A Spatiotemporal Model-Based Method for Dynamic Imaging using Phased Array Coils

D. Xu[1], L. Ying[2], Z-P. Liang[1]

[1]Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, United States, [2]Department of Electrical Engineering and Computer Science, University of Wisconsin at Milwaukee, Milwaukee, WI, United States

INTRODUCTION

In dynamic imaging, data are collected in tilted trajectories in k-t space due to time-sequential sampling constraint. These data, when processed using conventional methods, can produce significant motion artifacts and image blurrings. Many methods have been proposed to address these problems, which include fast-scan, reduced-encoding [1], and motion-compensation methods. This paper addresses these problems from a different perspective. Based on a previous method called Dynamic Imaging by Model Estimation [2]-[4], we propose to model the dynamic object function using a spatiotemporal model, where the temporal signal variations are absorbed in the temporal basis functions while the spatial signal variations are incorporated in the series coefficients. Parallel data acquisition is also used to improve the frame rate, thus reducing potential model fitting error.

PROPOSED METHOD

The central idea of the proposed method is to decompose the complex motion of a dynamic object $\rho(\mathbf{x},t)$ as

$$\rho(\mathbf{x},t) = \sum_{m=1}^{M} c_m(\mathbf{x})\varphi_m(t) \tag{1}$$

where M is the model order, $\varphi_m(t)$ are temporal basic functions, and $c_m(\mathbf{x})$ are spatial location-dependent series coefficients. By replacing Eq.(1) in the imaging equation

$$d_l(\mathbf{k},t) = \int_{-\infty}^{\infty} \rho(\mathbf{x},t) s_l(\mathbf{x}) \exp(-i2\pi\mathbf{k}\cdot\mathbf{x})\, d\mathbf{x}\,, \tag{2}$$

where $d_l(\mathbf{k},t)$ are the acquired data, $s_l(\mathbf{x})$ is the sensitivity function at the lth coil (assumed to be static over time), we get

$$d_l(\mathbf{k},t) = \sum_{m=1}^{M} \alpha_m^{(l)}(\mathbf{k})\varphi_m(t) \tag{3}$$

where $\alpha_m^{(l)}(\mathbf{k})$ are the k-space series coefficients that relate to $c_m(\mathbf{x})$ by weighted Fourier transform with weights being the sensitivity functions.

A. Data Acquisition

The proposed method collects a pilot-scan dataset prior to the dynamic imaging experiment to estimate the sensitivity functions of phased array coils [5]. During the experiment, two datasets are collected simultaneously: one navigator dataset for determination of $\varphi_m(t)$ and one dynamic imaging dataset for determination of $\alpha_m^{(l)}(\mathbf{k})$ (Fig. 1). We acquire one imaging signal and Q navigator signals for each excitation with an overall repetition time T_r. The navigator data samples are distributed along vertical lines in the k-t space, whose temporal sampling interval is T_r that often satisfies the Nyquist criterion and k-space locations are chosen in the center to get the largest possible signals. The imaging data samples are acquired in the conventional way except that k-space undersampling of a factor of R is adopted.

B. Image Reconstruction

We first estimate the sensitivity functions of the coils using the pilot-scan data [5]. Then, by using principal component analysis, we extract the first M principal components from the navigator signal to build $\varphi_m(t)$. Based on $\varphi_m(t)$, the series coefficients $\alpha_m^{(l)}(\mathbf{k})$ are estimated by fitting the acquired dynamic imaging data with the model. Using $\alpha_m^{(l)}(\mathbf{k})$ and $\varphi_m(t)$,we interpolate the k-t data (the black filled circles in Fig.2) along temporal axis to satisfy a prescribed temporal resolution (the gray filled circles in Fig.2). Finally, we remove aliasing (due to k-space undersampling) and sensitivity weighting at each time point by SENSE [5], which is equivalent to recover the k-space samples at the Nyquist interval (the empty circles in Fig.2).

RESULTS

A full set of sensitivity-weighted dynamic data was created by multiplying a gated cardiac data set (collected using a spin-echo sequence) with eight simulated coil sensitivity functions (using Biot-Savart's law), followed by Fourier transform. Two datasets with time-sequential samples were then simulated in k-t space by interpolation: (1) 8 frames with $R = 1$, and (2) 16 frames with $R = 2$. Note that the total sampling time is identical for both datasets. Six lines of navigator signals at the center of k-space) were also generated from the sensitivity-weighted dynamic data. Dynamic images were reconstructed using three methods: (a) direct Fourier reconstruction on dataset (1), (b) 2x SENSE reconstruction on dataset (2), and (c) the proposed method on dataset (2). To compare different methods, gold standard images were also reconstructed from the original gated data. Fig. 3 shows a representative frame of the reconstructed image sequences. "Direct FT" has serious motion artifacts due to the tiled sampling. Because of the smaller tilting angle of dataset (2), "2x SENSE" has less motion artifacts than "Direct FT". However, the motion blurring is still noticeable. The proposed method reconstructs an image sequence that has the highest fidelity with the gold standard sequence. In addition to a superb job in motion artifacts correction, reconstructions from the proposed method also have very high spatiotemporal resolution.

CONCLUSION

We propose a model-based dynamic imaging method using phased array coils. This method decomposes the temporal variation of moving objects into independent temporal basis functions, thereby converting the dynamic imaging problem to a parameter identification problem. Parallel data acquisition with phased array coils is used to improve the frame rate, thus reducing potential model fitting error. Simulations based on experimental data have shown that the proposed method can reconstruct motion artifact-free images with very high spatiotemporal resolution.

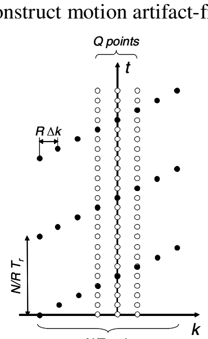

Fig. 1. The proposed data acquisition scheme with dynamic imaging (●) and navigator signals (○).

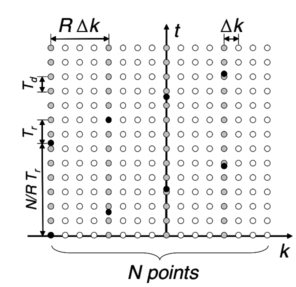

Fig. 2. Interpolation of samples in k-t space (●) using the acquired sample points (●). The rest of the samples (○) are filled using SENSE.

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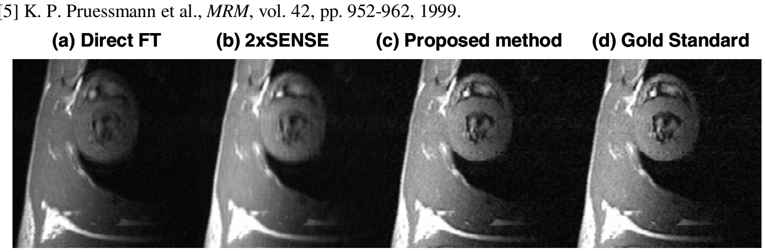

Fig. 3. Reconstructions by various methods on a dataset simulated from a gated cardiac dataset.