SPATIO-TEMPORAL CONSTRAINED RECONSTRUCTION OF SPARSE DYNAMIC CONTRAST ENHANCED RADIAL MRI DATA

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ABSTRACT

Dynamic Contrast Enhanced (DCE) MRI is a useful technique to probe physiology in an organ or area of interest over time. In this process a contrast agent is injected into the body and images are acquired over time to track the uptake and washout patterns of an area of interest. It takes a relatively long time to acquire full data in k-space for each time frame without tradeoffs in spatial and temporal resolution. We propose a Spatio-Temporal Constrained Reconstruction (STCR) technique that uses spatial and temporal constraints to reconstruct high quality images from undersampled dynamic k-space data. The proposed method was tested on angularly undersampled (sparse) radial dynamic contrast enhanced myocardial perfusion data and compared to standard inverse Fourier reconstructions from full data. The method reconstructed images faithfully from as little as 15% of full data and contrast to noise ratio was improved by 30%. Image quality was preserved even in the presence of some respiratory motion.

Index Terms: DCE MRI, myocardial perfusion, reconstruction, regularization.

1. INTRODUCTION

DCE MRI is used to measure the kinetics of enhancement in an object of interest. It is a promising technique to evaluate and characterize coronary artery disease and tumor uptake patterns among other applications. In DCE MRI a contrast agent is injected into the body and a series of images are acquired over time. The amount of data that can be acquired is limited due to relatively long acquisition times often resulting in tradeoffs in coverage of the organ, spatial, temporal resolutions and signal to noise ratios (SNRs). Various methods [1 – 4] have been proposed to accelerate dynamic imaging by acquiring fewer data in k-space for each time frame and resolving aliasing and degradation using *a priori* information about the data. High acceleration factors cannot usually be achieved for DCE MRI without using training data due to rapid variation in contrast in images, which requires more temporal bandwidth. We recently proposed a Temporally Constrained Reconstruction (TCR) technique [5] to achieve acceleration factors up to a factor of five. The method [5] was applied on sparse cartesian myocardial perfusion data with no respiratory motion. We propose to extend the method [5] to achieve higher acceleration factors by **(i)** incorporating spatial constraints, **(ii)** using radial data instead of cartesian data and **(iii)** testing the method with some respiratory motion.

2. METHODS

2.1. Theory

The standard approach to reconstructing DCE MRI data is to apply a 2D inverse Fourier transform on the full k-space data for each time frame (*k-t* space). Acquiring sparse data, $\tilde{d}$, in *k-t* space results in aliasing artifacts (streaking in the case of radial undersampling). Artifacts can be removed by using *a priori* information about fully sampled data as constraints in a regularization framework [5, 6]. Reconstruction of artifact free images can be obtained by minimizing the cost function C given by

$$\min_{\tilde{m}}(C) = \min_{\tilde{m}}(\phi + \alpha_1 T + \alpha_2 S) \qquad -(1)$$

Where $\tilde{m}$ represents the estimated complex image data, ϕ is the fidelity to the acquired sparse data, and T and S represent the temporal and spatial constraint terms respectively, which are based on characteristics of the fully sampled data. The fidelity term is given by $\phi = \left\|WF\tilde{m} - \tilde{d}\right\|_2^2$ where $\|.\|_2$ represents L_2 norm, W is the binary sparsifying pattern used to obtain sparse data from full data. The temporal regularization term we chose is a maximum smoothness functional [5] given by $T = \sum_{i=1}^{N}\left\|\nabla_t \tilde{m}_i\right\|_2^2$ where ∇_t represents the temporal gradient operator, N is the total number of pixels in each time frame and $\tilde{m}_i$ represents the time curve for pixel i. This choice was based on the fact that for fully sampled image data, the real and imaginary time curves for the pixels are generally smoothly varying in time [5]. The spatial regularization term S we chose is the popular total variation (TV) regularization [7] which is given by $S = \sum_{j=1}^{M}\left\|\sqrt{\nabla_x \tilde{m}_j^2 + \nabla_y \tilde{m}_j^2 + \beta^2}\right\|_1$ where $\|.\|_1$ represents L_1 norm, M is the total number of time frames in the dynamic sequence, ∇_x is the spatial gradient of the image in *x*-direction, ∇_y is the spatial gradient of the image in *y*-direction and β is a small positive constant. $\tilde{m}_j$ represents the time frame j in the dynamic sequence. The TV spatial regularization was chosen in order to reduce the streaking artifacts from radial undersampling, while preserving the spatial edges in the images by not penalizing the gradients excessively. In the above equation (1), α_1 and α_2 are the regularization parameters which control the amount of temporal and spatial regularization, respectively.

