by longitudinal relaxation time T1 and transverse relaxation time T2. As a result of compressed sensing, the image or data acquisition techniques work at a faster rate than conventional methods. Thus the number of k-space samples are said to be reduced by employing the CS in MRI machines and hence decreases the scanning period.

II. COMPRESSED SENSING MODEL

The Scanning time period can be minimized by the introduction of CS techniques in the MRI devices. This would be benefitted the health care units and patients. The 3 most and more important points[5,3] are highly needed in the application of CS. They are 1) Sparsity of the transformation i.e. the required image must be in a sparse signature of the known transformation domain (the image should be compressible in a well-known transform coding). 2) Less sampled artefact's incoherence i.e the artefacts are caused by k-space to minimise the sampling during the linear reconstruction and are said to be in coherent in the transformation domain.3) Reconstruction in the nonlinear way would enforce the sparsity the image signature with the possessed samples and should maintain the consistency in the reconstruction.

The MRI images which have hidden sparsity characteristics. These characteristics are exploited to minimise the samples of the k space data. These less sampled k space data of the sparse image are used for the recovery of the images. The Joint Picture Extension Group, Joint Picture Extension Group - 2000, Moving Picture Extension Group standards are used in the image compression algorithms. K SPACE is a signal which has only non zero coefficients. The large amounts of data are stored in the vector form because of the inconvenience for the storage and transmission. Vectors will be having the less amount of space that is very much needed to store all the k space data which is reduced by sparse approximation. The CS in MRI that uses the 2 key properties. They are the coded nature of possession of MRI images and the sparsity of MRI images [1].

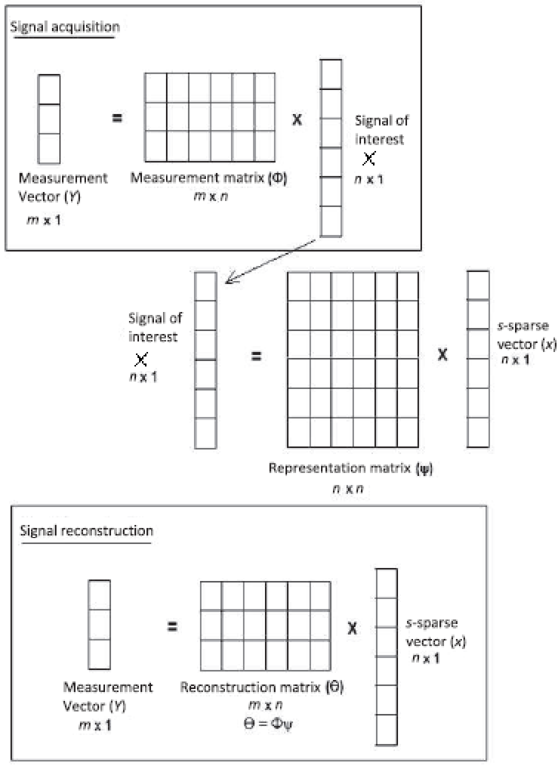

Fig 1. Computational Model of the Compressed Sensing

Figure 1 shows the signal possession model of Compressed Sensing. The sensing process of signal/image X sensed by the scanner is represented by

$$Y = \Phi X \tag{1}$$

where X is the signal of interest in the vector form (nx1) and Φ is the measurement matrix (mxn) and Y is the measurement vector (mx1). If the signal is sparse, then CS says that n must be far higher than m. Lesser values of m are suggested for sensing matrices that are more incoherent within the transform domain where signal is sparse.

III. WAVELET TRANSFORMS

Wavelet transforms are a kind of filters used to localize the time and frequency component of the signal. It is extended version of the Short Time Fourier Transforms (STFT). That means in the STFT Fourier transformation of the signal is applied by using the shifted versions of the window (W). In the case of the wavelet transforms (WT), window (W) used itself is the wavelet. This wavelet window can not only be shifted but also be scaled. The window in the un-scaled and un-shifted format is called as mother wavelet. Here filtering operation is called as convolution operation. The convolution operation of different scaled and shifted versions of the window with the signal of interest results in providing the different levels of frequency and time localizations of the signal. This frequency and time localizations are helped in different types of processing of the signal such as segmentation, enhancement, compression and reconstruction. The only difference between the STFT and Wavelets Transforms is that in the case of STFT the window size will always remains constant and in the case of WT, the window size will undergo compression and expansion. In the case of STFT, the window is rectangular window but in the case of WT, the window is the form of a fixed length wave (such as square wave (Haar Wavelet) or some kind of wave having some specified properties)). In the case of STFT, there is only one kind of window but in the case of wavelet transforms, there are two types of windows such as scaling window (scaling function (Φ)) and wavelet window (wavelet function(Ψ)).

