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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.

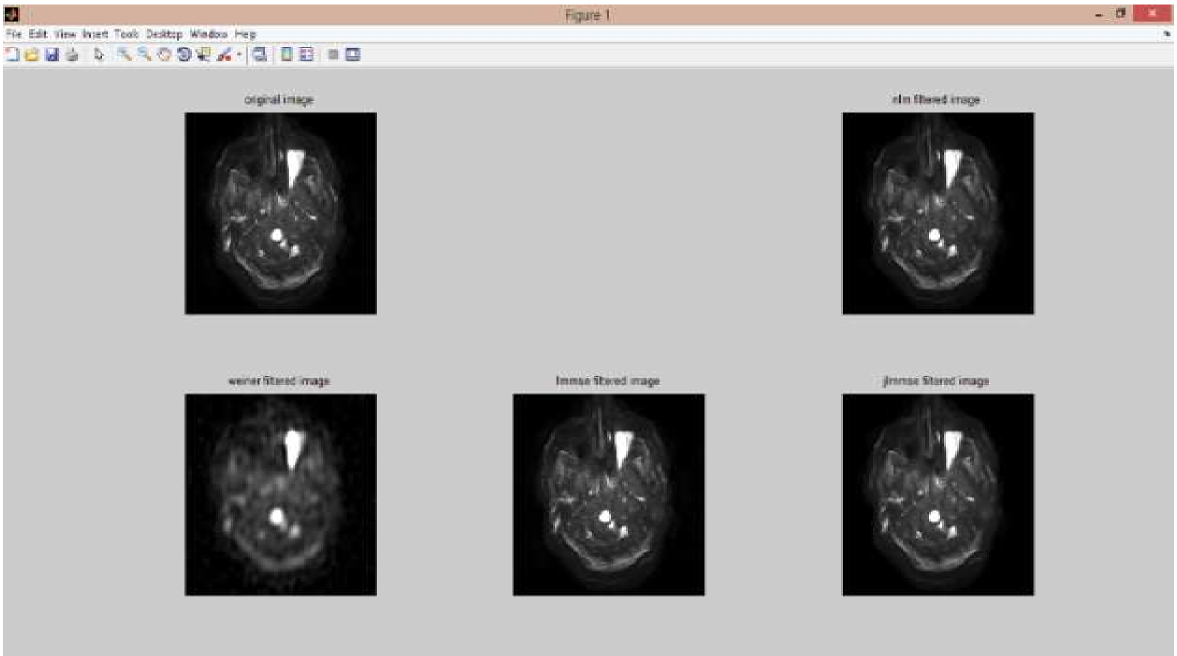

Figure 1. Denoising Results of DICOM Noisy Image (DWI Images)

2. LITERATURE SURVEY

Restoration of the MRI image can be classified in to filtering and stastical based methods (Model Based) in which the filtering approach can be enhanced by using stastical approach which includes conventional approach, EM based methods, ML based methods [2-6], are uses regularization and optimization techniques for Denoising [5]. In case of filtering based methods Perona Malik ADF Methods, PDE Methods, wavelet domain filtering methods, bilateral filtering [7-11]. From the above filtering based model noise in MRI is additive Gaussian noise. The limitation of above noise model is the effects of biasing taken in to consideration of Rician data, which defines magnitude MR images, which is not considered in the analysis of MR data and the effect of SNR directly related to biasing effect. In order to improve SNR, the most popular method to restore the MR images are the well-known approach is non-local means (NLM) algorithm. Recently the filtering based methods on diffusion weighted images are UNLM, LMMSE, JLMMSE, PCA, NLML, are proposed by authors [7-11].

