# An Efficient Framework for Denoising of Diffusion-Weighted MR Brain Images

**B. Srinivasa Rao, Kalyanapu Sriniavs**

***Abstract*: Improving the spatial resolution of diffusion weighted imaging (DWI) is quite significant and challenging task in recent days. Many researchers have made substantial attempts to face this challenge where the researchers aimed at accurate detection of elusive lesions and more faithfully solving fibre tracts of white matter (WM). In practice, signal-to-noise-ratio (SNR) restriction is the major pertain of high-resolution (HR) DWI, which is later counterbalance the benefits of high spatial resolution. In spite of the fact that the SNR of DWI data can be enhanced with the approach of denoising in the post-processing, the conventional approaches of denoising might possibly mitigate the anatomic solvable of HR imaging data. In addition, a signal bias that is caused by the non-Gaussian noise is also not possible to adjust every time. Therefore, this article presents an efficient framework for DW-MR brain image denoising that utilizes non-local Euclidean medians (NLEM) in non-subsampled contourlet (NSC) domain, which works based on multi-scale decomposition and directionality. Simulation results are tested with different kind of DW-MR images and the proposed NLEM-NSC approach shown the superiority over existing denoising approaches. Further, it is also provided that the qualitative analysis to disclose the robustness and effectiveness of NLEM-NSC method at lower strengths of noise.***

***Index Terms*: Magnetic resonance imaging, Diffusion-weighted imaging, Non-local means, Non-subsampled contourlet transform and non-local Euclidean medians.***

## I. INTRODUCTION

DWI can measure the microstructural alterations of brain tumours via characterizing attributes of proton diffusion form the diseases of neurological [1-2]. Moreover, data in DWI which is sampled accurately in q-space can be accommodate to a tensor model to qualify the WM structure. For instance, it has been proven that the diffusion tensor imaging (DTI) is a worthful tool for transforming the structural relation brain networks [3-5]. De-noising of a digital image is a frequently experienced issue in the area of image processing. Recent years, lots of research work has presented in the area of image de-noising. In general, the selection of most adoptable de-noising methodology relies on the sort of restored image. This article presents the DWI de-noising procedure, which utilizes the lower SNR qualification. These DWI de-noising approaches are gaining much concentration over the last decade. The acquisition of DWI data is done by employing diffusion-encoding gradients in accompaniment the three principal axes in space. This will generate a 3D delegacy of any body part into several slices. Every slice is considered 90 degrees via the patient and later multiple slices will be produced as the movement of tensor. In this direction, these images set compiles the 3rd dimension to render the 3D delegacy. The most advanced implementation by DTI, these DW image sequences had a structure of multiple directions attained by assuming the path of microscopic movement of water molecules in the biological tissue. Thus, the nature of direction in DW images provides to these a 4th dimension producing 4-D sequences in accompaniment axes s $(x, y, z, k)$ , where last dimension $k$ referred as the microscopic motion directions for every slice. In practice, to denoise, the computational complexity is a quite significant scenario in these sorts of image cases since there is a huge data needed to be processed. However, the quantitative analysis of data in DWI is generally disputed by noise, particularly, in high-spatial resolution (HSR) where the SNR is quite low. In areas, where the WM fibre clusters cross or separated into sections, the HSR-DWI is necessitated for the exact reckon of the fibre clusters orientation [6]. Be that as it may, the mitigated size of voxel in HSR-DWI will de-emphasize the values of SNR and challenge the measurement of parameters linked to diffusion. Moreover, high-b-value DW images are captured in multiple-b-value diffusion MRI for modelling the attributes of non-Gaussian diffusion in biological tissues [7, 8]. The lower SNR in the high-b-value DWI gets decrease the exactness and dependability of later quantitative analysis due to the rapid mitigation in the magnitude of signal [9]. By aggregating the iterated accomplishments, the SNR can be enhanced at the disburse of sustaining duration of scan and enhancing the susceptibility to subject motion. Or else, post-processing implementations can mitigate the noise in DWI and their impact on the measurement of parameters those doesn't influence the duration of acquisition. There are plenty of filtering techniques in the area of image processing which are employed to mitigate the noise in DW images. Practically, these filtering techniques are categorized into a couple of classes. One is to enforce the restraint of parameter smoothing [10] or to filter the measured parameter maps. Another class is to denoise the DW images primarily and later reckon the parameters of diffusion, this obviate the bias enclosed by the model of diffusion and can be unified with several models for further analysis. Hence, the second one is adopted widely to mitigate the noise impact on the mapping of diffusion parameters.

