Patch based low rank constrained reconstruction for diffusion MRI

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Introduction: Diffusion imaging is a promising tool to diagnose and characterize stroke. However an acquisition that is based on a standard diffusion tensor model cannot resolve crossing fibers. Resolving crossing fibers requires acquisition of a number of diffusion directions for different b-values, which can be very time consuming but may be important for a more accurate assessment of white matter tracts and applications such as the prognosis of stroke recovery. Several methods have been proposed that undersample k-space diffusion data and use advanced reconstruction methods like compressed sensing to remove undersampling artifacts [1-4] by exploiting redundancies across different diffusion directions. Low rank based constrained reconstruction methods offer a promising way to exploit redundancies in dynamic MR acquisitions and have been applied to cardiac and breast imaging, for example [5-8]. However, diffusion images may not satisfy the low rank property directly as image intensities are changing randomly across directions [2, 9]. Recently, a patch-based low rank method was proposed to accelerate cardiac imaging and was shown to outperform the standard low rank method [10, 11]. Instead of exploiting the low rank property of the Casorati matrix formed using entire image frame for different directions, a patch-based constraint more efficiently exploits low rank property by using smaller spatial patches. Here we explore the applicability of a patch-based low rank constraint on retrospectively undersampled multi-shell diffusion data.

Methods: Diffusion data was acquired with a standard EPI sequence on a stroke patient using a 32-channel head coil on a Siemens 3T Verio scanner. Data in four shells with b=500 (20 directions), b=1000 (30 directions), b=2000 (64 directions), b=5000 (64 directions) were acquired with identical echo time for all shells. b=0 image was acquired separately for each shell. Other scan parameters were TR=264 msec, TE=138 msec, FOV= 230 mm^2, matrix size=108 x 108 and 36 slices were acquired with a slice thickness of 3 mm. Fully sampled raw k-space data was retrospectively undersampled in a variable density pseudo-random undersampling fashion by a factor of three. Patch-based low rank reconstruction from undersampled data was performed by iteratively minimizing the cost function C in (1).

$$C = \|Em - d\|_2^2 + \alpha \sum_{j=1}^{np} \left\|P_j(m)\right\|_* \qquad -(1)$$

In (1) E is the forward encoding operator with coil sensitivities that maps the combined coil image estimate m to undersampled k-space data for all coils d. P_j is the patch-extraction operator that extracts a spatial patch across diffusion directions and rearranges the data into a Casorati matrix. $\| \quad \|_*$ represents the nuclear norm, np is the total number of patches and α is the weighting factor for the patch-based low rank constraint. Overlapping circular patches were chosen so that the entire image frame is covered with little overlap. Coil sensitivities were estimated using the fully sampled b=0 image and reconstruction of each shell data was done independently. Undersampled data reconstructions from (1) were compared to fully sampled inverse Fourier transform reconstructions using difference images for diffusion directions. Fractional anisotropy maps computed using all shells were also compared.

Results: Figures 1 and 2 compare the reconstructions from undersampled data with those from fully sampled ground truth data. Diffusion images and the corresponding greyscale and color-coded fractional anisotropy maps from patch-based low rank constrained reconstruction match well with those corresponding to ground truth reconstructions. The difference images have few structures and low signal revealing minimal loss in overall quality.

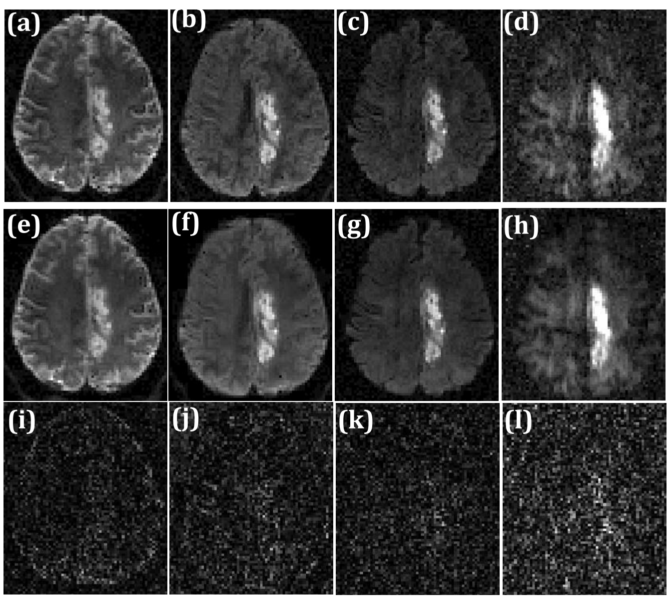

Figure 1: **(a-d)** Fully sampled ground truth images reconstructed using inverse Fourier transform. From left to right one diffusion direction in each shell corresponding to b=500, b=1000, b=2000, b=5000 are shown. **(e-h)** Corresponding R=3 images reconstructed using patch based low rank constraint. **(i-l)** Corresponding absolute difference images between (a-d) and (e-h) respectively. Peak intensity in (i-l) is 15% of peak intensity in (a-d) respectively.

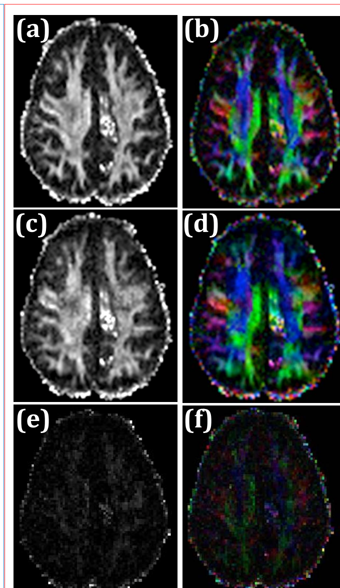

Figure 2: **(a-b)** Fractional anisotropy (FA) maps obtained from fully sampled data **(c-d)** Corresponding FA maps from R=3 data reconstructed using patch-based low rank constraint. **(e-f)** Absolute difference images between (a-b) and (c-d) respectively. Peak signal intensity in (e-f) is same as the peak signal intensity in (a-b) respectively.

Discussion and Conclusions: Patch-based low rank constrained reconstruction is a promising method to remove undersampling artifacts that can be applied to diffusion imaging data. Since diffusion preparation is the dominant time consuming part in acquiring a diffusion image, the proposed approach here can be used in conjunction with Simultaneous Image Refocusing methods [12, 13] that acquire multiple slices for a single preparation but suffer from long readout times.

References: [1] Alexander et al ISMRM #858, 2006. [2] Adluru et al IJBI, ID 341684, 2008. [3] Welsh et al, MRM 70: 429-40, 2013. [4] Wu et al MRM epub, 2013. [5] Liang et al IEEE ISBI 988-91, 2007. [6] Haldar et al IEEE ISBI 716-19, 2010. [7] Lingala et al IEEE TMI 30:1042-54, 2011. [8] Majumdar et al 30:1483-94, 2012. [9] Adluru ISMRM 2011. [10] Trzasko et al ISMRM #4371, 2011. [11] Chen et al ISMRM #4555, 2013. [12] Feinberg et al MRM 48:1-5, 2002. [13] Feinberg et al PLoS ONE 5(12), e15710, 2010.