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# CARDIAC CINE MRI USING COMPRESSIVE SENSING PRINCIPLES

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***Abstract*— MR images can be reconstructed from undersampled k-t space data to increase image acquisition speed. We propose a new method to undersample the k-space and reconstruct images based on Compressive Sensing (CS) theory. To this end, statistical features extracted from each trajectory are clustered by the fuzzy c-means (FCM) method. The resulting class labels are considered as the states of a Markov chain. A hidden Markov model (HMM) is then trained to find the transition matrix. Trajectories having more non-diagonal transition matrices are chosen to sample data along them. An iterative thresholding algorithm is then used for reconstruction of the image. The proposed method outperforms two other methods in reconstructing half sampled Cardiac Cine MRI data. The use of fuzzy clustering as an intermediate tool to study complicated phenomena by HMM, applicability to non-dynamic MRI data, robustness to noise, faster and more accurate reconstruction describe specifications of the proposed method.**

***Keywords- Cine Cardiac MRI; fuzzy c-Mean; HMM; Compressive Sensing; Inverse Problems.***

## I. INTRODUCTION

Some time-consuming applications of MRI such as fMRI, cardiac and spectroscopic imaging are developed in recent years. Consequently, it seems inevitable to find some solutions to increase MRI speed without losing the image quality. The hardware solution to reduce MRI data acquisition time, using more powerful gradient amplifiers, is limited by technical and biological considerations, though. Therefore, noticeable effort has been put into searching some methods to use intrinsic redundancy and correlation of MRI data in the k-t space to reconstruct images without a complete sampling of the k-t space. We can divide these approaches into the following three categories [1]:

1. Exploiting correlations in the k-space, such as parallel imaging [2], [3];
2. Exploiting temporal correlations, such as UNFOLD [4];
3. Exploiting correlations in both k-space and time domain, such as k-t BLAST [1].

We should emphasize that in the aforementioned methods, the image signal to noise ratio (SNR) decreases as the speed is increased. In this paper, we use CS to decrease the mentioned drawbacks.

In the next Section, we describe the used concepts in this article such as Compressive Sensing (CS) [5], [6], hidden Markov models (HMMs) and the iterative thresholding algorithm for sparse recovery [7], [8]. In the third Section, we attempt to detail the proposed method. Throughout the fuzzy clustering, we will study the k-space trajectories by the use of HMMs and then select the ones having more variations in time. Afterwards, we reconstruct the desired images by going through a sequence of thresholding iterates. In the fourth Section, we present some results of the successful application of the proposed method to reconstruct undersampled Cardiac Cine MRI data. Finally, we present the strengths and drawbacks of the proposed method and give some suggestions to improve it.

## II. THEORY

In this Section, we introduce the theory of compressive sensing [9]. Training the HMMs based on some observations is then discussed. Finally, we introduce our iterative thresholding algorithm for sparse recovery.

### A. Compressive Sensing

Let $x \in \mathrm{R}^N$ and the matrix $\Lambda = [\lambda_1, \lambda_2, \ldots, \lambda_N]$ be a basis for $\mathrm{R}^N$. We say that $x$ is $K$ - *sparse* if we have:

$$x = \sum_{i=1}^{K} \theta_i \lambda_i \tag{1}$$

and $K << N$. Consider also an $M \times N$ *measurement matrix* $\Phi$, $M << N$, where the rows of $\Phi$ are incoherent with the columns of $\Lambda$. Incoherenency between rows of measurement matrix and basis vectors means that we need all of the vectors in the second set to expand each of the vectors in first set and vice versa. Compressive Sensing theory, states that only *cK* incoherent *measurements,* $y = \Phi x$, are required to reconstruct the signal, *x*, with a high probability. It is important to know that the ratio, *c,* is always bigger than 1 and in the most of scientific applications is a number between 3 and 4. Incoherency is an essential condition for this theory to be successful. For example, if the rows of the measurement matrix are i.i.d. Gaussian random vectors, such a matrix is incoherent with any other fixed matrix, with a high probability. The problem of using CS in MRI is exactly lying here, because random sampling of k-t space can be more time-consuming than complete sampling.

