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Contourlet Transform Based MRI Image Compression using Compressed Sensing

Neha Madhukumar
M.Tech Scholar, Department of ECE
LBS Institute of technology for Women
Thiruvananthapuram, Kerala, India

Baiju P S
Assistant Professor, Department of ECE
LBS Institute of technology for Women
Thiruvananthapuram, Kerala, India

***Abstract*— Biomedical images are usually sparse in nature. Hence these images can be compressed for technical feasibility of storage, cost reduction and transmission. Compressed sensing can be applied to MRI images, which results in high compression rate and good quality of reconstruction. In the proposed method an MRI image is initially compressed using contourlet transform. Then we exploit the properties of k-space to remove the artifacts that occur during reconstruction while using the conventional compressed sensing method. The algorithm consist of two stages i.e., we consider both the low-frequency and the high frequency part separately. The image outline is recaptured using random sampled k-space centre, then the full image is reconstructed by combining the recovered low-frequency k-space and random sampled high frequency data. Since initially we use contourlet transform for compression, the algorithm produces a better result compared to wavelet transform. The accuracy and feasibility of the proposed method is tested on three typical MRI images.**
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Keywords—Compressed sensing (CS), Contourlet transform, k-space.

I. INTRODUCTION

Magnetic resonance imaging is an important medical tool with relatively slow data acquisition process. Thus for improving the speed of data collection, compressed sensing can be applied to MRI. This results in scan time reduction thereby providing benefits for patient and health care economics.

Compressed sensing has got a high demand for fast, efficient and inexpensive algorithms, application and devices. Compressed sensing exploits the sparsity of signal in transform domain and incoherency of the measurements made with the original domain. In compressed sensing we combine sampling and compression into a single step by measuring samples which contain maximum information about the signal and removing samples that are having minimal value. Compressed sensing finds application in diverse fields, ranging from image processing to gathering of geophysics data. This is possible because most of real world signals are sparse.

The theory of compressed sensing states that a signal can be recovered from much fewer samples than required by Nyquist paradigm. The recovered signal will be almost similar to original if it is sparse in nature, i.e., the recovery will be exact if it contains large number of zero coefficients. The number of samples required for reconstruction depends on the algorithm used for reconstruction. In the case of stationary 2-dimensional images, compressed sensing is not capable of providing accurate information; this is because of the residual artifacts that occur during reconstruction.

In this paper, we present a new method to avoid the artifacts caused during reconstruction. The method consists of two stage reconstruction. In this algorithm, the MRI image is initially compressed using contourlet transform. The image outline is created using the densely sampled k-space centre, and then a full image will be recaptured using the recovered low-frequency k-space data and sparsely sampled high frequency data. The accuracy of the proposed method is tested on typical cardiac, angiography and brain MRI images.

II. THEORITICAL EXPLANATION

A. *COMPRESSED SENSING*

Compressed sensing is a signal processing technique where the number of samples needed for reconstruction is much lower than that required in traditional sampling method. To make this possible compressed sensing follows two principles: sparsity and incoherence. Sparse matrix is a matrix in which most of the elements are zero. Sparsity is defined as the ratio of number of zero elements to total number of elements in the matrix [1]. Compressed sensing exploits the fact that natural images are usually sparse in nature; these signals can be compressed by projection on suitable domain. A signal is said to be k-sparse if it contain k non-zero coefficients [2].

Suppose X is the signal to be sensed, the sensing process is defined as:

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

Ø is called as the measurement matrix and Y is the measurement vector. The measurement matrix is having a size m×n, by the conventional sampling method perfect reconstruction will be possible if m is at least equal to n. But the theory of compressed sensing states that the reconstruction of the signal is possible if m is far less than n provided the signal is sparse. Lower values of m are allowed provided the sensing matrix is more incoherent within the domain in which the signal is sparse. In the receiver end, the reconstruction of the signal is done using non-linear algorithms. The signal of interest is X,

