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3D MR Images Denoising using Adaptive Blockwise Approached Non-Local Means (ABNLM) Filter for Spatially Varying Noise Levels

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Abstract: ***The uniform noise distribution over the image is assumed in most of the filtering techniques. The resulting filtering technique becomes problematic when noise not uniformly distributed. Magnetic Resonance images with spatially varying noise levels were produced by Sensitivity-encoded, intensity inhomogeneity and surface coil based acquisition techniques. To adapt these spatial variations in noise levels, we propose a new Adaptive Blockwise approached NL-Means Filter where denoising capability of filter is adjusted based on the local image noise level. Image Noise levels are spontaneously acquired from the MR images using a proposed new adaptive technique. To reduce the computational burden of NLM Filter, an Adaptive Blockwise Non-Local Means Filter is proposed to speed up the denoising process. With adaptive soft wavelet coefficient mixing, a multiresolution framework is adapted to ABNLM filter for denoising of 3-Dimensional MR images. The proposed Multiresolution filter adapts the filtering parameters automatically based on image space-frequency resolution. The outcome of the stated multiresolution Adaptive Blockwise Non-Local Means Filter shows better performance in considering the non uniform noise when compared to Rician NL-means filters where the noise parameters has to be specified initially.***

Index Terms**:** ***Non-Local Mean Filter, Blockwise approach, Magnetic Resonance (MR) Image, Wavelet Transform and denoising.***

I. INTRODUCTION

Denoising is a significant preliminary task used in Magnetic Resonance (MR) image analysis. The reliability of segmentation and registration automatic techniques are directly affected by the noise. Also required

Signal-Noise-Ratio (SNR) of images is to be improved at the time of image quantitative analysis. This can be achieved by denoising methods. However, the methods should have the ability to remove the noise elements by protecting all the image attributes. Several techniques have been stated to address problems in MR image denoising which are difficult [1]–[8]. NLM deals with natural redundancy of the images have been introduced by Buades et al. [9] for 2-Dimensional natural image denoising. Its simplicity and high denoising ability makes it as method.

The centre of interest of this paper is adaptive multiresolution Blockwise approached model of the Non Local-means (NLM) filter. The main contribution here is developing Adaptive Soft wavelet Coefficient Mixing (ASWCM) process which totally makes best denoising.

Across the image, spatially varying noise is produced by SENSE technique [11] or parallel acquisition GRAPPA technique[12]. This parallel MRI technique provides number of image collections simultaneously and spatially encoding with receiver array coil.

Proposed filter detects the noise variance locally present with wavelet decomposition with high frequency subband by removing edge pixels. By taking this local noise variance into consideration filtering is done with soft-thresholding in adjustable way. This local noise has Rician nature. The stated filter here takes the Rician Noisy Magnetic Resonance images having spatially varying noise.

II. TECHNIQUES

A. Non-Local Means (NLM) Filter

The weights between pixel p and its neighboring pixels p1, p2, p3 and p4 are w(p, p1), w(p, p2) and w(p, p3) respectively. By self similarity NLM filter gives more weight for similar pixels otherwise gives lower weight. Let y be the 3D restored intensity volume of a restored voxel y_i with S_i as a search volume of size $(2M+1)^3$, where M= Search volume S_i radius.

The restored intensity by NL-filter is given by equation (1).

$$NL(y)(y_i) = \sum_{y_j \in S_i} w(y_i, y_j) y(y_i) \quad (1)$$

Where the value $y(y_j)$ is assigned with weight $w(x_i, x_j)$ to restore the x_i voxel. These weights are used to measure the self similarity satisfies the conditions $\sum_{x_j \in S_i} w(x_i, x_j)$ equal to unity and $0 \leq w(x_i,x_j) \leq 1$. To know the self similarity, Euclidean distance is measured with equation (2).