2.1. Noise modelling

The acquired raw data from the MRI is usually considered as complex k-space data in which the noise is characterized by the Gaussian distribution function, due to the uncorrelated nature of the complex raw data, it can be modelled as magnitude Rician distribution the pdf of such magnitude image is defined in the Eq. (1):
$p_M(M_{ij}|Aij, \sigma_n) =$

$$\frac{M_{ij}}{\sigma_n^2} e^{-\frac{M_{ij}^2 + A_{ij}^2}{2\sigma_n^2}} I_0(\frac{M_{ij}A_{ij}}{\sigma_n^2}) u(M_{ij}) \quad (1)$$

With $I_0(.)$ is the 0^{th} order of the modied Bessel function of the first kind and u(.) being the Heaviside step function and σ_n is the standard noise variance, $M_{i,j}$ is the magnitude of the pixel (i, j) and $A_{i,j}$ is the original pixel without noise.

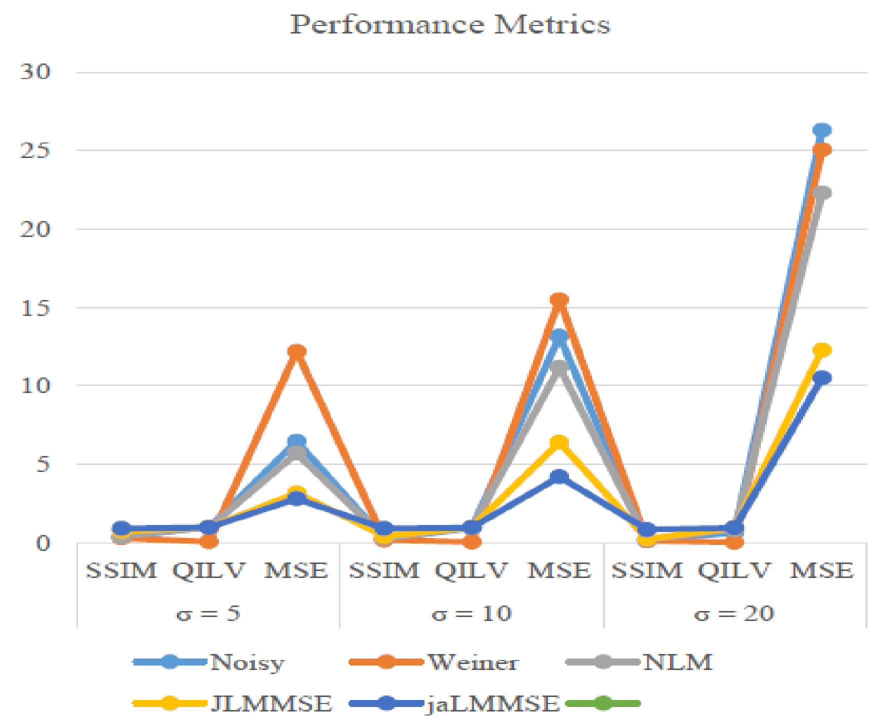

Figure 2. Performance Metrics

2.2. JaLMMSE Filter

2.2.1. Linear Filtering Model

With the background of LMMSE algorithm we compute $\widehat{A_2}$ from M_2 as the linear estimator with minimum squared error. The Eq. (2) shows the general form for many DWI filtering techniques.

$\widehat{A_2} = \langle M^2 \rangle$

$$\mathscr{N} - 2\sigma^{|2}.1 + C_{A^2M^2} C^{-1}_{M^2M^2} (M^2 - \langle M^2 \rangle_{\mathscr{N}}) \quad (2)$$

Where, the sample moments are now computed in an anisotropic vicinity. As opposed to LMMSE, here we assume that the channels are completely correlated, so the covariance matrices become $C_{A^2M^2} = \varsigma \langle A^2 \rangle_{\mathscr{N}} \langle A^2 \rangle^T_{\mathscr{N}}$:
$C_{A^2M^2} =$

$$\varsigma \langle A^2 \rangle_{\mathscr{N}} \langle A^2 \rangle^T_{\mathscr{N}} + 4\sigma^2 diag(\langle A^2 \rangle_{\mathscr{N}}) + 4\sigma^4 I_N \quad (3)$$

where,

$$\varsigma = \frac{1}{N} \sum_{i=1}^{N} (\langle A_i^4 \rangle_{\mathscr{N}} - \langle A_i^2 \rangle^2_{\mathscr{N}}) / \langle A_i^2 \rangle_{\mathscr{N}} \quad (4)$$

This assumption properly accounts for the joint information in the DWI [12], and grants also an efficient computation and inversion of $C_{A^2} M_{A^2}$. In practice, we split the estimates $\widehat{A_2}$ in those channels corresponding to either baselines or actual DWIs and the whole data volume and its effective parameter are calculated globally.

