Deformable registration for improved constrained reconstruction of ungated cardiac perfusion MRI

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Introduction: Ungated or self-gated cardiac perfusion imaging are recently proposed approaches to simplify imaging and to reduce reliance on good gating or to image patients with arrhythmias [1]. The method continuously acquires multiple slices by ignoring gating triggers [2]. However, when severe cardiac and respiratory inter-frame motion is present as is common in stress perfusion imaging, spatial and temporal blurring in the reconstruction may occur. Here we propose a reconstruction framework to improve the image quality in such cases by incorporating motion information into the reconstruction. While methods have been proposed to fold in motion estimation into compressed sensing reconstruction to reduce blurring from inter-frame motion in dynamic imaging [3-7], ungated perfusion imaging is more challenging as the contrast in the images is changing in addition to cardiac and respiratory motion. Here we use a model-based diffeomorphic image registration that can handle contrast variation in the images in conjunction with a self-gating method that can lead to improved reconstructions.

Methods: Undersampled radial cardiac perfusion data ignoring ECG gating and at pharmacologically induced stress was acquired on a Siemens 3T Verio scanner using a saturation recovery pulse sequence. Golden ratio based angle spacing of 111.25° was used between the rays. Scan parameters were TR = 2.2 ms, TE = 1.3 ms, matrix size = 288 x 24, [Gd] = 0.075 mmol/kg. Four slices were acquired after each saturation pulse for 250 time frames in ~1 minute. A preliminary spatiotemporal constrained reconstruction (STCR) [8] with total variation constraints as in eq. (1) was performed first. In (1), E incorporates the k-space sampling pattern and coil-sensitivities information that are estimated by using the last 360 spokes in the acquisition. TV_t and TV_s represent total variation constraints [9] along time and space respectively with weights α_t and α_s. d is the acquired k-t space data and m is the reconstructed complex image estimate.

$$\min_m \left(\left\| E(m) - d \right\|_2^2 + \alpha_t TV_t(m) + \alpha_s TV_s(m) \right) \qquad \text{- (1)}$$

Self-gating was performed using magnitude images obtained from (1) to identify cardiac motion. A region of interest around the heart was automatically found and signal intensities in the ROI were summed to obtain a self-gating signal. The image series were binned into (i) approximate systole and (ii) approximate diastole by finding troughs and peaks in the signal. In order to estimate residual cardiac and respiratory motion within each bin we compute diffeomorphic deformation maps using a model-based approach similar to the model-based registration with rigid shifts in [10]. Model reference images were generated by using a two-compartmental model with an input from a region of interest in the RV blood pool [10]. Each image was registered to its corresponding model reference image to obtain a deformation map. We used Advanced Normalization ToolS (ANTS) diffeomorphic registration tool [11], built using ITK [12]. ANTS was originally developed and used in the context of neuroimaging and outperforms several existing state-of-the-art registration methods [13]. The method performs bi-directional diffeomorphic registration that uses a cross-correlation cost function and a Gaussian regularizer on the velocity fields as described in [14]. A major advantage of this approach is that an inverse deformation map exists and it can handle both large as well as small deformations. The computed deformation maps D are used in the reconstruction of binned data as described in equation (2). d_{dia} represents radial k-space data for the diastolic time frames and m_{dia} are corresponding images. Systolic k-space data are reconstructed separately in the same fashion using its own set of deformation maps.

$$\min_{m_{dia}} \left(\left\| E(m_{dia}) - d_{dia} \right\|_2^2 + \alpha_t TV_t(D(m_{dia})) + \alpha_s TV_s(m_{dia}) \right) \qquad \text{- (2)}$$

Folding in the motion-suppressing deformation D into the temporal constraint results in improved temporal sparsity and more effective temporal regularization leading to improved reconstructions. Minimization of the cost function was done in a POCS framework in which temporal and spatial TV filters were applied in an alternating fashion along with projection on-to the fidelity term similar to the approach in [15]. The deformation maps were also updated at the end of every iteration.

Results: Figure 1 shows the results on a stress perfusion dataset. The diastolic and systolic images have improved visualization of the papillary muscles and the myocardial wall has less blurring with fewer motion artifacts after incorporating motion information. A visualization of the motion information incorporated into the reconstruction is shown as a deformed grid. Line profile images show fewer residual artifacts in the final reconstructions as pointed by arrows. Cardiac and respiratory motion are still present in the final reconstructions obtained from (2) as the deformation maps are applied only in the temporal constraint and the data fidelity term still has motion. Registered images can be obtained by applying the final deformation maps.

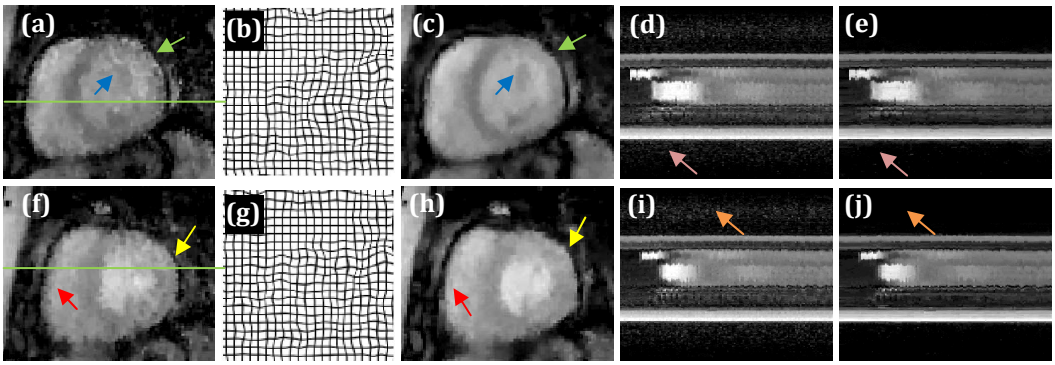

Figure 1: Results on a stress perfusion dataset. **(a)** STCR without incorporating any motion information. A diastolic time frame is shown with a horizontal line. **(b)** Motion information incorporated is shown as a deformed grid. **(c)** Corresponding STCR image after injecting deformation into the reconstruction. **(d, e)** Signal intensity profiles of the horizontal line over time for images in (a) and (c) respectively. **(f-j)** Corresponding images as in (a-e) for a systolic time frame.

Discussion & Conclusion: Estimating and applying diffeomorphic maps every iteration increases computational burden in the proposed multi-coil STCR reconstruction. Parallel computing using 12 CPU cores resulted in additional 14 minutes per iteration, but after this time investment and applying the deformations, the motion-compensated images can be used directly clinically or to compute quantitative perfusion parameters. Using GPUs can reduce the computational burden. Self-gating with deformable registration is a promising framework to improve the image quality of undersampled cardiac perfusion MRI with inter-frame motion.

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