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$$\|y(N_i)-y(N_j)\|^2_{2,h} = \|S_i(N_i)-S_i(N_j)\|^2_{2,h} + 2\sigma^2 \quad (2)$$

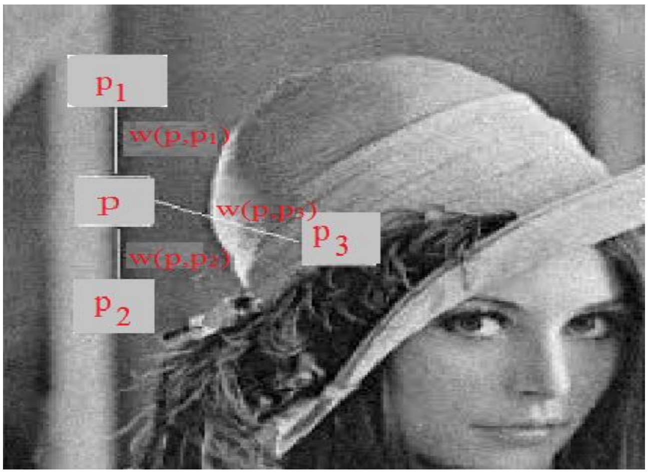


Figure 1: Non-Local Means filter approach

Where S_i is search volume and h is standard deviation of neighborhood filter, N_i and N_j are 3D neighborhood centered on voxels x_i and x_j of radius r. The weighting function between 3D patches $S_i(N_j)$ and $S_i(N_i)$ is given by the equation (3).

$$w(x_i,x_j) = \frac{1}{z(i)} e^{-\frac{\|S_i(N_i)-S_i(N_j)\|^2_{2,h}}{F^2}} \quad (3)$$

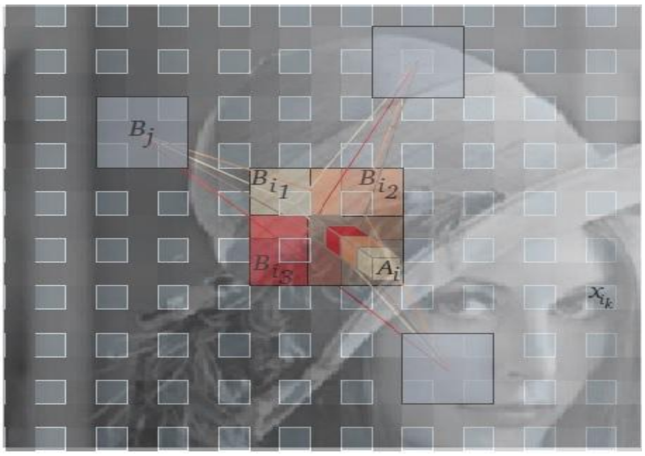


Figure 2: Blockwise Approach Arrangement

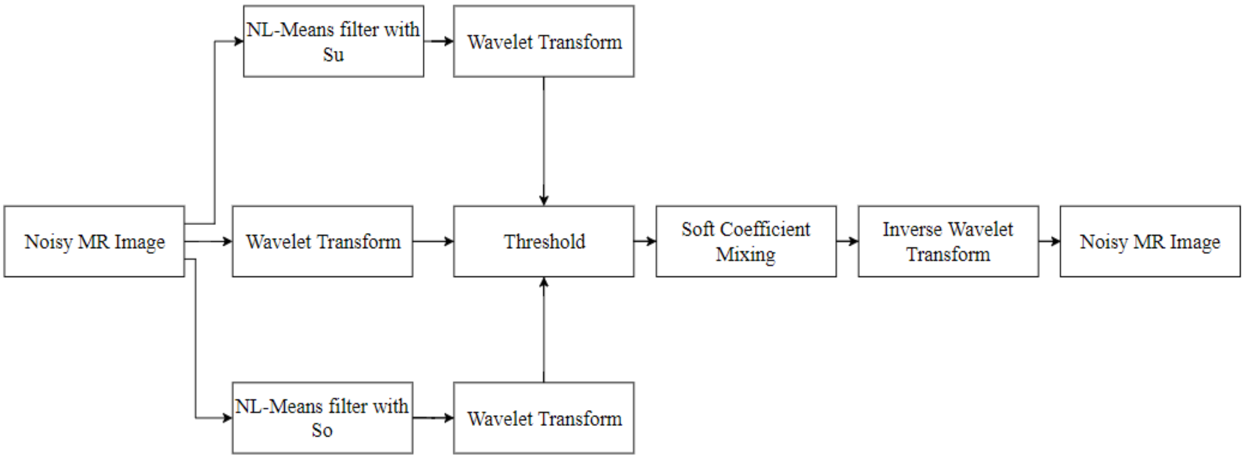
voxel x_i finally obtained by the equation (5).