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The current approaches of denoising the DW images includes, discrete wavelet decomposition [11], partial differentiation equations [12], separation of propagation [13, 14], non-local means [15, 16], principal component analysis [17, 18], low-rank approximations [19, 20] and sparsity between clustered patches [17]. Recently, higher order singular value decomposition (HO-SVD) approach is implemented for DW image de-noising, which provides a simple, natural and adaptive direction to feat the sparseness in accompaniment all dimensions of input data. Equated to the traditional MR images, DW images consists not only the redundant info in accompaniment spatial space but also largely correlated along various directions of diffusion. The delegacy of sparseness of multi-dimensional structures in DWI can be efficaciously extended to mitigate the noise by employing HO-SVD. The patch-based HO-SVD is presented stripe-like artifacts in the similar kind of areas of the denoised image, which was addressed in [23, 24]. To diminish these, [22] presented a global HO-SVD pre-filtering level to assist the patch-based local HO-SVD for enhanced DW image de-noising. Later, Biswas *et al.* addressed the benefits of curvelet transform (CT)- based denoising approaches. This approach integrates the benefits of CT thresholding and wiener filtering in distinct scales of the CT like approximation, coarser and fine scale. Wiener filter assures the noise elimination in the approximation scale and assists in the saving well related edges with small details of image in the fine scale. However, the fine-scale details of image at lower strengths of noise quite hard to preserve. In addition, it is very complicated to sample on a rectangular grid since the implementation of CT is in analogous space and the directions apart from horizontal and vertical are much distinct on rectangular grid. Therefore, to address these issues, an efficient framework for denoising of DW-MR brain images is proposed. Our proposed de-noising approach utilizes NLEM in NSC domain, which works based on multi-scale decomposition and directionality.

The rest of the article is organised as follows: The proposed algorithm is explained in Section 2. The experimental results in terms of denoising quality and computational complexity are presented and discussed in Section 3. Finally, Section 5 concludes the paper.

## II. PROPOSED FRAMEWORK

### Non-local Euclidean medians

Major idea of NL-means [16] is easy and non-rational. It seeks for same kind of picture elements and reckons the actual noiseless value as a weighted mean, where these weights dilapidate in an exponential manner as the resemblances diminish. More exactly, assume $U_i$ and $V_i$ are the values of actual pixel and the noise pixel, for $i = 1,2,\ldots,M$, where pixels in an image is denoted with $M$. Therefore, the followed pixel of noise is $U_i + V_i = Z_i$. NL-means estimates $U_i$ as

$$\hat{Z}_i = \frac{1}{c}\sum_{j\in N_i} W_{ij} Z_j \qquad (1)$$

Where the window of searching which is centered at $i$ is referred as $N_i$, and this could be as prominent as the entire image and generally preferred by trial and error. The weights are denoted as $\{W_{ij} \mid j \in N_i\}$ and is cited as an enhancing similarity function or equivalently a mitigating operation in few distance $U_i$ and $U_j$, those are generally unknown and $Z_i$ and $Z_j$ are utilized alternatively. The NL-means assumed the squared Euclidean separation and was evidenced to be much efficacious. More exactly, the separation among two noisy picture elements is as follows:

$$D_{pixel}(Z_i, Z_j) \stackrel{\text{def}}{=} (Z_i - Z_j)^2 - 2\sigma^2 \qquad (2)$$

NLM extends to the pixel comparison to patch comparison to produce very hardy distance to noise. Similar patches have similar centres founded on the reflexion that in real-time images. NL-means used the following patch based squared distance.

$$D_{patch}(Z_i, Z_j) \stackrel{\text{def}}{=} \sum_{k=1}^{d} \left(Z_i(k) - Z_j(k)\right)^2 - 2d\sigma^2 \qquad (3)$$

