A FAST COMPRESSED SENSING OF 3D MRI IMAGE RECONSTRUCTION FROM RESIDUAL SPARSE SIGNAL

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Abstract— In medical science, the resolution of each & every part is must which can be recover from the reduced frequency acquisition sequence. While studying, the some researchers drawn analysis that some part is missing at the time 3D reconstruction. Our aim to recover missing information. For this purpose several methods are proposed. The information achieve by pressing suitable constraints on the reconstructed image. Using the forward-Backward splitting approaches, first update the sequence nature & in the second stage uses the different nonlinear filtering strategy. By modifying the algorithm showing the fast & more stable result. It gives the optimize performance even the highly under sampled image sequence. The several experiments shows that the improvement in the high resolution performance.

Keywords— Compress Sensing, Splitting Approach, Total Minimum Variation, Filtering Strategy.

I. INTRODUCTION

Three dimensional reconstruction technique is widely used in studied and diagnosis of the disease in medical science. Large research has been done on the three dimensional high resolution problem. But still now there is some problem are not solved so needs to improving these problem of resolution. Also reduces the artifact which are produced during the reconstruction. To reduce these artifact uses algebraic reconstruction techniques & some filtering strategy. In MRI don’t use directly radiations but needs very long time to access complete data used for high resolution reconstruction. Initially this can be achieved by using 3D accelerated MRI using parallel imaging with multiple channel receiver or data sharing methods Using accelerated function MRI using KLT basic showing very accurate result by increasing number of blocks to make total number of measurement comparable

But remaining in the artifact due to reduction in the scan time. Also, aliasing effect reduces the signal to noise ratio this makes the controversial if parallel imaging used for the high temporal resolution. In later stage, increases the temporal resolution that is the temporal resolution refers to the precision of a measurement with respect to time often there is a tradeoff between temporal resolutions due to uncertainty principle which is an inherent property of Fourier transform. It is defined as the amount of time needed to reconsider & acquire data for the exact same location. Particularly, in high temporal resolution is difficult to monitor dynamic process such as cardiac process (motion), brain process. For example functional MRI is technique to detect activated area in the brain with respect to given task by evaluating the temporal resolution even at each instant change in the pressure of the particular area. Since the change of pressure is very small compared to full MR signal. To prevent the noisy signal due to motion require fast scan method. Dynamic event change at each instant of time. New algorithm has been developed recently last year such as k-t FOCUSS, FISTA, k-t BLAST, UNFOLD [7], [8]. These provides spatio temporal correlation of the imaging sequence.

Compressed sensing approach has been developed for image reconstruction from highly under sampled sequence [4]. MRI obeys two conditions for successful application of compressed sensing approach first in medical image is compressible by sparse coding into Fourier transform domain. And second MRI scanner naturally acquire encoded samples rather than direct pixel sample k-t SPARSE is largely successful for cardiac imaging problem. But the computational burden is large [[1]]. To overcome these problem unify the approaches k-t SPARSE & k-t BLAST & introduce the new approach called as k-t FOCUSS. Further improves the performance of algorithm by efficient prediction & residual encoding was inserted into better sparsely residual domain. The limit of k-t FOCUSS is that occur of dynamic process during periodic motion. The recently developed minimum l1 norm solution generally have been used by investigators to analyze MEG provides high spatial resolution images. But conventional minimum L1 norm approach suffer from instability in spatial reconstruction & poor smoothness of the reconstructed source time-course some. Using nonlinear filtering [2], we have ability to take advantage of correlation existing between neighboring pixels & obtain high resolution from accelerated frequency acquisitions. It is a combination of adaptively weighted soft thresholding and exponentially weighted adaptive parallel projection algorithm was introduced to achieve better steady state performance. It gives the better result using forward-backward splitting approach [3].