### B. Hidden Markov Models

Markov chains [10] are mathematical descriptions of Markov models with a discrete set of states. Markov chains are characterized by:

- A set of states {1, 2, …, M},
- An $M \times M$ transition matrix (T) whose (i,j) entry is the probability of a transition from state i to state j,
- A set of possible outputs or emissions $\{s_1, s_2, \ldots, s_N\}$,
- An $M \times N$ emission matrix (E) whose (i,k) entry gives the probability of emitting symbol $s_k$ given the model is in the state i.

A hidden Markov model is a Markov chain in which we observe a sequence of emissions, but do not know the sequence of states the model went through to generate the emissions. In this paper, we use the Baum-Welch algorithm [10] to estimate the HMM parameters (T and E) for time variations of k-space trajectories, after fuzzy clustering.

### C. Iterative Thresholding Reconstruction

Iterative thresholding algorithms are widely used in the context of inverse problems. In particular, they prove to be very efficient in recovery of sparse signals and images from underdetermined linear equations [11]. Application of iterative thresholding has been very well studied and several algorithms have been proposed by different authors. In this paper, an iterative thresholding algorithm is used to reconstruct the images from limited k-space trajectories. This algorithm can be casted as the following sequence of iterates [7], [8]:

$$f^n = K^*(g + S_\gamma(f^{n-1}) - KS_\gamma(f^{n-1})) \tag{2}$$

With $f^0 = K^* g$.

Where $K$ is the sampling operator and $K^*$ denotes the adjoint operator. $S_\gamma$ is the thresholding operator defined as:

$$S_\gamma(g) = \sum_i s_\gamma(< g, \psi_i >)\psi_i \tag{3}$$

Where $s_\gamma(x) = \begin{cases} x + \dfrac{\gamma}{2}; x \le -\dfrac{\gamma}{2} \\ 0; |x| < \dfrac{\gamma}{2} \\ x - \dfrac{\gamma}{2}; x \ge \dfrac{\gamma}{2} \end{cases}$. (4)

and $\{\psi_i\}$ is the set of orthogonal basis functions.

## III. The Proposed Method

As noted previously, speeding up the MRI by undersampling k-t space contributes to a decrease in SNR of the reconstructed images. On the other hand, the reconstruction step in CS is robust to noise. Furthermore, MR images may have sparse or compressible representations in appropriate transform domains, such as the wavelet domain. Also, use of CS in MRI does not need any specific hardware changes. Therefore, in this research we focus on increasing MRI speed by the idea of CS. Different steps of the proposed method, are described below:

1) Detaching the organ under study from the available images (Heart region from the surrounding area).
2) Making the k-t space corresponding to this organ (for each array coil channel) by 2D Fourier transforming of the detached images.
3) Feature extraction of each k-space Cartesian, radial or spiral trajectory. These features are: average, standard deviation, median and maximum.
4) Clustering the time samples of each k-space trajectory (using the features described above and for each channel of the array coil) by the fuzzy c-means algorithm. The number of clusters is assumed to be a quarter of the number of time samples.
5) Training a hidden Markov model for each k-space trajectory using the Baum-Welch algorithm. The results of the above clustering (for each channel) are considered as the training sequences for the HMM describing time behavior of each k-space trajectory.
6) Using the transition matrix obtained above to decide about selecting or rejecting a k-space. We assume that the trajectories which have more non-diagonal transition matrix carry more information. Thus they are more adequate to be sampled.
7) Reconstruction of the image from the obtained trajectories by (2). In particular, a set of wavelet basis functions will be used in (3).

## IV. Results

The proposed approach was applied to two Cardiac Cine MRI datasets, from an 8-channel coil. To prove the performance of our iterative method, we applied our method, L1+TV minimization by the conjugate-gradient method [12], and the k-t FOCUSS [13] algorithm to a specific undersampled set of data. The results are presented in Fig. 1.