The Wavelet transforms is given by the following equation as follows

$$F_{Hig\square\ Pass}(a,b)=\int_{-\infty}^{\infty} f(x)\Psi^{*}_{(a,b)}(t)dt \qquad (2)$$

$$F_{Low\ Pass}(a,b)=\int_{-\infty}^{\infty} f(x)\Phi^{*}_{(a,b)}(t)dt \qquad (3)$$

where * is the conjugate complex symbol. 'Ψ' is wavelet function to get high pass filter frequency components and 'Ψ' can be replaced by the scaling function ('Φ') to get the low pass filter frequency components. 'a' and 'b' are the dilation and translation factors respectively. f(x) is the input signal. 't' is the time axis.

IV. RECONSTRUCTION ALGORITHMS

The Reconstruction of MRI images that are compressed during the compressed sensing methods, will undergo greedy approach[14] which is step by step recursive method. In each iteration, the resulting image is updated by selecting only those columns of the restoration matrix. The selected columns, once included are not to be the part succeeding iterations of the algorithm. This approach will minimise the computational complexity of the algorithm. The greedy approach is simple, faster and less computational complexity. One of such greedy approach is Matching Pursuit (MP). It includes the matching pursuit algorithms such as Matching Pursuit (MP)[12] like Orthogonal Matching Pursuit(OMP). The algorithm goes in this way. It takes input as measurement matrix A of m by n size, m dimensional vector y and a sparsity level k of the signal x. The output is an estimate x` in Rn for the signal x. Some of such a kind of algorithms are Stagewise Orthogonal Matching Pursuit[13], the gradient pursuit algorithms like Gradient Pursuit (GP) and Conjugate Gradient Pursuit(CGP) and Compressive Sampling Matching Pursuit (CoSaMP). Restricted isometric property of the MRI images helps the Compressed Sensing methods to exploit the sparsity and hence it helps in reconstruction algorithms to rebuild the original image by using far less number of samples than conventionally required.

A. Matching Pursuit:

Matching pursuit is applied to signal or image video encoding etc. It performs better than Discrete Cosine Transforms (DCT) coding for bit rate in both the efficiency of coding and quality of image. The matching pursuit has the problem with the computational complexity of the encoder. The compressed sensing makes use of the Matching Pursuit and and its members like Multipath Matching Pursuit (MMP), Orthogonal Matching Pursuit (OMP), Compressed Sampling Matching Pursuit (CosaMP), Generalised OMP. Matching pursuit is a class of iterative algorithms that decomposes a signal into a linear expansion of functions that form a vector space.

The best approach for CS recovery of signal is OMP. The solution is the one with minimum l0 norm due to sparsity. But commonly used technique includes l1 minimization such as Basis Pursuit (BP) and greedy pursuit algorithm such as Orthogonal Matching Pursuit algorithm. In each iteration OMP calculates the new signal approximation Xn. The approximation error rn is calculated as rn = X-Xn. Next iteration determines which is the next element to be selected. The selection is based on the inner product between the current residual and rn and column vector Φi. Ler inner product be in α= ΦiTrn.

Stagewise Orthogonal Matching pursuit (StOMP) transforms the original signal into negligible residuals starting from intial residual r0=y where y= Φx. It enters each stage in StOMP. Here OMP takes many states but StOMP takes fixed number of stages (say 10).

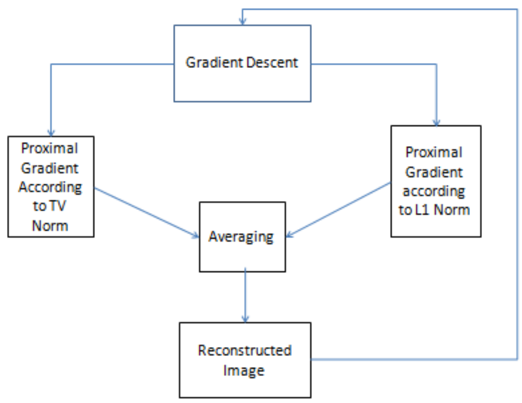

Fig 2: The reconstructed image is obtained from missing solution of the sub problem in a repetition passion.

