Dynamic Imaging Using Sparse Sampling with Rank and Group Sparsity Constraints

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INTRODUCTION

A lot of work has been done in the last few years on fast imaging using sparse sampling. Two key signal properties that have enabled sub-Nyquist sampling are: a) partial separability (PS), which leads to a the formulation of a low-rank matrix [1]; and b) sparsity (à la compressed sensing), which can be seen in various forms in different transform domains [2,3]. Joint use of partial separability and sparsity has also been successfully performed in the past [4,5]. More recently, group sparsity has also been successfully exploited for dynamic imaging [6]. In this abstract, we present a new approach to enforcing partial separability and group sparsity in an integrated manner.

METHODS

For a spatiotemporal image $\rho(\mathbf{r}, t)$, the PS model is expressed as $\rho(\mathbf{r}, t) = \sum_{n=1}^{N} \psi_n(\mathbf{r})\varphi_n(t)$, where $\psi_n(\mathbf{r})$ is the nth set of spatial coefficients with corresponding temporal basis function $\varphi_n(t)$ [1]. When the image is arranged as a matrix $\mathbf{C}$ with rows corresponding to time points and columns corresponding to image voxels, $\mathbf{C}$ will have a rank of at most N and can be factored as $\mathbf{C} = \mathbf{\Phi\Psi}$, where $\mathbf{\Phi}_{ij} = \varphi_j(t_i)$ and $\mathbf{\Psi}_{ij} = \psi_i(\mathbf{r}_j)$ [1]. This model lends itself to interleaved acquisition of two subsets of $(\mathbf{k}, t)$-space data: one set with high temporal resolution (to directly determine the estimated temporal basis $\hat{\mathbf{\Phi}}$ through subspace estimation techniques such as singular value decomposition) and another set with high spatial resolution. We can then obtain the reconstructed spatial coefficient matrix $\hat{\mathbf{\Psi}}$ by fitting $\hat{\mathbf{\Phi}}$ to the sparsely sampled data. Sparsity of the reconstructed image can be enforced during this fitting step by incorporating the penalty $\|T\{\mathbf{C}\}\|_1$ for some linear transform $T\{\cdot\}$ [4,5]. Common choices for $T\{\cdot\}$ include finite-difference operators, wavelet transforms [2], or the temporal Fourier transform [3]. When PS and sparsity are enforced jointly, the model order N of the PS model functions as a tradeoff between the two models: as N increases, the strength of the rank constraint gives way to the sparse constraint and the solution approaches the standard compressed sensing solution. We propose to use group sparsity as a means of controlling the effective PS model order in different spatial regions, thereby exerting more control over the tradeoff between the PS and compressed sensing elements by spatially varying the degrees of freedom. We formulate this as

$$\hat{\mathbf{\Psi}} = \arg\min_{\mathbf{\Psi}} \left\|\mathbf{d} - E\{\hat{\mathbf{\Phi}}\mathbf{\Psi}\}\right\|_2^2 + \|W\{\mathbf{\Psi}\}\|_{1,2}$$

$$\|W\{\mathbf{\Psi}\}\|_{1,2} \triangleq \lambda_1 \left\|T\{\hat{\mathbf{\Phi}}\mathbf{\Psi}\}\right\|_1 + \lambda_2 \sum_{n=N_0+1}^{N} \left(\left\|\psi_{n,\mathrm{ROI}}(\mathbf{r})\right\|_2 + \left\|\psi_{n,\overline{\mathrm{ROI}}}(\mathbf{r})\right\|_1\right),$$

where $\mathbf{d}$ is the measured data, $E\{\cdot\}$ is the imaging operator which describes data acquisition, $\{\psi_{n,\mathrm{ROI}}(\mathbf{r})\}_{n=1}^{N}$ are the spatial coefficients over the region of interest (ROI), and $\{\psi_{n,\overline{\mathrm{ROI}}}(\mathbf{r})\}_{n=1}^{N}$ are the spatial coefficients over the remainder of the image. This allows the ROI to have an effective model order between N_0 and N (inclusive), and the majority of the image outside of the ROI to have the effective model order N_0. In this way, the model order over the ROI can be increased to capture more subtle image features without increasing the degrees of freedom outside of the ROI. We solve the above optimization problem using an additive half-quadratic optimization algorithm with a continuation procedure [4]. It should be noted that the above formulation can be extended to handle multiple spatial regions with multiple effective model orders.

We have implemented an application example of real-time cardiac imaging on a Siemens TRIO 3T scanner using 12 channels of a phased array receiver coil and a customized FLASH pulse sequence with typical imaging parameters as follows: T_R = 5.2 ms, T_E = 3.4 ms, FOV = 344 mm × 380 mm, matrix size 232 × 256, in-plane spatial resolution = 1.5 mm × 1.5 mm, slice thickness = 6 mm. Data were collected continuously with neither ECG gating nor breath holding. The ROI was chosen over the cardiac region. The temporal Fourier transform was used for $T\{\cdot\}$ in order to promote spatial-spectral sparsity.

RESULTS AND DISCUSSION

Fig. 1 shows images reconstructed using sliding window SENSE (left) and using the proposed method (right). Fig. 2 shows the effective ranks of the proposed images by way of normalized singular value curves from the different regions of each reconstruction (the effective rank is N=48 over the cardiac region and N=24 over the remainder of the image). In the proposed method, there are more degrees of freedom over the cardiac region to capture the more subtle image features and complicated motion of the ROI. The images from the proposed method capture the cardiovascular dynamics at a frame rate of 19 fps.

CONCLUSION

We have developed a novel sparse sampling dynamic imaging method which uses a group sparsity constraint to allow flexible integration of sparse sampling approaches exploiting both the partial separability and sparsity of dynamic. This imaging method allows spatially varying model orders for flexible control over the degrees of freedom of the imaging model, balancing the tradeoffs between partial separability and sparsity. We have experimentally demonstrated this method at 1.5 mm in-plane resolution and 19 fps.

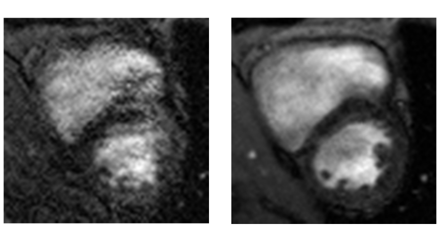

Figure 1. Frames from image sequences reconstructed using sliding window SENSE (left) and the proposed method (right).

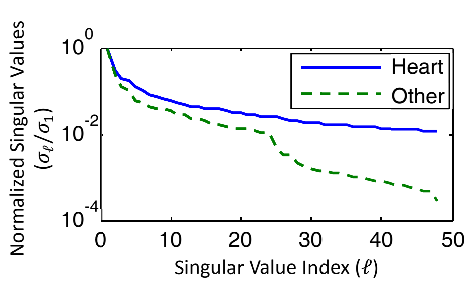

Figure 2. Normalized singular values from the cardiac and non-cardiac regions of the reconstruction.

REFERENCES

[1] Liang, Z.-P. *IEEE-ISBI* 2007. pp. 988-91.
[2] Lustig, M. et al. *MRM* 2007. pp. 1182-95.
[3] Jung, H. et al., *MRM* 2009. pp. 103-16.
[4] Zhao, B. et al. *IEEE-EMBS* 2010. pp. 3390-3.
[5] Zhao, B. et al. *IEEE-ISBI* 2011. pp. 1593-6.
[6] Usman, M. et al. *MRM* 2011. pp. 1163-76.