Reconstruction from the sparse data is performed by minimizing the cost function, C, given by

$$C = \begin{bmatrix} \left\| WF\tilde{m} - \tilde{d} \right\|_2^2 + \alpha_1 \sum_{i=1}^{N} \left\| \nabla_t \tilde{m}_i \right\|_2^2 \\ +\alpha_2 \sum_{j=1}^{M} \left\| \sqrt{\nabla_x \tilde{m}_j^{\,2} + \nabla_y \tilde{m}_j^{\,2} + \beta^2} \right\|_1 \end{bmatrix} \quad -(2)$$

An iterative gradient descent with finite forward differences was used to minimize the above cost function. The dynamic set of images were updated iteratively according to

$$\tilde{m}^{n+1} = \tilde{m}^n - \lambda C'(\tilde{m}^n);\ n = 0,1,2... \quad -(3)$$

In the above equation $C'(\tilde{m})$ is the Euler Lagrange derivative of C with respect to $\tilde{m}$ which is given by

$$C'(\tilde{m}) = \left\{ \begin{matrix} 2*(F^{-1}(WF\tilde{m}) - F^{-1}(\tilde{d}) - \alpha_1 \nabla_t^2 \tilde{m}) \\ -\alpha_2 \begin{pmatrix} \nabla_x \left(\dfrac{\nabla_x \tilde{m}}{\sqrt{\nabla_x \tilde{m}^2 + \nabla_y \tilde{m}^2 + \beta^2}} \right) \\ +\nabla_y \left(\dfrac{\nabla_y \tilde{m}}{\sqrt{\nabla_x \tilde{m}^2 + \nabla_y \tilde{m}^2 + \beta^2}} \right) \end{pmatrix} \end{matrix} \right\} \quad -(4)$$

In the above equation (4) ∇_t^2 represents the temporal laplacian operator.

2.2. Myocardial perfusion data

The STCR method was tested on simulated sparse radial data obtained from cartesian data and also on sparse actual radial data for dynamic myocardial perfusion, which is a good example of DCE MRI. Cartesian and radial perfusion data were obtained from a Siemens Trio 3T scanner using an eight channel cardiac coil. A saturation recovery turboFLASH sequence with TR/TE ~ 2.2/1.2 msec, flip angle=12 deg., slice thickness=8mm, was used to acquire cartesian and the actual radial data.

Full cartesian k-space data for each time frame were used to simulate radial data by taking 96 equi-angular radial lines passing through the center of k-space to simulate 96 projections. We chose 96 radial lines as the images reconstructed using IFT on the simulated data matched closely with the IFT reconstructions from full cartesian data. The % sparsification for the simulated radial data is defined as the fraction of the total number (96) of radial lines taken for each time frame. The set of projections for the sparse radial data was rotated by a random angle for different time frames. A typical radial mask for a single time frame is shown in figure 1.

Sparsification of full actual radial data was done by sampling a fraction of the total projections in an interleaved fashion. That is, for a given acceleration factor R, for the first time frame the projections nearest to 1, R+1, 2R+1,… were taken, for the second time frame projections nearest to 2, R+2, 2R+2,… and so on were taken. The % sparsification for the actual radial data is defined as the fraction of the total number of projections taken.