The compressed sensing MR images using wavelet transforms introduces the L1 Norm and total variance (TV) regularisation. The problem is divided into total variation and L1 norm subset problem respectively. The reconstructed image is obtained from missing solution of the sub problem in a repetition passion [4]. The process is shown in the figure 2.

The CS MRI with total variation and frame based regularisation provides a new sparse regularisation mode for the frame based image restoration. In frame based l1 regularisation image restoration, there are 3 forms 1) synthesis based 2) analysis based 3) Balence based approaches.The Compressed sensing based MRI can be expressed as shown in equation 1.

V. APPLICATIONS OF COMPRESSIVE SENSING

The CS has been got many applications in many fields of engineering including image processing to geophysics applications. The signals like sound, images videos have many inherent features like sparsity. Because of sparsity, it has been using in many many fields of engineering. Compresed sensing is kept using in Cameras, Medical Imaging, Seismic Imaging, RADARs etc. Our interest lies in the medical image processing applications [6]. The application of CS is mainly used in image processing [11] i.e. mainly in MRI scanners.

These applications of CS are the main focus of our survey paper, with added attention given to the application of this signal processing technique [11]. Compressed sensing is kept using in Cameras, Medical Imaging, Seismic Imaging, RADARs etc. Our interest lies in the medical image processing applications [6].

A. Rapid 3-D Angiography:

All the k-space data of 3D imagesis not fully used for every reconstructed time frame. Instead, the low frequencies of the signals are used mainly for the image reconstruction and missing data are obtained by interpolating the data collection [7]. The compressed sensing method is applied on the RAPID 3-D ANGIOGRAPHY for the faster acquisition of the k-space data.

B. Whole-Heart Coronary Imaging:

The Flexible selection of the delay timings is accepted by Whole heart coronary imaging approach [8] by performing k-space sampling over a larger acquisition window. The temporal window with minimum cardiac motion for each artery region is determined by the coronary motion in an interactive way.

The major source of artefacts in cardiac MRI is the respiratory motion of the patient. The Respiratory motion is suppressed by free breathing techniques with pencil beam navigators. The pencil beam navigator offers a strong potential for automatic patient dependent calibration for getting high resolution coronary artery images. Hysteretic effects, navigator position, and temporal delays between the navigators and the image acquisition affect the correlation between the measured navigation position and the original position of the heart. The poor scanning is the result of irregular breathing patterns.

C. Brain Imaging:

There are two brain imaging techniques based on 1)brain structure and 2)brain function. MRI is used for brain imaging in case of Brain structure. FelixBloch abd Edward Purcell independently discovered the tendency of certain nuclei to resonate when placed in a magnetic field. The MRI is based on Nuclear magnetic Resonance (NMR). 1.5 to 4.0 Tesla is used for human imaging by magnetisation of the hydrogen atoms in the human body. The Electro- and Magnetoencephalography (EEG, MEG), Positron Emission and Single Photon Emission Computed Tomography (PET, SPECT), Functional Magnetic Resonance Imaging (fMRI), Functional Near-Infrared Spectroscopy (fNIRS)[9] are used to determine of brain function for next level of MRI scanning using CS Methods.

D. Application To Dynamic Heart Imaging:

The Validation of camera system is done by dynamic heart phantom which is a precision instrument that simulates the realistic motion of an typical human heart. The dynamic cardiac MRI that uses Compressed Sensing (CS) to reduce the data acquisition period. Here the sparseness of the dynamic image series has been exploited in the spatial and temporal frequency domains. A new k-t iterative support Detection (k-t ISD) is proposed to improve the CS restoration for dynamic cardiac MRI [10].

VI. CONCLUSION

The patients under go a lot of difficulties during the MRI scanning. They should not keep their body steadily and should not halt their breath for some moments. By doing all these activities, he/she will scare and frighten suddenly. Hence their body position changes and their heart beat increases. So the best pattern of the image cannot be obtained. In order to obtain the best pattern of the image, Compressed Sensing technique is used and the period taken to acquire the image/signal is reduced. The signal obtained is sparse signal. The original content of the image can be reconstructed by exploiting the sparsity of the signal.

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