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II. DETAILS EXPERIMENTAL

2.1 Compressed Sensing Approach
The transform sparsity of MR images & coded nature of MR acquisitions are two keys of enabling compress sensing in MRI. Let us see the mathematical analysis of compressed sensing method X be the total image volume reconstruction

\[ X = \{x_l \in \mathbb{R}^{N_x \times N_y}, l = 1, ..., NF \} \quad (1) \]

Where the \( x_l \) denotes the number of images in total volume \( L \) denotes the number of dynamic frames in the case of dynamic image MRI. Also R which can be expressed as the number of images sequence & the data of reconstruction problem can be solved by image volume in Fourier domain. Formed by suitable selected frequency encoding of each frame. Image volume transforming into Fourier domain Y & the image volume represented by

\[ Y = \{y_l \in \mathbb{R}^{N_x \times N_y}, y_l = F(x_l) \quad l = 1, ..., NF \} \quad (2) \]

Where \( y_l \) denotes acquisition binary mask \( F(x_l) \) represents the under sampling in Fourier domain. The compressed sensing reconstruction also stated in this case as constrained minimization. Using convex sparsifying function \( F(U) \). They are especially important in the study of optimization problems where they are distinguished by a number of convenient properties. Even in infinite-dimensional spaces, under suitable additional hypotheses, convex function continue to satisfy such properties and, as a result, they are the most well-understood functional in the calculus of variations. \( U = \{u_l \in \mathbb{R}^{N_x \times N_y}, l = 1, ..., NF \} \) that solves

\[ \min_U \| F(U) \| \quad \text{subject to} \quad y_l = F(x_l) \quad l = 1, ..., NF \]

(3)

The random noise get added into image & it gets corrupt \( (g_l) \) \( g_l = F(x_l) + e_l \quad l = 1, ..., NF \)

(4)

Using triangular equality the reconstruction problem can be solved as

\[ \min_U \| F(U) \| \quad \text{subject to} \quad \| F(x_l) - y_l \|_2 < e_l^2 \quad l = 1, ..., NF \]

We remarks about formalization are not truly for 3D reconstruction. We cannot use in 3D Fourier domain. Instead of using 2D-3D formulation exploit the theoretical results, we can choose the suitable sparsifying function under consideration of suitable hypotheses. If the image forming volume X are sparse in any domain, like frequency domain & time domain.

2.2 Different Strategy for Reconstruction
The necessity of two condition complete full fulfillment of the compressed sensing measurement. First, assumed that measurement of large matrices in Fourier domain and using piecewise smooth filtering makes the well approximation of the medical images. First uses Fourier transform and after that \( l_1 \) norm variation in the k-t Focuss approach. This reconstruction method prowess the spread data of the gradient of the images. Uses the suitable Convex sparsifying function for finding gradient of the image.

\[ F(U) = \| \nabla U \| \]

(5)

Where U is gradient vector which is in the three direction respectively x, y & z axis. It take part mainly to minimize the total variation of the medical image. The differentiability of the sparsifying convex function makes easy to solve these initially constrained problem. For easy convert initially constrained problem into unconstrained problem. To convert the constrained problem into unconstrained sub problem using the sequential penalization approach. To achieve our aim we use the approach of in the form of with a sequence unconstrained subsamples of sequence which originally approximates the constrained problem. So the form can be represented as below

\[ \min_{\alpha} \left\{ \| \nabla U \| + \frac{1}{2} \sum_{l=1}^{NF} \| F(x_l) - y_l \|_2 \right\} \]

(6)

Where \( \alpha \) denotes the penalization parameter \( l_1 > l_2 > l_3 > \cdots \)

Shows that decreasing sequence of penalization parameter which makes the sequence of unconstrained subsamples for small values of approximates the original constrained problem. This formulation makes the larger numerical difficulties, huge dimension of the minimization and smaller values of the penalization parameter \( l_k \). Using the forward and backward splitting approach overcome both difficulties. The main advantage of this approach using two iterative aspects. First sequence of 2D updating steps corresponds to 2D sequential acquisition strategy. The solution process for 3D phase is performed in real time domain & consists of 3D total variation denoising step [3]. To obtain better reconstruction from under sampled acquisition ,uses the gradient estimation function in this involves many neighboring point .aim to exploit inter & intraframe correlation[9]. So it is better to achieve the 3D MRI reconstruction. Also uses the 3D MRI discrete total variation minimization step to reduce the large variation into a small variation change. In this uses the 3D version of Rudin-Osher-Fatemi model for denoising. Initially used for the continuous signal [2]. While it is used for the digital image it must be discretized & it overcomes the problem of nonlinearity due to Lagrange’s equation. Recently many method developed for the reconstruction of 2D image.