$$NL(y)(y_i) = \frac{1}{|V_i|} \sum_{p \in V_i} V_i(q) \quad (5)$$

where the q^{th} element of the vector V_i is $V_i(q)$.

C. Adaptive Soft Wavelet Coefficient Mixing mechanism

The method suggested here simultaneously adapts soft wavelet coefficient mixing mechanism depending on the



Where F is smoothing parameter. The major problem with NLM filter is Low PSNR and $\tilde{Q}$ value.

B. Blockwise Approach

The weighted average of blocks of voxels is taken instead of individual voxel to reduce the computational burden present in NLM Filter.

For each block of voxel, the similar restoration is performed as NLM filter with the following equation (4).

$$NL(y)(B_i) = \sum_{y_j \in S_i} w(B_i,B_j)\, y(B_j) \quad (4)$$

Several blocks Bi consisting of voxel y_i several restored intensity $NL(y)(y_i)$ values are estimated and different noise and spatial content present in sub-bands. Same as $NL(y)(B_i)$, these finding are placed in a V_i. The reconstructed wavelet thresholding denoising method, wavelet coefficients lower than threshold treated as noise and other as data information.

Initially f_n is decomposed into $\hat{f}_u$ and $\hat{f}_o$ subbands with the help of a 3D DW Transform. For, The signed weights among absolute noisy wavelet coefficients $d_{m,n}$ for each subband of f_n are computed along with a threshold. Then among wavelet coefficients, $\hat{d}_{m,u}$ and $\hat{d}_{m,o}$ a soft mixing is performed with this weight or distance with two denoised images as obtained from Figure. 3.

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When this weight or distance is greater than zero, then corresponding noisy wavelet coefficient indicates data with denoised wavelet coefficient $\hat{f}_u$. When the distance is less than zero, then the corresponding noisy wavelet coefficient indicates noise with denoised wavelet coefficient $\hat{f}_o$

D.Multiresolution Scheme adaptation

The Selection of the filtering specifications is critical in NL-means-denoising when compared to all other denoising filters. The correct proportions of noise reduction and structure retaining are difficult assignments. A multiresolution scheme is adapted with wavelet transformation to Non-Local-means filter for 3-Dimensional MR images. This scheme allows and adapts filtering with respect to space-frequency resolution of an image. In this method NLM is set to the noisy image volume with NL Means(3,1) and NL Means(3,2) values and mixing them with subband mixing for each restored volume. This approach is shown in Figure. 4.

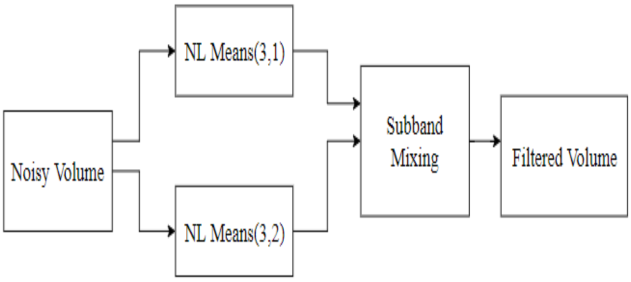

Figure 4: Proposed Method on 3D MR Image for Denoising

III. EXPERIMENTAL RESULTS ILLUSTRATION

The experimental results were conducted with Rician Noise model with β=1 and patch size 3x3x3x voxels. Rician noise Standard Deviation (std) over all the images using background mask and object mask are computed and are shown in figure 5.

