Simultaneous Estimation of Dynamic Cardiac MR Images and Deformation Maps

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Purpose: Many spatiotemporal models based on image intensity have been used to accelerate cardiac image acquisition [1,2]. Their performance is limited by the fact that the local pixel intensity can abruptly change due to cardiac motion, and particularly the motion of tissue boundaries. In this work, we consider spatiotemporal models based on 2D deformation and propose an approach for simultaneous estimation of dynamic cardiac MR images and deformation maps from under-sampled k-space data. The working assumption is that myocardium deforms continuously and smoothly, and may result in a lower order model that fully captures the dynamics.

Methods: We denote the dynamic MRI images as $f(\vec{r}_0 + \mu(\sum w_j B_j(\vec{r},t)))$, where $f(\vec{r}_0)$ is a reference image, $\mu()$ is the deformation map, $B(\vec{r},t)$ is the spatiotemporal basis function, which could be thin-plate spline basis as in [3] or pixel basis as in this work, and w_j are the unknown basis coefficients to be estimated. Given partially sampled k-space data d, we can estimate the whole dynamic image series and the deformation map by solving the following optimization problem: $\min_w \left| d - Hf(\vec{r}_0 + \mu(\sum w_j B_j(\vec{r},t))) \right| + \beta R(\vec{w})$, where H is under-sampled Fourier encoding matrix, and β is a parameter to weight smoothness of the deformation map using a Gibbs prior $R(\vec{w})$. The optimization was performed using a conjugate gradient method with Armijo-Goldstein line search. To reduce the computational load, we only estimated one image at a certain time frame, t, using the corresponding partial k-space data, d_t. To simplify the optimization, we also used a mask (yellow boxes in Figure 1) to exclude the relatively static part of the image from the estimation, similar to [4]. We performed SSFP cardiac CINE imaging in a healthy volunteer. The imaging parameters used were: TR= 3.9 ms, FOV= 30×30 cm^2, flip angle= 45º. The k-space data consisted of 34 frames of 192x128 matrixes, which were considered to be fully-sampled k-space data and the corresponding reconstructed images were considered as ground truth. We selected one image from the systole phases and one image from the diastole phases for analysis of the proposed method. The systolic image was used as the reference. The k-space data for the diastolic image was uniformly down-sampled by a factor of 4 in phase encoding direction, and reconstructed using the proposed algorithm. For comparison of deformation map, the true systolic image was then registered to the true diastolic image using nonlinear least square fitting [5].

Results: The top row of Figure 1 shows the true images of systole and diastole, the estimated image of diastole using the proposed method. The diastolic heart structure was reasonably reconstructed with only slight degradation of blood-myocardium contrast. The bottom row of Figure 1 shows the deformation maps inside the mask region estimated from the conventional image registration and from the proposed algorithm.

Conclusions: It is possible to simultaneously estimate dynamic cardiac images and deformation maps between the images from under-sampled MRI data. The current implementation utilized the spatial correlation between two frames for simple proof of concept. Future work will include the combination of images of all time frames for more accurate estimation. Validation of deformation maps estimated by the proposed method should involve comparison with approaches used in myocardial strain imaging. Incorporation of sensitivity encoding [5] and compressed sensing [6] [7] will be also investigated for further acceleration as well as more accurate reconstruction.

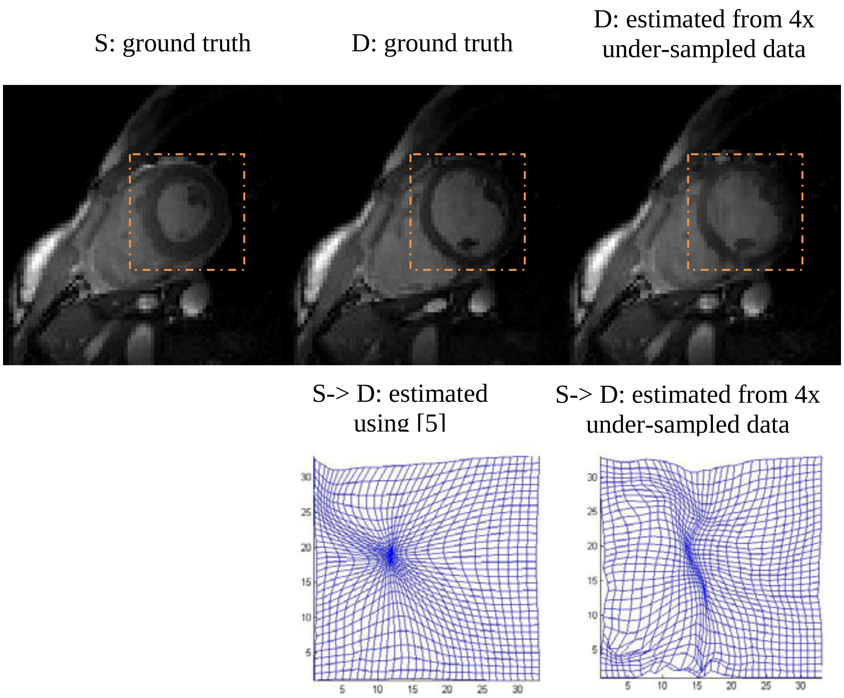

Figure 1. top: ground truth images and estimated image;
bottom: estimated deformation maps.

References:

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