Where the pixels in the patches are denoted as $Z_i(k)$ and $Z_j(k)$ which are centered at $i$ and $j$ pixels severally, and number of pixels in the patch are referred to $d$. In practice, an exponential kernel is utilized as a function of weight:

$$W_{ij} \stackrel{\text{def}}{=} exp\left(-\frac{max\{D_{patch}(Z_i,Z_j),0\}}{d\sigma^2T^2}\right) \qquad (4)$$

Where normalization is obtained with $d\sigma^2$, the dilapidate argument is denoted as $T$ and $max$ is applied hence the 1 is fixed for weight when there is a negative distance. Usually, this procedure of de-noising is done in a pixel by pixel manner and the same can be elaborated to patch wise implementation. Like, the procedure of pixel wise, a weight operation is determined between two patches, but every patch is denoised as a weighted mean of complete patches centered in the search window of the primary patch.

The execution of NL-means de-noising totally reckon on the weights $W_{ij}$ dependability, however these weights are calculated from the noisy image not the actual image. Practically, weights propagation is influenced by noise especially when there is a large amount of noise. Hence, it is required to enhance the performance of NL-means de-noising at larger levels of noise. To obtain an enhanced performance at even larger noise levels, mean in NL-means is replaced with the Euclidean medians to develop NL-Euclidean medians (NLEM). The procedure of NLEM is demonstrated in algorithm 1 where step 2(b) differs from NLM that involves in the Euclidean median computation.

**Algorithm 1: NLEM**

**Input:** Noisy image $Z_i$ and parameters $h, k, N$

**Output:** Denoised image $\hat{Z}_i$

**Step 1:** Extract patch $\boldsymbol{P}_i$ of size $k \times k$ at each pixel $i$

**Step 2:** For every pixel $i$, do

(a) Set $W_{ij} = exp\left(-\|\boldsymbol{P}_i - \boldsymbol{P}_j\|^2 / h^2\right)$ for every $j \in N_i$.

(b) Find patch $\boldsymbol{P}$ that minimizes $\sum_{j\in N_i} W_{ij} \|\boldsymbol{P}_i - \boldsymbol{P}_j\|$.

(c) Assign $\hat{Z}_i$ the value of centre pixel in $\boldsymbol{P}$

### Non-subsampled contourlet

The main motive behind the implementation of nonsubsampled contourlet is the lack of shift invariance in traditional contourlet transform. The ground for this, originates in the up and down sampling nature exists in the Laplacian and direction filter banks. Therefore, one must regain the attributes of directional and multi-scale which is obtained by replacing the conventional pyramidal and directional filter banks with the nonsubsampled versions that results in nonsubsampled pyramidal filter bank (NSPFB) and nonsubsampled directional filter bank (NSDFB), where the first one regains the attributes of multi-scaling whole the second one hold back the directional properties. The initial noteworthy conflict is that the up and down sampling will be eliminated from both the NSPFB and NSDFB. The overall architecture of NSC is depicted in fig. 1, where the DW-MR image is an input to the NSC. The figure shown that the NSDFB is applied to the outcome of NSPFB to get the bandpass directional subband coefficients. This is due to the impact of aliasing and low-resolution issue of NSPFB when it deals with the pyramidal coarser levels. Since the nature of NSDFB is a structure like tree, the directionality reaction at the lower and upper recurrences endures from the aliasing impact, that could be a crucial problem in advanced levels, where the DFB pass band region is labelled as “Good” or “Bad.”