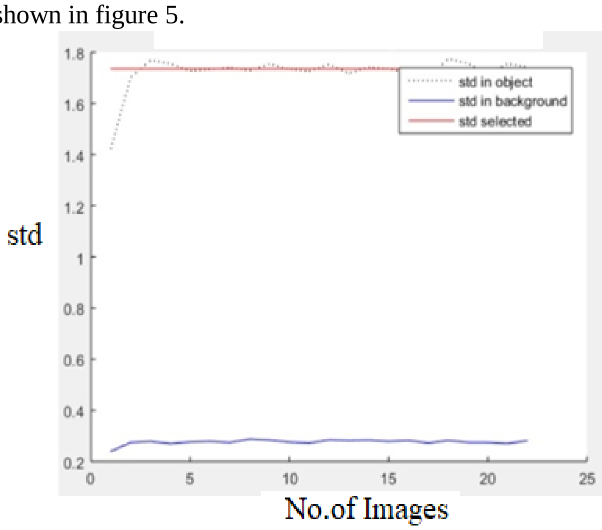

Figure 5: Estimated Std of noise along direction axis

The following figure 6 shows masks used for filtering and the Brain web phantom is used.

Figure 6: (a) Used Object mask

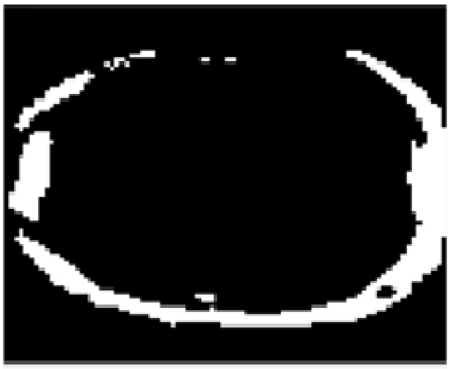

Figure 6: (b) Used Background mask

The proposed technique automatically detected std values(h) which are spatially vary in each noisy images are tabulated in table-1.

Image Number	h- value using Background Mask	h- value using Object Mask
1	0.27	1.70
2	0.29	1.73
3	0.28	1.73
4	0.27	1.72
5	0.28	1.75
6	0.28	1.72
7	0.28	1.74
8	0.28	1.74
9	0.27	1.72
10	0.27	1.70
11	0.28	1.75
12	0.28	1.72