2.2.2. From Anatomical Contents to Adaptive Neighbourhoods

With the same philosophy behind the NLM [13], we define the moments of $I(x_i)$ at (x_i) inside a shaped vicinity N as

$$\langle I(x_i) \rangle_{\mathscr{N}} = \frac{1}{Z} \sum_{l \in \mathscr{N}} exp(-\frac{d(x_i, x_l)}{h.\alpha^2}) I(x_l) \quad (5)$$

Where, d $(x_i,\ x_l)$ is the distance between the voxels x_i and x_l that measures their structural similarity, α^2 is the expected value of such distance for similar voxels and h is a parameter which controls the smoothness parameter.

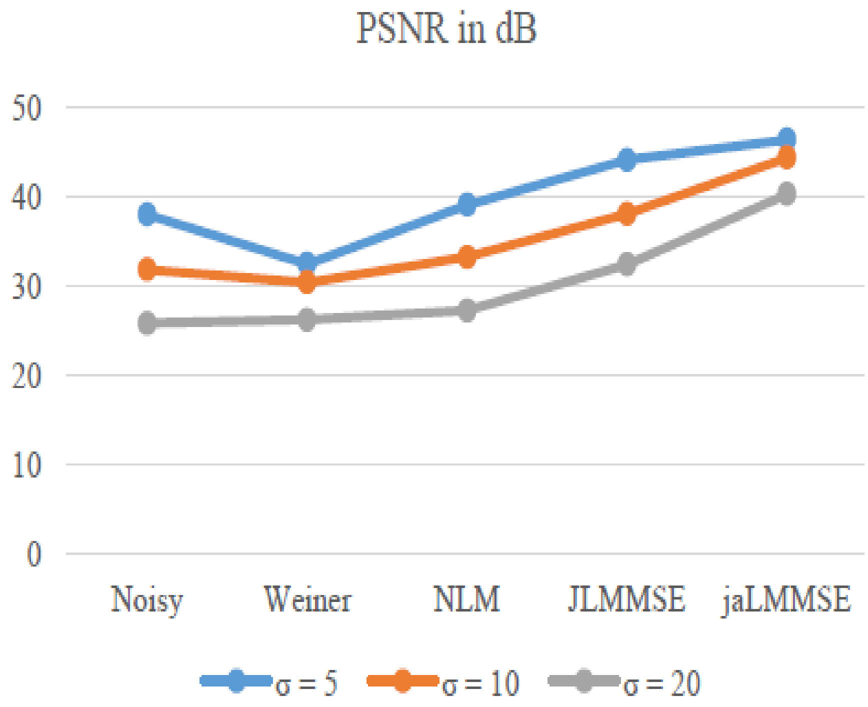

Figure 3. PSNR in DB

Normalization constant Z assures the mean value of I which is edge preservation parameter.

2.2.3. Proposed Algorithm Implementation

1. Load the DWI-MRI image.
2. Estimate the noise from the real time noisy DWI image, and σ is the standard deviation of noise.
3. Use jaLMMSE filter to the noisy image with specified gradient directions.
4. The PSNR is calculated for the filtered image with the original image
5. The execution time, and the performance quality metrics for the filtered image is calculated.