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

where x is the sparse vector representing projection coefficients of X on Ψ. The measurement vector can now be defined as:

$$Y=\Theta x \quad (3)$$

where Θ is the reconstruction matrix having size m×n

B. CONTOURLET TRANSFORM

Contourlet form a multi-resolution directional tight frame designed to efficiently approximate images made of smooth regions separated by smooth boundaries. The Contourlet transform has a fast implementation based on a Laplacian Pyramid (LP) decomposition followed by directional filter banks applied on each bandpass subband. This is actually a filter bank structure that takes the smooth contours in an image. The resulting image expansion is a directional multi-resolution analysis framework composed of contour segments, and thus is named contourlet. It gives better results compared to wavelet and curvelet transform since it is a double filter bank structure. It is implemented by pyramidal directional bank filter (PDBF) which decomposes image into directional sub-bands at multiple scales. Based on structure, Contourlet transform is a combination of Laplacian pyramid and directional filter banks i.e., here first we use wavelet-like transform for edge detection, and then a local directional transform for contour segments. The contourlet transform provides a sparse representation for two-dimensional piecewise smooth signals that resemble images.

The Contourlet transform provides a better result due to the grouping of nearby wavelet coefficients. These wavelet coefficients are locally correlated because of the smoothness of the contours. Therefore the sparse expansion of image is obtained by applying a multiscale transform followed by directional transform to gather the nearby basis function at the same scale into linear structure [3].

C. K-SPACE

K-space was introduced in 1979 by Likes and this is widely used in magnetic resonance imaging. K-space is formed by taking the 2-D or 3-D Fourier transform of MR image [4]. The k-space has low frequency information at the center and high frequency data along the border. The central part of the k-space contains signal to noise and contrast information of the image and the peripheral region contain information determining the image resolution.

The Fig. 1(a) is the input MRI image; the k-space of the input MRI image is obtained by taking the 2-D Fourier transform of the input image. We know that the k-space distribution concentrates in the region of origin while it has low levels at the borders (see Fig.1 (b)). The non-uniform signal sparsity can also be seen in 2-D Fourier transform.

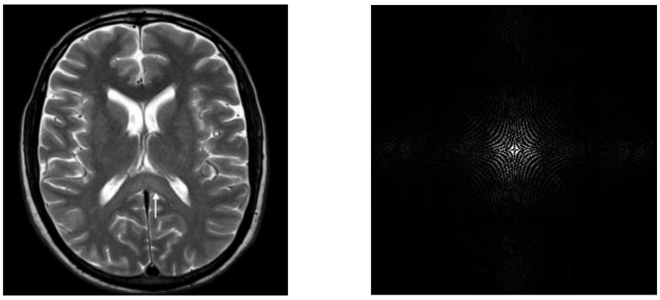


Fig1.Relationship between input image and k-space (a) Brain MRI image (b) k-space formed by taking the Fourier transform of input image.

The energy of the k-space is usually concentrated in the central region for majority of MR images. The 2-D random sampling pattern generally collects more data near the center of k-space. The size of segmented region of the k-space many vary depending upon the different sampling pattern used.

Suppose the input image is having a size N×N, the size of the segmented region is n×n. the sampling density of the selected part is given by $D=k/n^2$, where k is the number of sampled points [4]. With increase in size of n, the quality of the reconstructed image increases and the compression ratio decreases. Thus there is always a tradeoff between compression ratio and the quality of the reconstructed image.

The second factor contributing to the faithful reconstruction of the representative outline is the k-space power (P). If the central part is very small to obtain a high sampling density, then the information content will be very less. Thus the image outline corresponding to the input image cannot represent the whole image. This leads to residual artifact in the reconstructed image.

For the perfect reconstruction of the input MR image we must maintain a proper balance between the sampling density and the power ratio of the selected central part. When the sampling rate is high, there will be more information in the selected k-space center. When the power ration is high, then the k-space data contains more information about the whole image. To balance between these two we consider the average power of the selected part. The average power is given by:

$$AP=D\times P \quad (4)$$

III. PROPOSED METHOD

The proposed method consists of two-stage reconstruction.