Table 1: Automatically detected std values from input noisy images

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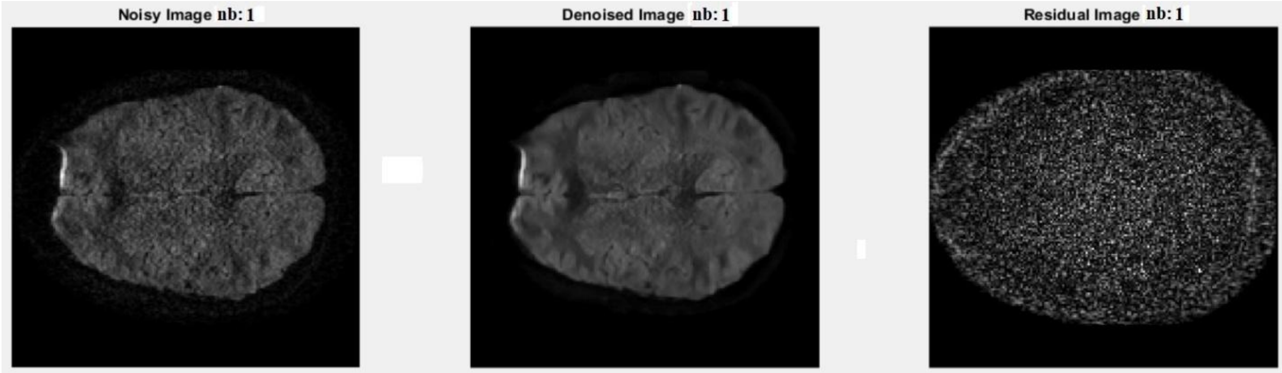
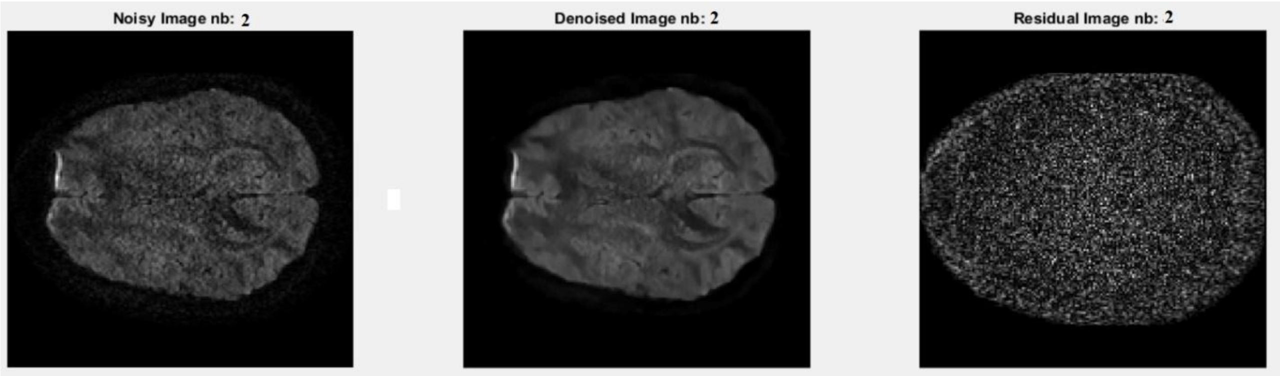
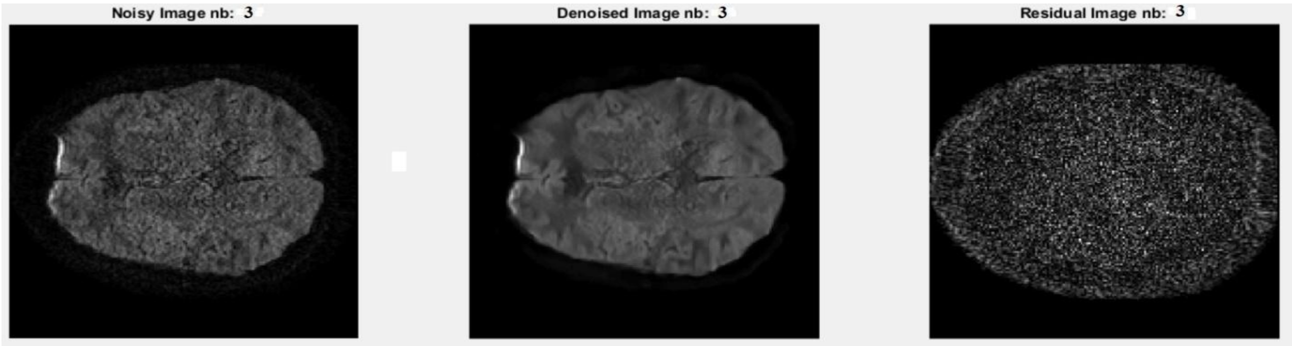
The outcomes of the proposed method are shown in figure 7.



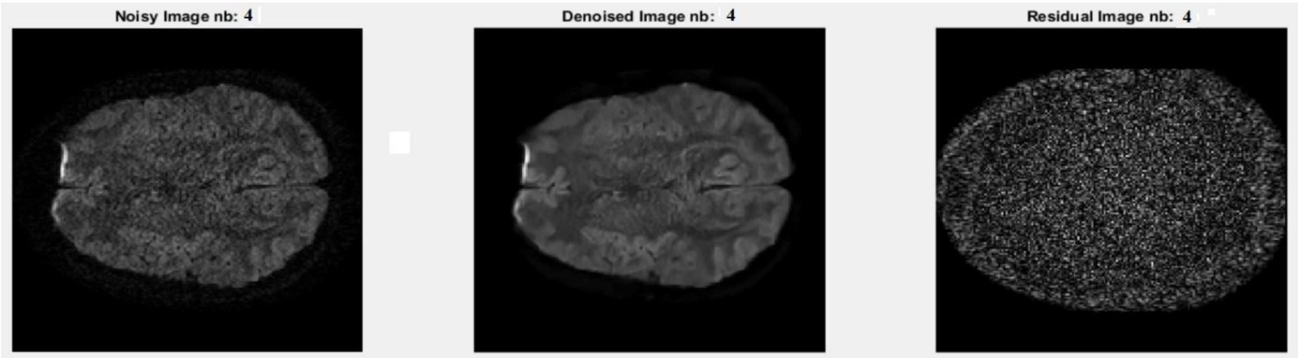
(a) (b) (c)



