Region adaptive motion compensated dynamic CS for cardiac perfusion imaging

Huisu Yoon[1] and Jong Chul Ye[1]
[1]*Dept. of Bio & Brain Engineering, KAIST, Dae-jeon, Korea*

Purpose: One of the technical difficulties of perfusion MRI comes from that the image contrast rapidly changes along time while suffering from respiratory motion. In this paper, we extend a motion compensated dynamic CS using patch-based low-rank regularization technique[1] to cardiac perfusion imaging. We exploited that in cardiac perfusion imaging only small portion of the image is moving due to breathing, while the other parts are relatively stationary. Experimental results show that the proposed region-dependent patch search method clearly reconstructs drastic movement of dynamic perfusion image with much reduced computational complexity compared to the entire search method[2].

Method: The reconstruction problem is formulated as a minimization problem of the following augmented cost function[1]:

$$\mathrm{C(W,x)} = \left\|y - Fx\right\|^2 + \Sigma_p \lambda_p \left\{ \frac{1}{\mu} \left\| V_p(x) - W_p \right\|_F^2 + \left\| W_P \right\|_{g_{\mu,\nu}} \right\}$$

where y is a k-t space data, F is a 2-D Fourier sampling operator, and x is an unknown spatio-temporal image. The second/third terms correspond to the patch-based low rank regularization with augmented patch variable W_p, which is derived using half-quadratic regularization technique for Huber-based non-convex low rank penalty for the temporal patch groups V_p. The similarity patch groups are obtained using overlapping patches. The solutions $x^{(k)}$ and $\{W^{(k)}\}$ are resolved by alternating minimization. Due to the non-convexity, the final solution depends on the initialization, and we use the k-t FOCUSS with Karhunen-Loève transform (KLT) as an initialization[3]. To verify the performance, real *in vivo* perfusion data was obtained from *http://www.engineering.uiowa.edu/~jcb/software.html*. The size of the data was 90×190 and 20 radial spokes were sampled per frame with random rotation. The number of time frame was 70. Initially reconstructed image facilitates the search of similar patches, enabling fast reconstruction with the small number of iterations. Furthermore, it was used to partition the moving and stationary regions. Specifically, using total variation values of the image along the temporal direction and sorting them, we can partition the image into the moving and stationary regions as shown in Figure 1(b) and (c). For the pixels in moving region, we search for similar patches spatiotemporally to catch cardiac motion. For stationary region, we just collect the fixed number of patches along temporal direction assuming that there is little or no motion. For patch-based regularization, parameters were set as follows: Patch size 4 × 4, window size 11 × 11 × 5 for moving region, μ=0.001 and ν=0.003. λ=10 and 5 patches were collected.

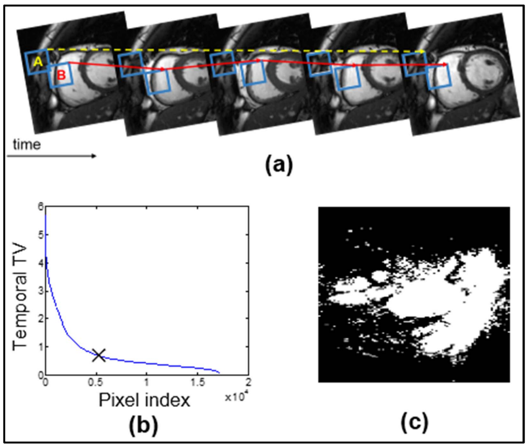

Figure 1. (a) A patch in moving area (B) has similar patches along cardiac wall motion, while patch in static area (A) has similar patches at the same position in temporal frames. (b) Temporal total variation is sorted and one value can be chosen as a threshold which separates moving and stationary regions. (c) Partitioned region of a dynamic image. White region represents moving region while black region represents still area.

Results: We compared the proposed algorithm with k-t FOCUSS with KLT[3] and k-t SLR[2]. k-t SLR is another low-rank based algorithm for dynamic imaging by exploiting the low-rankness of an entire image. In Figure 2, while k-t SLR and the proposed algorithms show better results than the k-t FOCUSS with KLT in the moving frames (B), the proposed algorithm shows improved reconstruction quality than k-t SLR as the arrows indicate. This is due to the motion adaptive nature of the patch-based low rank penalty. Furthermore, the proposed algorithm has the lowest MSE value.

Finally, we compared the proposed region-dependent patch regularization scheme with the scheme that searches for similar patches in spatiotemporal neighborhood in the whole pixel positions[1]. Table shows that the proposed algorithm offers highly reduced computation time while improving image quality.

Conclusion: In this work, we applied motion-compensated dynamic CS using patch-based low-rank regularization technique to non-periodic cardiac perfusion imaging. Moving and stationary regions were separated for efficient computation. Experimental results show that the proposed method is advantageous in both quality and complexity compared to the existing methods.

Search type	MSE	Running time
Region dependent	0.0135	798.4sec
Entire image	0.0137	1368.6sec

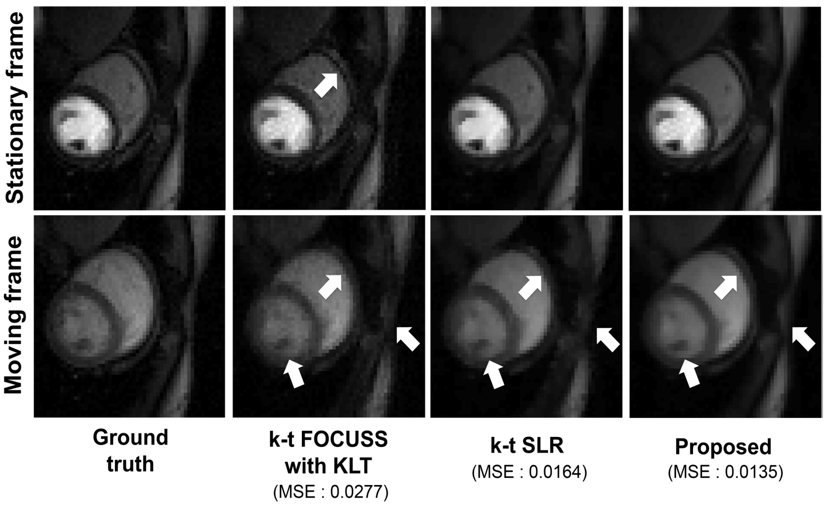

Figure 2. The reconstructed images using various algorithms are compared in the ROI regions. The first row shows the reconstruction images in the stationary frames, while the second row shows them in the moving frames. Also, the mean squared error (MSE) values were computed for the reconstruction methods.

References: 1.Yoon H, *et al.* ISMRM 2013, p3803; 2. Lingala S, *et al.* IEEE Trans Med Imag 2011; 30:1042-1054; 3. Jung H, *et al.* MRM p 103, 2009;