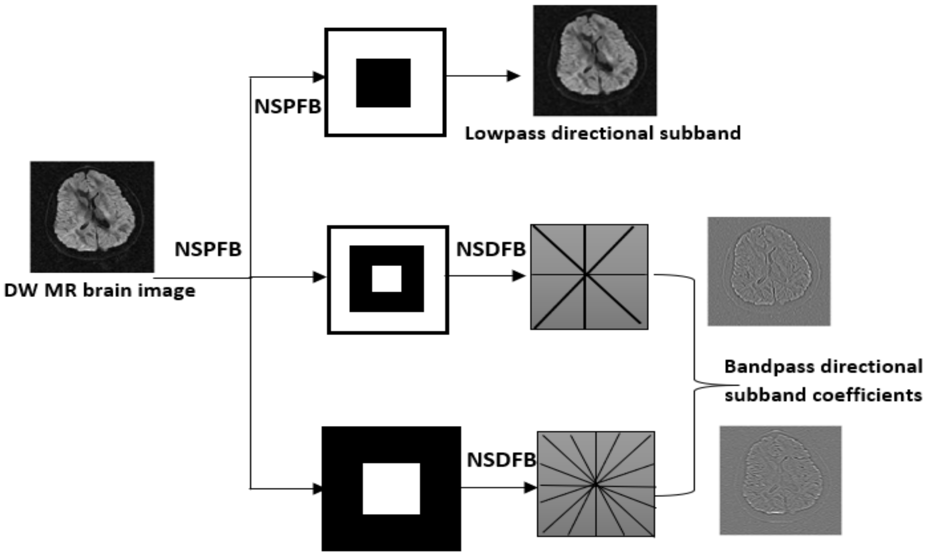


**Fig. 1 Structure of NSCT frame work with the integration of NSPFB and NSDFB for DW MR brain image**

Hence, one can view that for coarser scales, the high-pass channel in effect is filtered with the DFB pass band bad portion, which leads to the effect of severe aliasing and in some observed cases a considerable loss of directional resolution. This problem gets overcome by judiciously up sampling the NSDFB filters. Denote the $k^{th}$ directional filter by $\mathfrak{U}_k(z)$. Then for higher scales, we substitute $\mathfrak{U}_k(z^{2^m I})$ for $\mathfrak{U}_k(z)$ where $m$ is chosen to ensure that the beneficial section of reaction intersects by the pass band of pyramid. We can notice that this alteration maintains the accurate reconstruction and more significantly, the filters of up-sampling will not enhance the difficulty of computation. Particularly, attaining the outcome of $y[n]$ for a rendered matrix $\mathbb{S}$ and $\mathbb{H}(z)$ that denotes the 2-D filter, which effecting from $x[n]$ filtering by $\mathbb{H}(z^{\mathbb{S}})$, the convolution expression utilized is as follows:

$$y[n] = \sum_{k \in supp(h)} h[k]x[n - \mathbb{S}k] \qquad (5)$$

The above expression also referred as an algorithm of ȁtrous filtering. Thus, every filter existed in the tree structure of NSDFB has the same kind of ramification as that of the making block fan nonsubsampled filter banks. Similarly, every filtering level of nonsubsampled pyramid has the equal ramification as that attained with the primary level. Hence, the complexity of NSC is specified with the nonsubsampled filter banks complexity. IF every nonsubsampled filter bank in the structure of nonsubsampled pyramid and nonsubsampled direction require $\mathcal{L}$ operations per a sample of outcome, then for an image having $\mathcal{N}$ pixels, $\mathcal{BNL}$ operations are required by the NSC, where $\mathcal{B}$ denotes the sub bands quantity.

### Proposed methodology

Fig. 2 demonstrates that the proposed approach for the denoising of DW MR brain images, which utilizes the NSC transform as described in section 2.2. and NLEM filtering as discussed in section 2.1. First NSCT is applied to the noisy DW MR brain image to extract the lowpass and bandpass subband coefficients as shown in fig.1. Next, NLEM is applied to these extracted subband coefficients to mitigate the artifacts present in the noisy DW MR brain image. Due to the multiscale decomposition and multi dimensionality nature of NSCT, coefficients are filtered a different scale by utilizing the NLEM filtering process. Finally, inverse NSCT is applied to get reconstructed DW MR brain image. Furthermore, quality evaluation is done to disclose the effectiveness of proposed denoising model with existing denoising approaches.