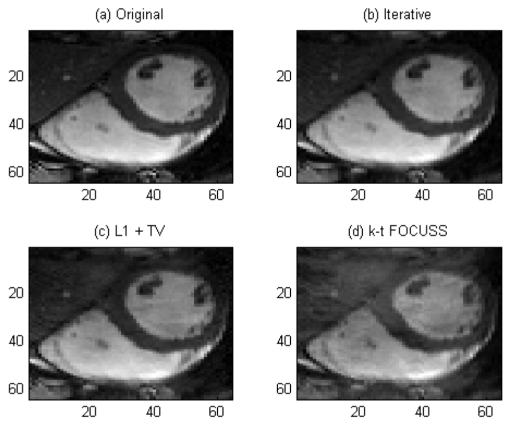


Fig. 1 (a) desired image, (b) image obtained by proposed iterative method, (c) image obtained by L1+TV min. and (d) image obtained by k-t FOCUSS algorithm.

Fig.2 shows the central lines of the images obtained by the above reconstruction methods. It is noted that our iterative method has the lowest relative error.

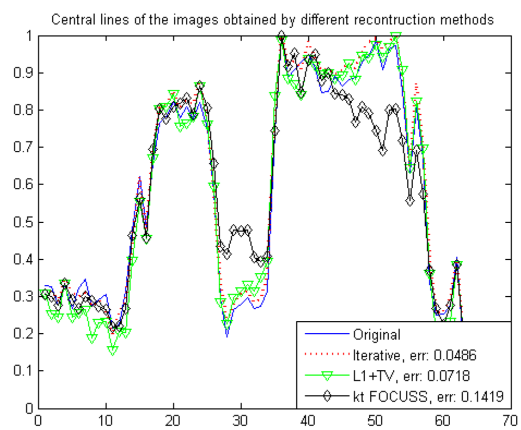


Fig. 1 central lines of the images obtained by different (Iterative, L1+TV min. and k-t FOCUSS) reconstruction methods and relative errors.

To compare some possible trajectories, we produced Cartesian, radial and spiral masks. To this end, we used our proposed method to select 32 of 64 possible trajectories. The results are presented in Fig. 3. Fig. 4 shows the obtained masks and the central lines of the images obtained by different sampling operators (masks). It must be noted that the Cartesian sampling has the lowest relative error.

## V. Discussions and Conclusion

In this article, we presented an approach to increase Cardiac Cine MRI speed by undersampling k-t space. To this end, we studied time behavior of the k-space trajectories by HMM and selected the ones that have large time variations. We used CS principles to reconstruct the desired images. We successfully applied our method to increase speed of Cardiac Cine MRI by factor 2.

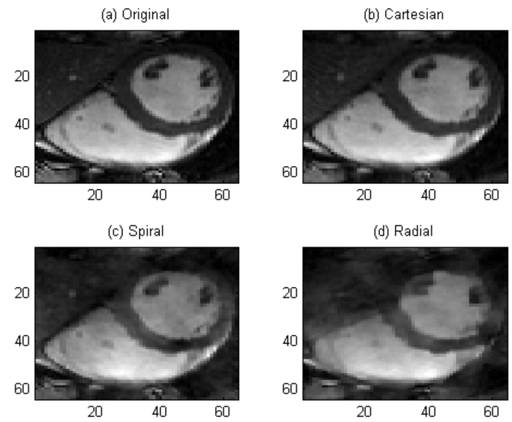


Fig. 2 (a) desired image, images obtained by proposed iterative method and (b) Cartesian, (c) spiral and (d) radial masks.

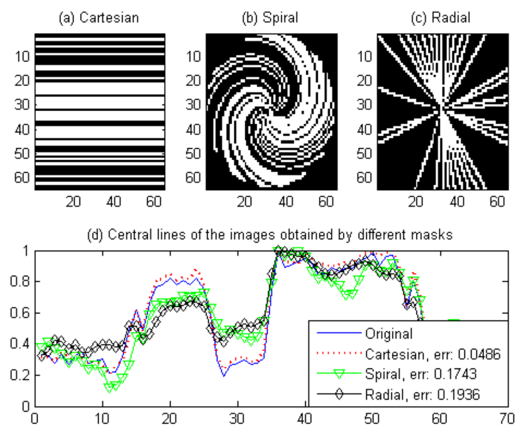


Fig. 4 (a) Cartesian, (b) spiral and (c) radial masks obtained by our HMM-based method. In the all cases we chose 32 of 64 trajectories. (d) central lines of the images obtained by different masks and relative errors.