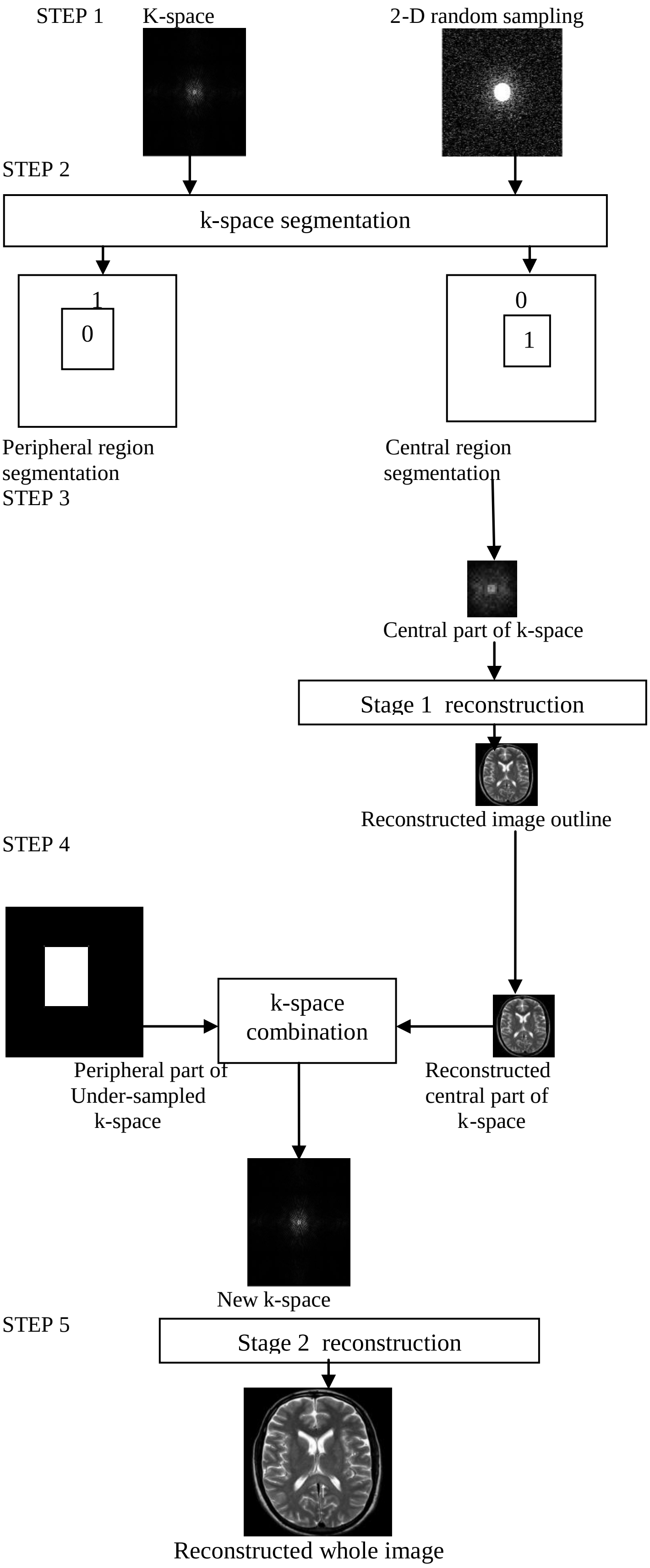


Fig.2. Flow chart of the proposed algorithm

Step1: The Contourlet transform of the input image is taken for first stage compression.
Step 2: k-space is formed by taking the 2-D Fourier transform of the image obtained after step1.
Step3: 2-D random sampling is applied to k-space.
Step4: The central part of the k-space is segmented out using the strategy explained in Section C, II Theory.
Step 4: The reconstruction of the image outline involves taking the inverse Fourier transform of the central part of k-space.
Step 5: k-space combination involves combining the peripheral part of the k-space with the Fourier transform of the image outline obtained in the above step.
Step 6: The inverse Fourier Transform of the k-space so obtained is taken to obtain the input image.

IV. METHOD AND MATERIALS

The performance of the proposed method is tested on three typical MRI images: cardiac cine MR data, sagittal brain MR data and angiography MR data.