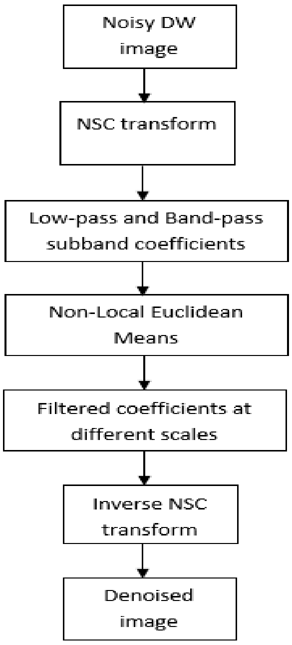


**Fig. 2 Proposed denoising framework for DW MR brain images**

## III. RESULTS AND DISCUSSION

All the experiments have done in MATLAB 2016b with several real DW MR brain images from healthy volunteers. The effectiveness of the proposed denoising framework is disclosed by comparing it with existing denoising approaches both visually and qualitatively through peak signal-to-noise ratio (PSNR) and mean square error (MSE). Figure 3 disclosed that the noisy DW MR brain image and obtained denoised images using proposed frame work and existing approaches like NLM [16], LR + edge [20] and GL-HOSVD [22]. Form the figure 3 it is clear that the proposed denoised work prevents good texture and fine details without degrading the visual quality of noisy image whereas the approach presented in [20] has over smoothen the noisy image which degrade the perceptual quality and doesn't preserve the texture information as shown in fig 3(c). Fig. 3(b) shows that the obtained result of NLM algorithm which is slightly better over the noisy image and didn't look good at visuality. Fig. 3(d) shows the obtained result of denoising approach presented in [22], it is a well denoised over NLM and LR + edge. However, there are few missing texture and fine detail information which is a vital part in diagnosing the DW MR brain image.

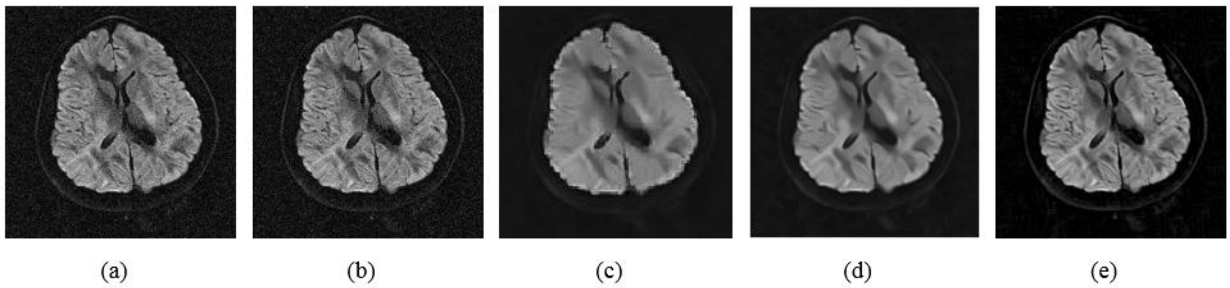


Fig. 3 (a) noisy DW MR brain image, denoised images of (b) NLM [16] (c) LR + Edge [20] (d) GL-HOSVD [22] and (e) proposed work

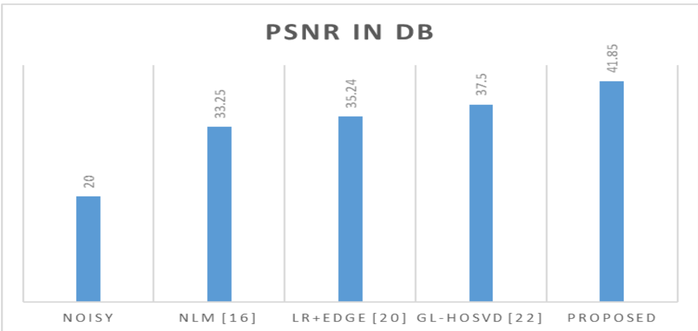


Fig. 4 Performance comparison of existing and proposed denoising approaches with PSNR values

Performance comparison of PSNR is shown in figure 4 where the proposed denoising method got a value of 41.85 dB which is quite higher than the NLM [16], LR + edge [20] and GL-HOSVD [22]. It is shown that the effectiveness and robustness of proposed framework disclosed both quantitatively and qualitatively

## IV. CONCLUSION

An efficient framework for denoising of DW MR brain images is presented. Proposed denoising framework utilized NLEM in non-subsampled contourlet (NSC) decomposed layers of noisy input image, which works based on multi-scale decomposition and directionality. The performance of the proposed hybrid technique is tested on several DW MR images and it works well at low-noise strengths. Comparative analysis of existing denoising approaches also provided to disclose the effectiveness of proposed denoising method. Further, this can be extended to design an effective denoising method with enhanced qualitative performance.

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