Application of Low-Rank Matrix-Completion Reconstruction Combined with Segmentation and Parallel Imaging in Lower Extremities Perfusion Imaging

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Target Audience: MR engineers, scientists and clinicians interested in image reconstruction, perfusion imaging or lower extremities imaging.

Purpose: Perfusion imaging in the lower extremities can provide significant help in the assessment of peripheral arterial disease, but remains challenging due to the requirement of large volumetric coverage and high temporal resolution. A low-rank matrix-completion reconstruction method has been proposed for accelerating dynamic contrast-enhanced (DCE) perfusion imaging [1]. To further improve the reconstruction accuracy and temporal resolution, a reconstruction method that combines the low-rank matrix-completion reconstruction with an image-based segmentation and parallel imaging is developed and tested *in vivo*.

Methods: In perfusion imaging, the Casorati form (each column depicts the image at one time frame) of the image series is a low-rank matrix X [2][3] because of data redundancy between multiple time frames, and limited number of basis functions in the perfusion dynamics. Defining the undersampled k-space data as y, the matrix X can be recovered by solving [4]:

$$\min_X \mu||X||_* + ||PFX - y||^2$$

$||X||_*$ is the sum of singular values of X and μ is the regularization coefficient. P is the undersampling operator and F is the Fourier transform operator.

To improve the reconstruction accuracy and increase the frame rate, we combine parallel imaging, and modify the optimization problem as:

$$\min_X \mu\Sigma_i||X_{Si}||_* + ||PFSX - y||^2$$

X_{Si} is the Casorati form of segmented images. The segmentation is based on the three types of dynamic behavior in DCE perfusion imaging: (1) blood with a signal amplitude overshoot; (2) muscle with signal amplitude increasing continuously with time; (3) fat with signal remaining static over time. The segmentation improves low-rank property and avoids temporal blurring between different dynamic behavior, thereby improving reconstruction accuracy.

S is the coil sensitivity map, which is a constraint between the true image and the acquired data. By including this constraint in the measurement error term, parallel imaging is combined with the low-rank matrix-completion method, enabling higher acceleration factors. Several time frames are fully sampled at the beginning and end of scan, from which the coil sensitivity map can be estimated.

Results and Discussion: DCE images were acquired on a GE 1.5T scanner using a uniformly random undersampled 3DFT SPGR sequence with an 8-channel cardiac coil and the following parameters: TR/TE = 4.4/1.7ms, flip angle = 20°, matrix size = 128x64x40, FOV = 36x18x32 cm^3, acceleration factor (AF) = 4.4, temporal resolution = 2.7 s. The center axial slice images (Fig. 1(a)) and corresponding normalized images (Fig. 1(b)) show that the dynamics of various tissues are clearly captured. Time curves reconstructed with different methods are shown in Fig. 2. The view-sharing method [5] is noisier and suffers more temporal blurring because it simply uses the nearest neighbour's value for data not acquired, while the low-rank constraint denoises the time curves. Low-rank reconstruction without segmentation recovers the muscle signal well but underestimates the arterial signal. The proposed method gives the least temporal blurring in this dataset. In addition, the acquired data were retrospectively undersampled to AF = 7.3 and reconstructed with the proposed method. The results agree well with the time curves of AF = 4.4, suggesting possible higher acceleration factors. As a semi-quantitative analysis, the maximum slope of signal rise and the Fermi impulse response [6] are shown in Fig. 3.

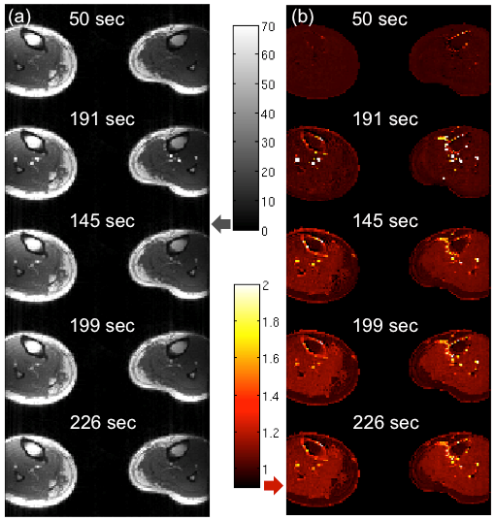

Figure 1. *(a) Perfusion images of the center axial slice at different time. (b) Images normalized to average of 5th to 7th time frames (80 time frames in total).*

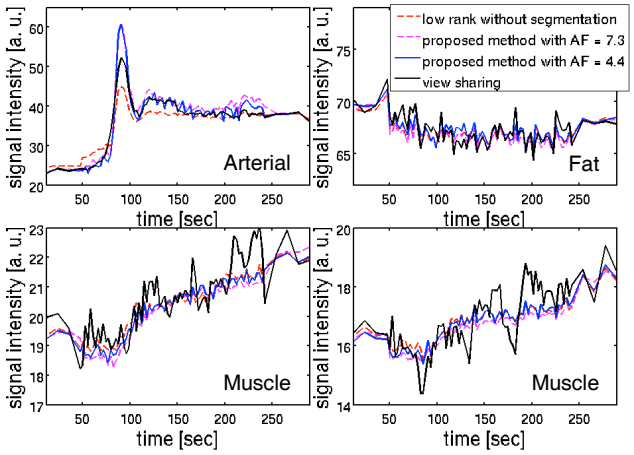

Figure 2. *Time curves reconstructed with different methods (single pixel in arterial, fat and muscle). The proposed method shows the least temporal blurring. Reconstruction with AF = 7.3 also agrees well with AF = 4.4, showing potential higher acceleration factor.*

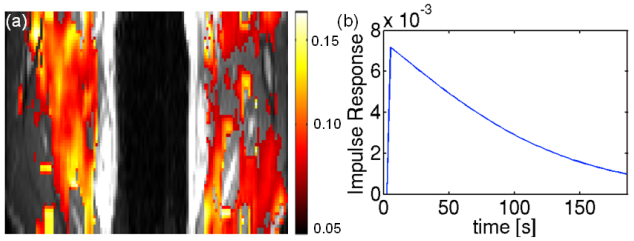

Figure 3. *(a) Maximum slope (calculated with spatial average of 5x5 ROI) overlaid in the coronal image. (b) Impulse response estimated by Fermi deconvolution of normalized muscle signal intensity (5x5 ROI) with normalized arterial input.*

Conclusion: Combined with image-based segmentation and parallel imaging, the low-rank matrix-completion method can achieve better reconstruction accuracy and higher acceleration factors. The proposed method can recover perfusion dynamics with less temporal blurring, and is promising for quantitative perfusion imaging in the lower extremities.

References: **[1]** Luo J, *et al.*, ISMRM, 2012; **[2]** Haldar J and Liang Z, Proc. ISBI 2010; **[3]** J Trzasko, *et al.*, Proc. 19th ISMRM, p. 298, 2011; **[4]** Candés EJ, *et al.*, CACM 55: 111-119, 2012; **[5]** Foo TK, *et al.*, Radiology 195: 471–88,1995; **[6]** Axel L , *et al.*, Radiology 18: 94–99, 1983.