The parameters for the spatio-temporal method were empirically chosen based on the results for a single dataset. The regularization parameters α_1 and α_2 were chosen as 0.04 and 0.005 respectively and the step size for the gradient descent λ in equation (3) was chosen as 0.5. The value of β was chosen on the order of machine precision. A fixed number of iterations (1000) were performed to minimize the cost function C. We found that regularization parameters α_1 and α_2 were robust to slight perturbations (by a factor of $\pm$ 0.5). In [5] we used the L-curve technique to determine the optimal regularization parameter for the temporal constraint. We found that for a given undersampling and for a class of data, the optimal value of the regularization parameter did not change significantly [5]. We note that for the current method, techniques like L-surface [8] can be used to determine the optimal values of multiple regularization parameters.

3. RESULTS

3.1. Simulated radial data – No respiratory motion

The results of the STCR approach on a simulated sparse radial perfusion dataset from a single coil with no respiratory motion are shown in figure 2. Figure 2a shows a single time frame in the sequence reconstructed using the standard inverse Fourier transform (IFT) on the full cartesian data with a region of interest in the left ventricular (LV) blood pool region. The corresponding time frame reconstructed using IFT from ~15% (R~6.5) of full data is shown in figure 2b. Figure 2c shows the reconstructed time frame using the STCR approach from the sparse data. The intensity time curves in the reconstructed images for the region shown in figure 2a are compared in figure 2d. From the results we see that the artifacts from undersampling *k-t* space data are significantly reduced and the dynamics are well preserved. SNR for an image frame picked from the center of sequence was computed as $\mu_{LV} / \sigma_{noise}$, where μ_{LV} is the mean signal intensity of a region in the LV blood pool and σ_{noise} is the standard deviation of noise from a region in the background. Contrast to noise ratio (CNR) for the image from the center was computed as $(\mu_{LV} - \mu_{Myo}) / \sigma_{noise}$, where μ_{Myo} is the mean signal for a region in the myocardium. An improvement of 40% was observed in SNR and 38% was observed in CNR over the standard IFT reconstruction.

3.2. Simulated radial data – With respiratory motion

Although it is possible with some patients to acquire rest perfusion data with a good breath hold, it is very difficult for patients to hold their breath during stress perfusion scans. Reconstruction from sparse data with respiratory motion is challenging as it adversely combines with artifacts from undersampling of full data. The proposed method was able to reconstruct faithfully from sparse (~25% of full data) radial data with respiratory motion. The results from single coil data are shown in figure 3. Figure 3a shows a single time frame reconstructed using IFT from a full dataset with considerable respiratory motion along with a region of interest in the LV blood pool. Figure 3b shows the corresponding time frame reconstructed from ~25% of full data and using IFT. Figure 3c shows the corresponding time frame reconstructed from sparse data using the current method. Figure 3d compares the average signal intensity time curves in the reconstructed images for the region shown in figure 3a. Higher sparsification could not be achieved in this case and led to streaking artifacts in the reconstructed images.

3.3. Actual radial data – Minimal respiratory motion

The results of the STCR approach on actual radial data from a single coil are shown in figure 4. Gridding technique using bi-linear interpolation was used to reconstruct images from radial data. The radial data was first density compensated using a ramp filter to account for the oversampling of the center region. Density compensated data was then sampled onto a cartesian grid using bi-linear interpolation. Figure 4a shows a single time frame reconstructed from full radial data using the gridding method followed by IFT. A region of interest in the LV blood pool is also shown. Figure 4b shows the corresponding time frame reconstructed using the gridding method followed by IFT from ~15% (R~6.5) of full data. Figure 4c shows the corresponding time frame reconstructed using the STCR approach from ~15% of full data. Figure 4d shows the mean signal intensity time curves for the region shown in figure 4a. We see that the image features and dynamics are well preserved for reconstruction from sparse data. SNR and CNR, computed as described in section 3.1, were improved by 33% and 31%, respectively, over the standard reconstruction from full data.