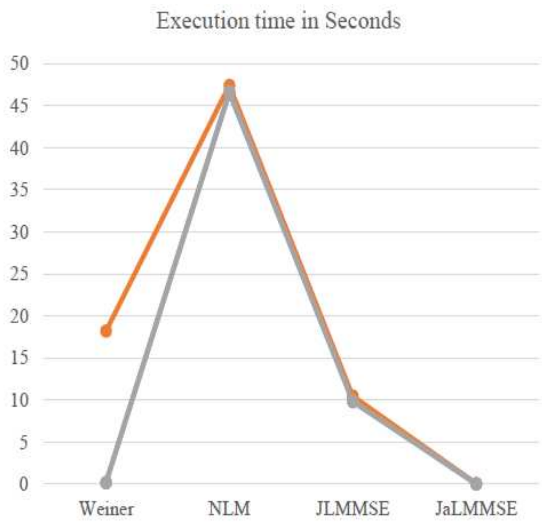

Figure 4. Execution Time in Seconds

3. EXPERIMENTS AND RESULTS

We compare the restoration performance of jaLMMSE filter for diffusion weighted real time

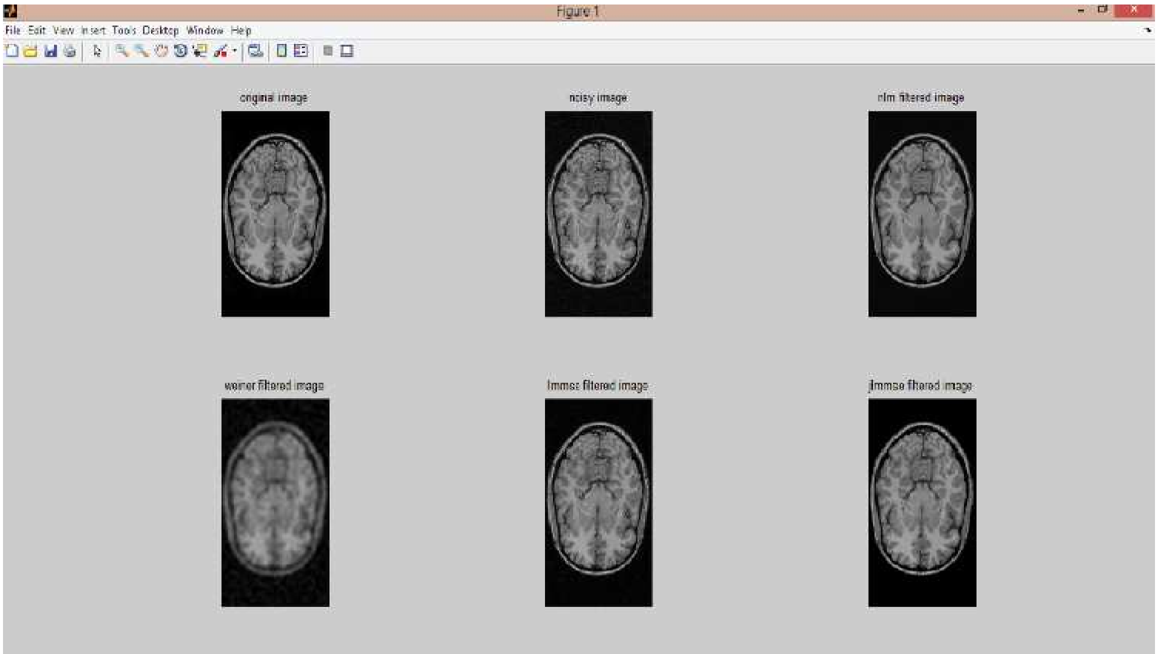

Figure 5. Denoising Results of T1 Weighted Axial Brain Image

noisy images as shown in Figure 1. with the conventional standard filters Weiner filter, NLM filter and jLMMSE filter. To perform the quality of each filtered image, we compute four quality indices [15] are shown in the following Figure 2 and Figure 3 for real time DWI noisy image. The RMSE and SSIM its values demonstrate that jaLMMSE is a more efficient noise removal engine than the other two approaches for all the range of input SNR. If we look at the QILV index the response of jLMMSE is quite flat, meaning this index is governed by the blurring the isotropic vicinities produce in the output. The jaLMMSE, however, exhibits the nice capability of NLM to preserve fine details for high SNR (small σ), and it better removes the noise for low SNR (high σ) than any other method. With regard to the QILV measure, the JLMMSE correction of jaLMMSE proves itself useful to better preserve fine details in the output over the pure UNLM which is as shown in Figure 2. The performance of the proposed filter respect to execution time is