DWI denoising using overcomplete Local PCA Decomposition

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Introduction

Diffusion weighted (DW) images have an inherent low Signal to Noise Ratio (SNR) due to the impact of thermal noise. To increase the Signal to Noise Ratio (SNR) is common to increase the number of acquisitions thus reducing the noise variance. On the other hand, denoising techniques can be applied to improve data quality as a postprocessing step. In this work, we propose a new denoising method based on local PCA designed to take advantage of the natural pattern redundancy of these images.

Methods

We propose to use a local PCA decomposition based method. In brief, for each point x of the image, the 3D patches surrounding x in each channel k are reordered as a column vector of a matrix. This matrix is a NxK matrix where N corresponds to the number of elements of the 3D patch around the point of interest (N=27, i.e. a 3x3x3 voxel patch) and K is the number of image components. After PCA decomposition, the obtained components are processed using soft thresholding prior to recompose the original matrix. Finally, after reconstruction the filtered intensity value for a particular pixel can be obtained through averaging over the multiple overlapping windows estimates. Such averaging allows removing more noise and minimizes Gibbs artifacts.

Results and conclusion

Simulations using a synthetic phantom several noise levels showed that the proposed method improved state of the art methods [1,2] significantly. We also applied the proposed method to real DWI data and the results were consistently better than the other compared method (see figure 1 were denoised results and corresponding image residuals are showed).

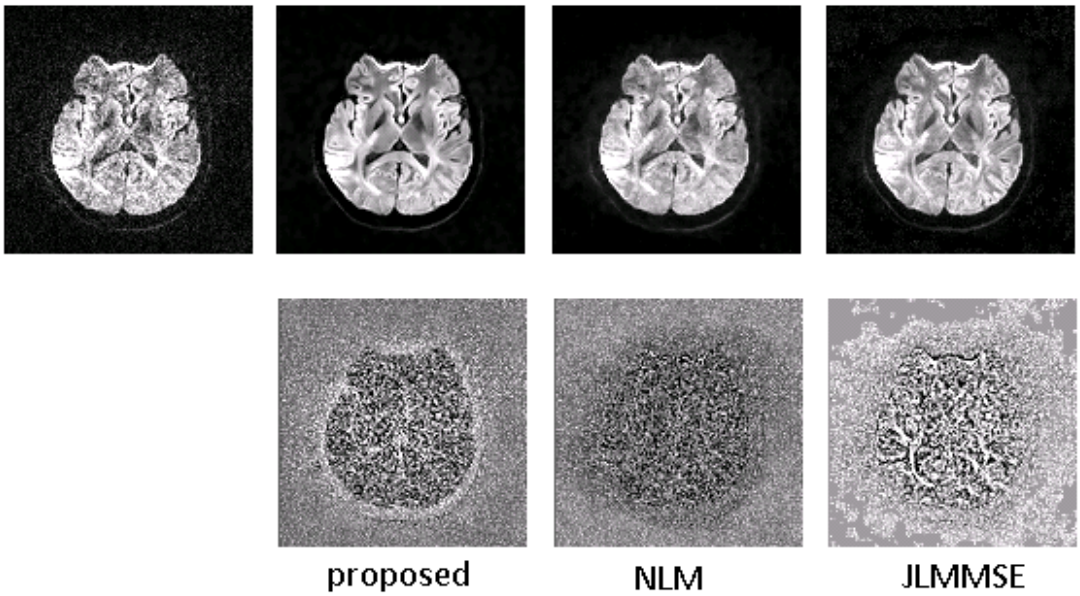

Figure 1. Example results of the different denoising methods compared. Upper row, from left to right: original noisy data, proposed method, Non-local means and JLMMSE results. In the lower row the corresponding image residuals computed subtracting noisy data with its corresponding filtered data.

References

1. Wiest-Daesslé et al. Non-local means variants for denoising of diffusion-weighted and diffusion tensor MRI. MICCAI 2007 :p344-351.
2. Tristán-Vega et al. DWI filtering using joint information for DTI and HARDI. Med Image Anal. 2010. 14(2):205-18.