4. DISCUSSION

Spatio-temporal regularization method to speed up the acquisition of DCE MRI has been presented. Although the results presented here are for dynamic myocardial perfusion, the method can be easily applied to reconstructing other sparse DCE MRI studies like tumor imaging where high accelerations can be achieved as motion is less of an issue.

Although not shown here, in the presence of motion, we found that the STCR approach with radial undersampling produces better results as compared to cartesian undersampling. This can be due to the fact that in general the artifacts arising from radial undersampling are more benign than those from cartesian undersampling.

Simulating radial data from a cartesian acquisition is a limitation of part of this study. The limitation is shown not to be severe by the fact that comparable results were achieved with an actual radial acquisition.

Only single coil results were presented. The method can be applied independently on multi-coil images and the images can be combined in a square-root-of-sum-of-squares fashion. Alternatively the current method can be combined with parallel imaging techniques to achieve higher accelerations.

Although spatial and temporal regularization terms both help in reducing the artifacts in images due to undersampling, temporal regularization performs significantly better than spatial regularization for a given acceleration factor. As we go to higher acceleration factors and in the presence of motion, the temporal regularization when combined with spatial regularization helps in reducing the streaking artifacts. Figure 5a shows the zoomed image of the dataset in figure 3a which had respiratory motion. Figure 5b shows the corresponding zoomed image frame reconstructed using temporal regularization only, that is α_1 is chosen appropriately and α_2 is set to zero in equation (1). Figure 5c shows the corresponding zoomed frame reconstructed using the STCR approach. We see that the streaking artifacts present in the LV blood pool in figure 5b are reduced in figure 5c.

The algorithm was implemented in Matlab and took about 19 min to reconstruct a sparse dataset with 36 time frames obtained from ~15% of full data on a linux machine with an AMD dual core processor and 4GB ram.

5. CONCLUSIONS

A promising spatio-temporal regularization technique to significantly speed up the acquisition of DCE MRI was presented. Images were reconstructed faithfully using as little as 15% of full data. The method can be used to improve coverage of an organ, spatial and temporal resolution and signal to noise ratios even in the presence of some respiratory motion by using STCR on undersampled radial data.

6. FIGURES

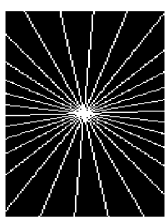
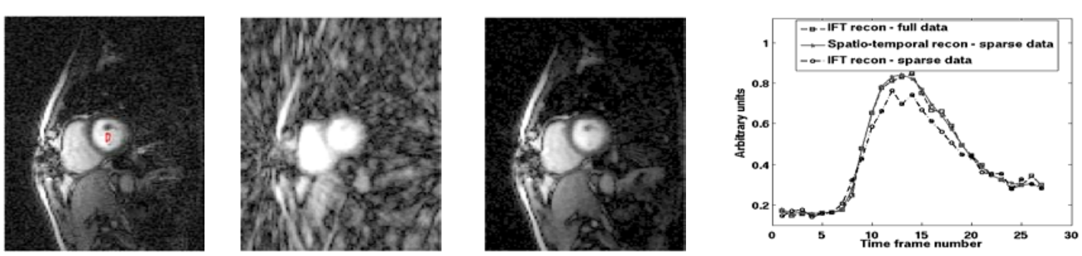