The quality of the reconstructed image was assessed using peak signal to noise ratio. All the reconstruction was implemented using a desktop computer utilizing MATLAB. The peak signal to noise ratio is given by:

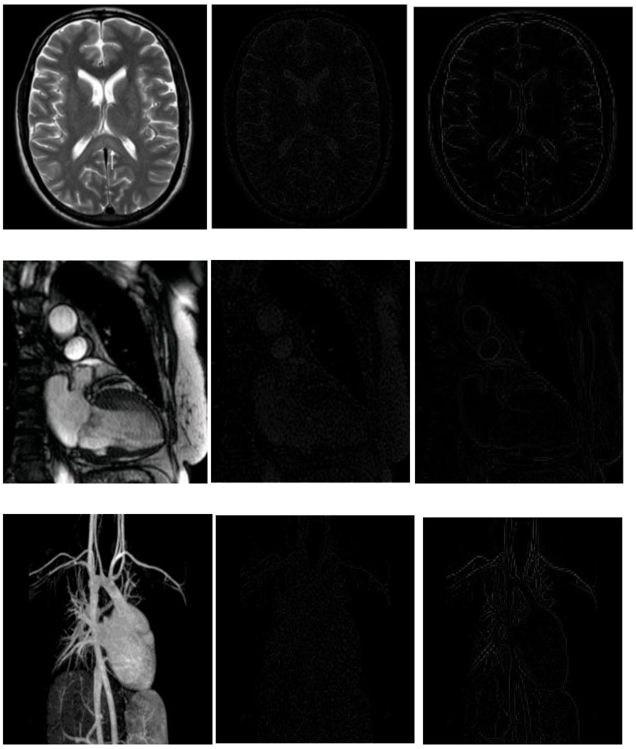
$$PSNR=20log_{10}\left(\frac{MAX_I}{\sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j)-I_{rec}(i,j)]^2}}\right) \quad (5)$$

MAX_I is the maximum possible value of pixel in the image and I_{rec} is the reconstructed image. The difference between the input image and the reconstructed image was taken to visually asses the quality of the reconstructed image.

V. SIMULATION RESULTS

Compared with wavelet transform method, the proposed method shows a better result. Fig 4 shows the difference images for three different MR images. From the figure it is clear that the difference between the input image and the reconstructed image is large when we are using wavelet transform but it is less when we are using the proposed method. This is because here we exploit the inhomogeneous distribution of the k-space power and the variable-density of the sampling pattern. Due to the higher sampling rate of the selected k-space center, the image outline obtained after stage-1 reconstruction is having better quality.

After the experimental analysis the PSNR value obtained for brain MRI was 29.79 when we are using conventional method and 30.51 when we are using the proposed method. Similarly for cardiac and angiogram the PSNR value obtained was 33.32 and 28.53 when we are using conventional method and it is improved to 35.82 and 30.93 for the proposed method.



(a) (b) (c)

Fig.4 (a) Three different MR images: brain, angiogram, cardiac(from top to bottom), (b) difference image obtained after applying the proposed method, (c) difference image obtained after applying conventional compressed sensing

The PSNR value is increased by almost 1dB after using the proposed method. This increase in PSNR is due to the two stage reconstruction method. The image was reconstructed using the low frequency and the high frequency component of the k-space. Here we are using 2-D random sampling. The 2-D random sampling pattern is having a high level of incoherence, thus reconstruction of the image outline will have less residual artifacts.

VI. CONCLUSION

In this paper we have proposed a new method that reduces the artifacts that naturally occur while reconstruction by using two-stage reconstruction algorithm. The method recovers the central and peripheral part of k-space in sequential manner. We have used 2-D random sampling pattern for sampling the k- space, thus the central part of the k-space is less affected after sampling. The new method was tested on three typical MR images. The PSNR value was calculated using (5). The value obtained for brain, cardiac and angiogram MR images are shown in Table1.

MR data	Brain	Angiogram	Cardiac
PSNR	30.51	30.9393	35.82
MSE	60.51	72.5	36.99

Table1. PSNR and MSE value for different MR images

VII. FUTURE WORK

The proposed method was developed on static MR images. The work can be extended to dynamic MR images. 2-Dimentional random sampling can be replaced with pseudorandom sampling which can potentially increase MR imaging speed.

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