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Denoising of Diffusion Weighted Images Using Statistical Based Method: An Extension of Joint LMMSE Approach

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Due to low Signal to Noise Ratio (SNR) in the Diffusion Weighted Images (DWI) in the presence of noise which causes the effect of bias in the estimation and analysis of diffusion weighted imaging parameters before tensor estimation. The proposed work, that considers the many-directional DWI datasets which employed in diffusion weighted sequence. The proposed work which is an extension of the Linear Minimum Mean Square Error Estimator (LMMSE) *i.e.*, adaptive wiener filter is better preserving anatomical details in the edge which is important for clinical practice. The standard LMMSE method addresses the Rician distributions and jointly accounts for DWI channels. The proposed work which employ a Non-Local Means (NLM) algorithm which differentiate entire volume of data corresponding to different data sets, which is able to improve the anatomical structures of the DWI. The results demonstrated that both synthetic and clinical DWI data sets the proposed work outperforms the standard LMMSE method on DWI data sets degraded with Rician distribution of noise. However, with respect to the standard LMMSE filtering method employing the analysis and estimation of effective voxel wise parameters, the proposed method give better results in terms of SNR. The results demonstrate that new proposed work outperforms several existing methods for different noise levels. The joint anisotropic LMMSE filter for DWI which provides a nice trade-off between the dramatic improvement of the SNR and the preservation of anatomical details required for clinical practice. Specifically, it is able to clean the DWI channels without introducing a systematic bias in the FA and tractography before tensor estimation.

Keywords : Denoising, Diffusion Weighted Images, High Angular Resolution Diffusion Imaging (HARDI), Signal-to-Noise Ratio, Tensor Estimation.

1. INTRODUCTION

In Diffusion weighted images, the selected gradient direction depends on the direction of white matter fibers in the brain which helps to identify brain connectivity [1] and Alzheimer disease detection especially for HARDI data. In the diffusion sequence MRI, where the white matter appears as a region of similarity pixels *i.e.*, uniform intensity in the entire field of view, but DW-MRI image intensities dependent on the direction of diffusion which is measure of fibre tracking [1] to measure brain connectivity before tensor estimation.

The low SNR in the large diffusion causes low signal intensity is improved by repeated imaging and which causes long acquisition time and introduces artifacts. However, in case of HARDI DWI data, it requires multiple data to be acquired with many gradient directions to be needed in which it causes prohibitive scan durations and physical averaging procedures. In such cases, post processing algorithm is necessary to improve SNR from degraded DW images is required. Various algorithms are studied in the MRI literature which is help to improve the analysis and estimation of diffusion parameters like ADC (anisotropic diffusion coefficient) and FA (fractional Anisotropy) and tractography.

peak at the cc as show in Figure 10(a) and Figure 10(b).

3.1. Image quality evaluation metrics

The PSNR is widely used performance quality metrics [15] and is directly related to mean squared error (MSE) after restoration. The peak signal to noise ratio in decibel (dB) is defined using the following formula.

$$PSNR = 10 \log \frac{255^2}{MSE} \tag{6}$$

$$MSE = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=0}^{N} [u(x,y) - v(x,y)]^2 \tag{7}$$

The PSNR defines the equivalence between gray levels not for pixels. And need to define another performance parameter called image quality index (IQI) which considers the equivalence between the reconstructed image and the original noiseless image are defined using the following formula.

$$IQI = \frac{\sigma_{fg}}{\sigma_f \sigma_g} \frac{2\overline{f}\overline{g}}{(\overline{f})^2 + (\overline{g})^2} \frac{2\sigma_f \sigma_g}{\sigma_f^2 + \sigma_g^2} \tag{8}$$

3.1.1. Validation on Real Clinical MR Data

The experiments are based on MRI datasets. The dataset are clinical MRI collected from JSS Hospital, Mysore, Karnataka, India. DWI data set (60 gradients, 1 baseline, matrix: 128×128 × 66, isotropic resolution 2 × 2 × 2 m^3) with a dual b value of 800 s/mm^2 and 1000 s/m^2, we filter each volume with the UNLM technique and JLMMSE. The proposed approach is simulated with clinical images acquired from Philips MRI scanner 3.0T using fast echo Spin Sequences having long and short acquisition time as shown in Figure 1.

4. CONCLUSIONS

The proposed filter is the improvement of the paper [14] and can be applied to structural and diffusion weighted (DWI) images which shows better improvement of execution time and performance metrics compared to standard filters. The joint anisotropic LMMSE filter for DWI provides improvement of the SNR and the preservation of anatomical details important for clinical practice and to improve the measurement of diffusion parameters. The current scheme may also be further developed in several ways. First, we have considered a stationary Rician model for the noise pattern (*i.e.*, a constant value of σ for the entire Field of View), the entire evaluation of our proposal has been intended for DTI-like data sets. With High Angular Resolution volumes, which are usually acquired with larger b values, the optimal parameters inferred from the experiments may be no longer appropriate. Indeed, an adaptive value of h fitted to the SNR and the level of detail at each voxel is an interesting improvement for the future enhancement.