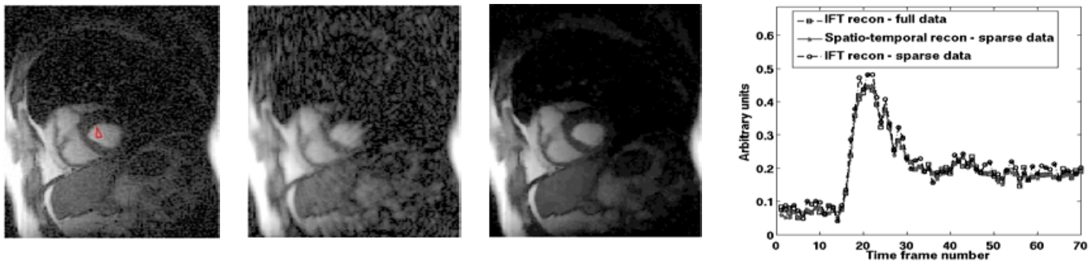
Figure 1. Image showing the binary radial mask for a single time frame used to sparsify full k-space data. The white region represents the sampled data.



(a) (b) (c) (d)

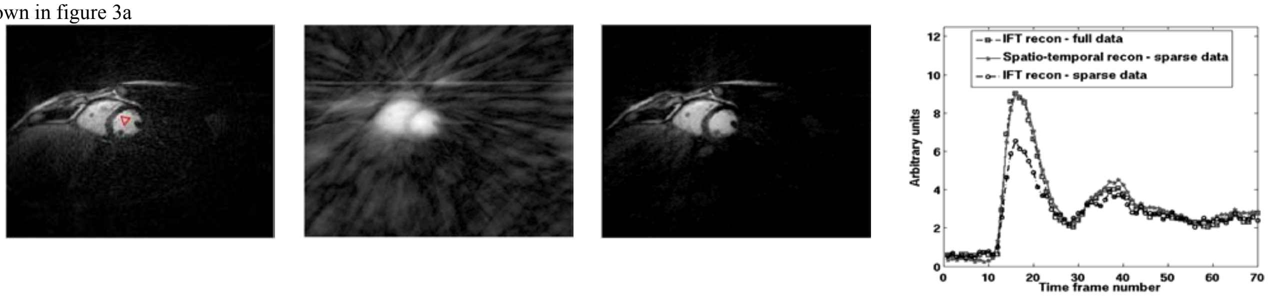
Figure 2 – Results of reconstruction from simulated sparse radial data from a single coil using STCR, no motion case. **(a)** A single time frame reconstructed from full data using IFT with a region of interest in the LV blood pool. **(b)** Corresponding time frame reconstructed using IFT from ~15% of full data **(c)** Corresponding time frame reconstructed from sparse data using STCR. **(d)** Comparison of mean signal intensity time curves for the region shown in figure

2a. Even when selecting a large uniform region, the time curve from the conventional IFT reconstruction from sparse data did not match well with that from full data.



(a) (b) (c) (d)

Figure 3 – Results of reconstruction from simulated sparse radial data from a single coil using STCR, with respiratory motion. **(a)** A single time frame reconstructed from full data using IFT with a region of interest in the LV blood pool. **(b)** Corresponding time frame reconstructed using IFT from ~25% of full data. **(c)** Corresponding time frame reconstructed from sparse data using STCR. **(d)** Comparison of mean signal intensity time curves for the region shown in figure 3a



(a) (b) (c) (d)

Figure 4 – Results of reconstruction from actual radial dataset with little respiratory motion from a single coil using STCR. **(a)** A single time frame reconstructed from full data after gridding followed by IFT. **(b)** Corresponding time frame reconstructed from ~15% of full data after gridding followed by IFT. **(c)** Corresponding time frame reconstructed from sparse data using STCR approach from ~15% of full data. **(d)** Comparison of mean signal intensity time curves for the region shown in figure 4a.

(a) (b) (c)

Figure 5 – Comparison of spatial and temporal regularization, with respiratory motion. **(a)** A single time frame reconstructed from full data using IFT (Zoomed image of the dataset shown in figure 3a). **(b)** Corresponding time frame reconstructed from ~25% of full data using only temporal regularization. An arrow pointing to the streaking in the LV blood pool is shown. **(c)** Corresponding time frame reconstructed from ~25% of full data using STCR. The arrow pointing to the LV blood pool shows the streaking is reduced.

7. REFERENCES

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