better than the conventional filters is as shown in Figure 4. The proposed filter is compared with the T1weighted axial brain image and it is better preservation of image details than the standard filters which is important for clinical practice is as shown in Figure 5. To assess the quality of the image is judged by the performance metrics and the PSNR is as shown in Figure 6 and Figure 7. With respect to execution time the proposed filter is less execution time than the others is as shown in Figure 8.And it can be integrated in to real time MRI pipeline. Finally, we have computed corresponding DTI volumes from one of the images used to generate the phantom b = 1000 s/mm2 and from its filtered versions. We have estimated FA histograms over partial segmentations of the corpus callosum (cc) and the cingulum (cg), and its filter versions see Figure 9. While jLMMSE seems to negatively bias the FA due to the increased partial volume effect caused by the isotropic computations, jaLMMSE shows approximately the same FA values as the noisy image .On the contrary, UNLM overestimates the FA, as suggested by the displacement of the histogram 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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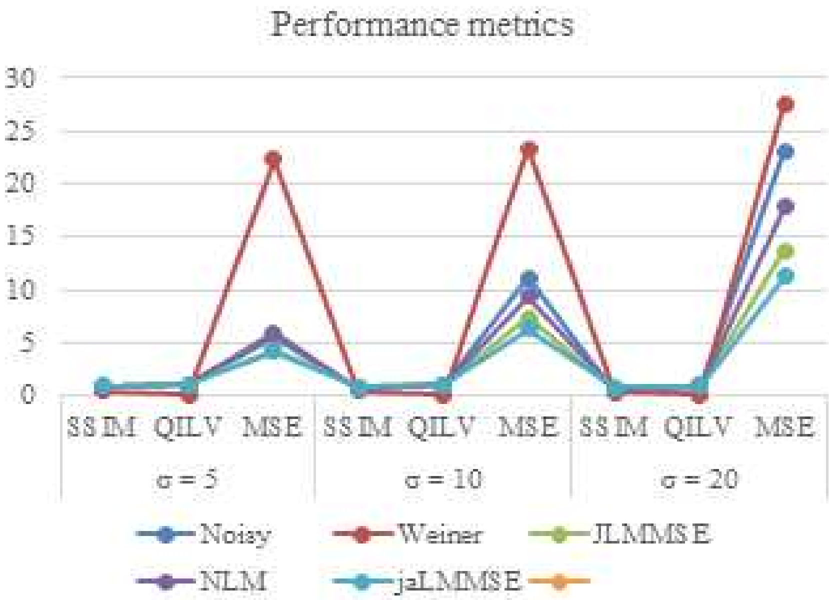
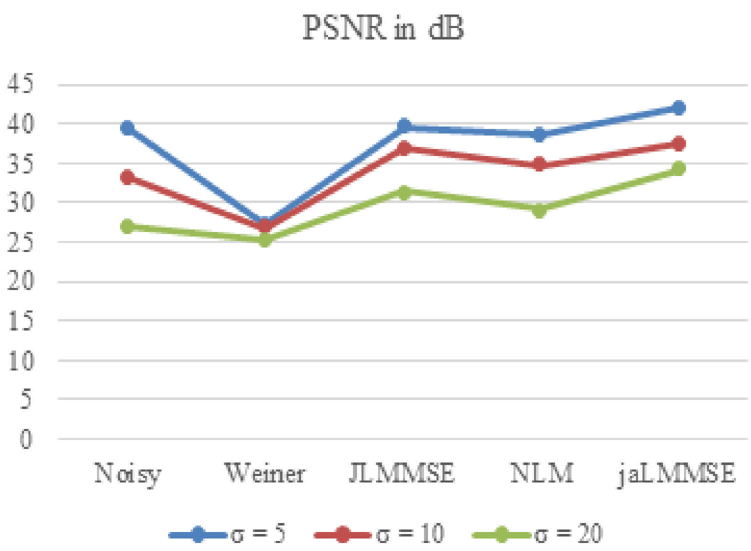