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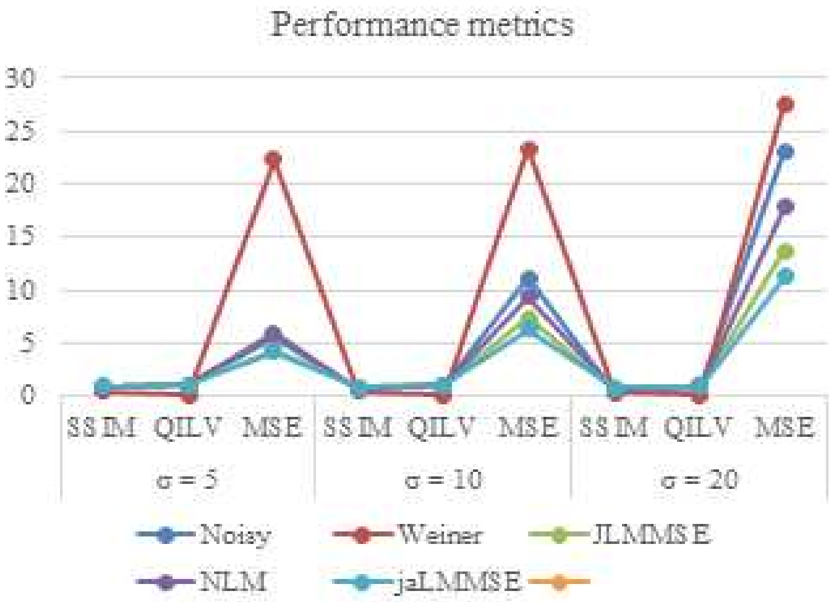

Figure 6. Performance Metrics

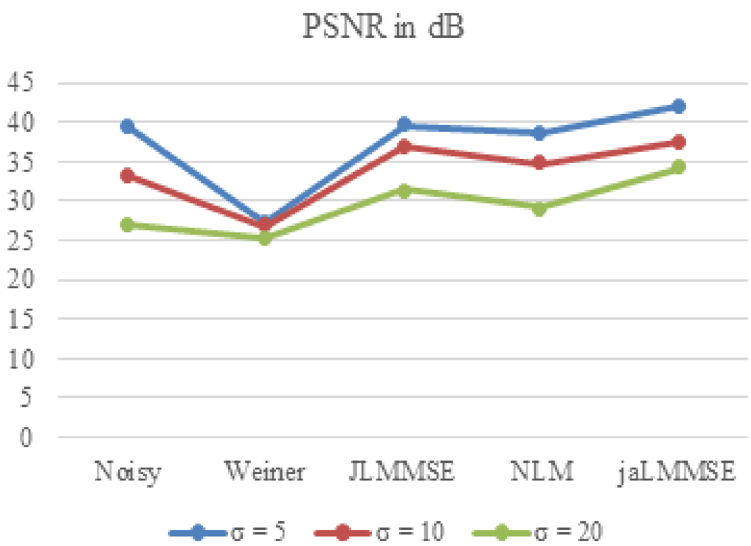

Figure 7. PSNR in DB

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Figure 8. Execution Time in Seconds

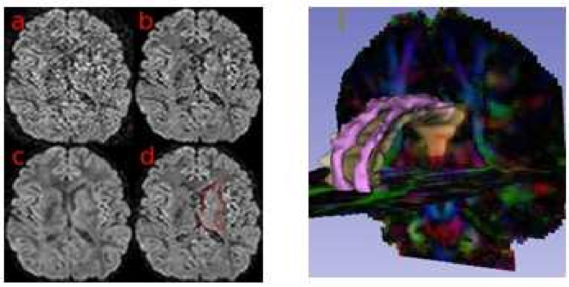

Figure 9. The corpus callosum and cingulum have been partially segmented in a DWI data set with b = 1000 s/mm2 (right above fig) and its filter version shown in (left above fig) a) original, b) UNLM-filtered, c) jLMMSE-filtered, d) jaLMMSE-filtered -compare the more effective noise removal of jaLMMSE over UNLM in the highlighted section.

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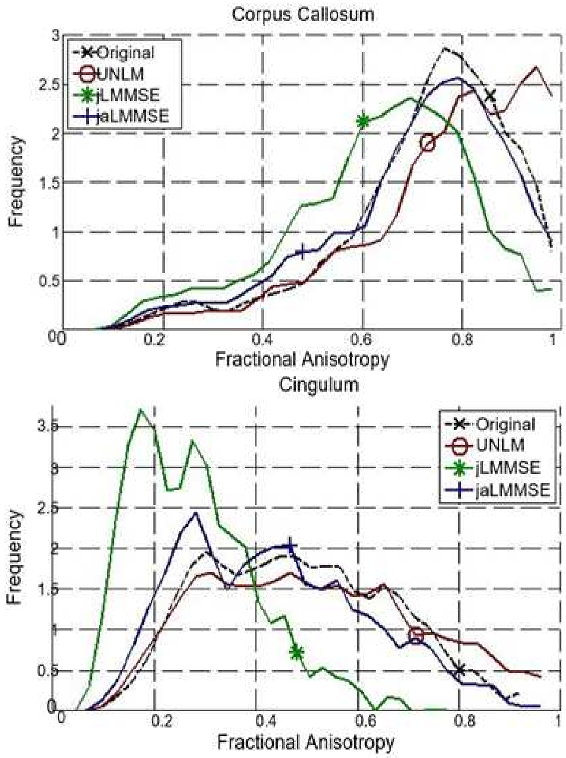

Figure 10. The fractional anisotropy (segmented tract) of corpus callosum and its histogram shown in Fig.10(a). The fractional anisotropy of cingulum (segmented tract) and its histogram shown in Fig.10 (b).

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