2.3 Median filtering For TV Denoising
Median filter are generally nonlinear filters. In these use a window of mask along the three dimension of the total image. It apply the mask three directions x, y and z axis. The digital TV filter is for denoising and enhancing digital images. The digital TV filter is a data dependent low pass filter for denoising, capable of data without blurring images [2]. It solves using
To denoise digital images or general digital noise is filtered out. Denoise data via linear filter does give satisfactory result. So any practical filter has to be design. In this paper we use a nonlinear dependent filter called digital TV denoising filter. It is capable of denosing of the image without blurring or distorting the total image volume. The filter possess the following minimum property. The \( \mu \) defines minimizing value. The output of the median filter acting on the set \( \{ u_j, j = 1, \ldots, (2l+1)^3 \} \) while in 3D shift the binary mask by \( (2l+1)^3 \) windows, let

\[
L(\mu) = \sum w_i |u_i - u_0| 
\]

where \( w_i \) are positive weights for minimization we use the optimize value of \( \mu \). Let us now consider the more general minimization problem

\[
\min_{\mu} \{ L(\mu) = \sum w_i |u_i - u_0| + \frac{1}{\lambda} |u_i - \mu|^2 \} \}
\]

It states that \( w_i \) are positive weights while \( \mu^0 \) are the noise contaminated version of a clean signal.

\[
\mu_{opt} = \text{median} \{ u_1, u_2, \ldots, u_n \}
\]

Where the minimizer \( \mu^0 + \frac{1}{\lambda} \sum_{i=1}^{n} w_i (u_i - \mu^0) \}

Using this we built general solution to obtain algorithm for the denoising of the image for total variation. The TV anisotropic model invented by RUDIN, OSHER and FATEMI, is one of the best model for restoration of the image as compared to the least square restoration model. By using ROF model we estimate the gradient function.

\[
|\nabla u| = |\nabla x u| + |\nabla y u| + |\nabla z u| 
\]

Using this gradient function find discrete value of a 3D grid point along any axis. For this consider any number of grid point set, also consider a central point value \( u \).

We fix a number of set around the central value \( u \). Some pixel around the central value may be dark gray or medium gray circles.

\[
|\nabla u| = \sum_{i=1}^{n} w_i |u_i - u_0| 
\]

Using the gradient discretization method we find the optimize value

\[
\mu_{opt} = \text{median} \{ u_1, u_2, \ldots, (2l+1)^3 \} 
\]

The ROF has two main two drawbacks [2]. The first drawback is that it can stagnate at a differential point while second is high Computational burden. To reduce the computational cost uses the iteration of its recursion version [1]. While the image reconstruction in the scanning at the front of the image generates electric field. Electric field generates due the inductive coil present in the scanning. Due to this the intensity of the original image has been changed value of the original. So it is necessary to reduce this instability & make it better for 3D MRI reconstruction.

IV Algorithm

Uses the Iteratively Regularized Gauss Method to reconstruction of the 3D MRI image [1]. This method is used to obtain stable solution to nonlinear problems. The algorithm can be explained as below.TGV is generally computes the updates, means using the forward backward splitting approach.DU, DC are the image and coil sensitivities respectively in the IRGN method. Iteration Used for image and coil sensitivities. Initially guess \( u_0 \). The parameter uses \( M \) which is linear operator with maximum iteration. While the parameter \( \gamma \) denotes sensitivities for the L2 penalty.Inverse L2 penalty indicates the Laplacian function. Also the parameter \( \rho \) for the TGV penalty.

### III. RESULTS & DISCUSSION

Results indicate the time required for processing the image while MRI scanning & during the reconstruction.

#### 3.1 Reconstruction of image using TV method.

![Fig 1 indicates iteration no(5,6,7) from left to right](image)

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#### 3.2 Reconstruction using TGV method

![Fig 2 indicates iteration no(5,6,7) from left to right](image)

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### CONCLUSION

We modified the efficient algorithm which is developed previously in the biomedical field for the 3D MRI image reconstruction. Also uses the under sampled frequency samples. Compressed sensing
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approach also used to solve the image reconstruction problem. Modifies the fast Fourier transform into NUFFT. Because of this the reconstruction time reduce which is seen by the result. Also uses the forward & backward splitting approach using the penalized splitting approach. For the denoising the image uses the TGV method. Compare the results with the previously obtained result using the modified method.

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REFERENCE