Figure 6. Performance Metrics



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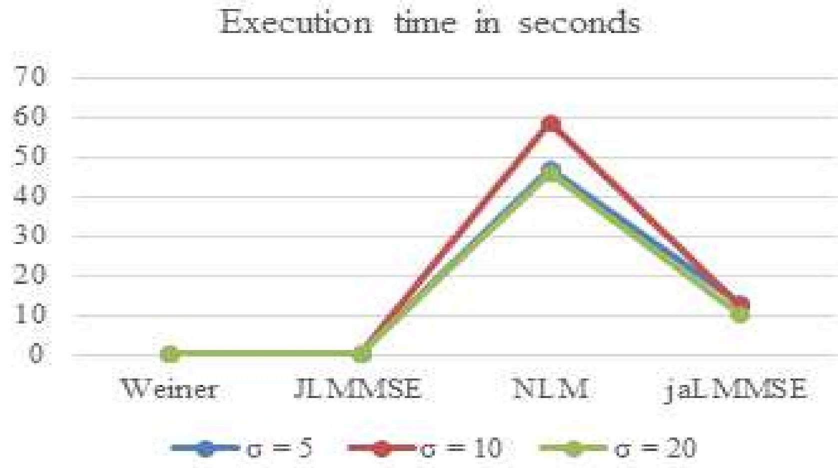

Figure 8. Execution Time in Seconds

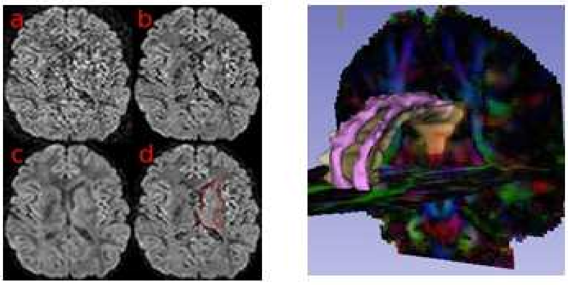

Figure 9. The corpus callosum and cingulum have been partially segmented in a DWI data set with b = 1000 s/mm2 (right above fig) and its filter version shown in (left above fig) a) original, b) UNLM-filtered, c) jLMMSE-filtered, d) jaLMMSE-filtered -compare the more effective noise removal of jaLMMSE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

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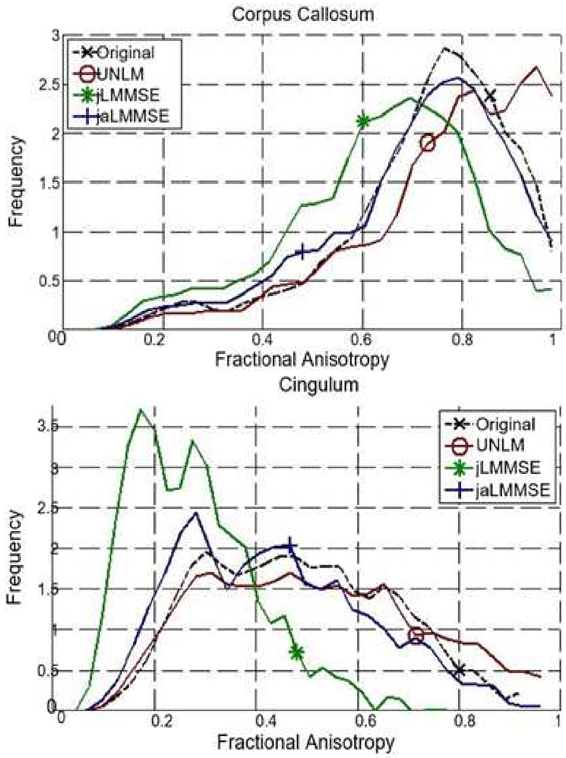

Figure 10. The fractional anisotropy (segmented tract) of corpus callosum and its histogram shown in Fig.10(a). The fractional anisotropy of cingulum (segmented tract) and its histogram shown in Fig.10 (b).

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