The use of fuzzy clustering as an intermediate tool to study complicated phenomena by HMM, applicability to nondynamic MRI data and simplicity can be accounted as the specifications of our proposed method. Our iterative reconstruction method is fast, accurate and robust to the noise. It must be noted that we assumed to have access to all of the k-t space data to develop our algorithm. However, in practice we want to know the most important part of the k-t space data to reconstruct acceptable images. On the other hand, we can use the resulting pattern of an individual or a group for the others by assuming similarity of MRI data of an organ in different individuals [14]. Furthermore, we can divide the acquisition process to the two steps: in the first (training) step we fill k-space completely, in the second (undersampling) step we sample along the trajectories which have determined by processing the results of step one.

In the proposed method, we did not use the correlation between two adjacent k-space trajectories to decide about selecting them or not. However, it may be possible to use Distributed Compressive Sensing (DCS) [15] to enter this correlation and get improved results. In addition, we can decide about suitable trajectories by studying a set of different MR Cardiac images. Bayesian CS [16] can be used to study the mentioned set and reconstruct the images.

## REFERENCES


[1] J. Tsao, P. Boesiger, and K. P. Pruessmann, "k-t blast and k-t sense: Dynamic mri with high frame rate exploiting spatiotemporal correlations," Magn Reson Med, vol. 50, no. 5, pp. 1031–1042, 2003.

[2] D. Sodickson and W. Manning, "Simultaneous acquisition of spatial harmonics (smash): Fast imaging with radiofrequency coil arrays," Magn Reson Med, vol. 38, no. 4, pp. 591–603, 1997.

[3] K. Pruessmann, M. Weiger, M. Scheidegger, and P. Boesiger, "Sense: Sensitivity encoding for fast mri," Magn Reson Med, vol. 42, no. 5, pp. 952–962, 1999.

[4] B. Madore, G. Glover, and N. Pelc, "Unaliasing by fourier-encoding the overlaps using the temporal dimension (unfold), applied to cardiac imaging and fmri," Magn Reson Med, 1999.

[5] E. Candes, J. Romberg, and T. Tao, "Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information," IEEE Trans. Inf Theory, vol. 52, pp. 489–509, 2006.

[6] D. Donoho, "Compressed sensing," IEEE Trans. Inf Theory, pp. 1289–1306, 2006.

[7] M.H. Kayvanrad, "Reconstruction from Random measurements," Proceedings of the 9th International Conference on Signal Processing, Beijing, China, 2008, pp. 2697-2701.

[8] M.H. Kayvanrad, D. Zonoobi, A.A. Kassim, "Modified Papoulis-Gerchberg algorithm for sparse srecovery," Preprint, 2009.

[9] M. Duarto, M. Wakin, and R. Baraniuk, "Wavelet-domain compressive signal reconstruction using a hidden tree model," in ICASSP, Las Vegas, NV, USA, Mar–Apr 2008, pp. 5173–5140.

[10] R. Duda, P. Hart, and D. Stork, Pattern Classification, 2nd ed. Wiley-Interscience, 2000, isbn:0471056693.

[11] I. Daubechies, M. Defrise, C. D. Mol, "An Iterative Thresholding Algorithm for Linear Inverse Problems with a Sparsity Constraint," Communications on Pure and Applied Mathematics, vol.57, pp.1413-1457,2004.

[12] M. Lustig, "Sparse mri," Ph.D. dissertation, Dept. Of Electrical Engineering, Stanford University, Sep 2008.

[13] H. Jung, K. H. Sung, K. S. Nayak, E. Y. Kim, and J. C. Ye, "k-t FOCUSS: a general compressed sensing framework for high resolution dynamic MRI," Magn Reson Med , vol. 61, pp. 103-116, 2009.

[14] P. Zamani, H. Soltanian-Zadeh," Reconstruction of Undersampled Cardiac Cine MRI data Using Compressive Sensing Principles," Proceeding of SPARS'09, Saint-Malo, France, April 2009.

[15] D. Baron, M. Duarte, S. Sarvotham, M. Wakin, and R. Baraniuk, "Distributed compressed sensing," Rice University, Tech. Rep. TREE0612, Nov 2006.

[16] Sh. Ji, Y. Xue, L. Carin, "Bayesian Compressive Sensing", Preprint, 2007.