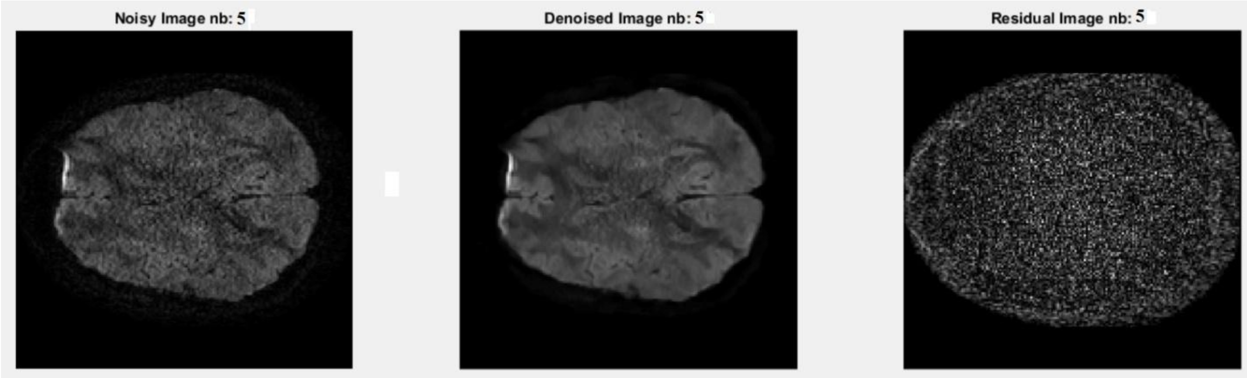
(d) (e) (f)



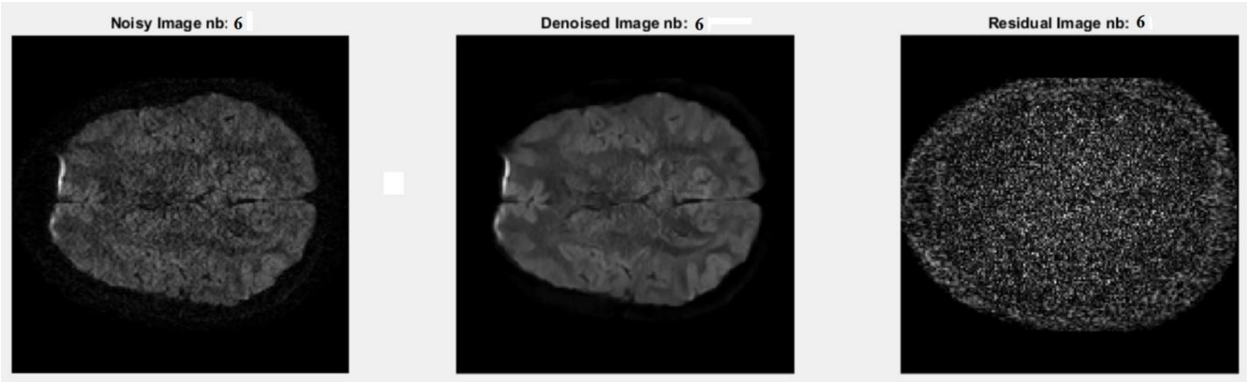
(g) (h) (i)



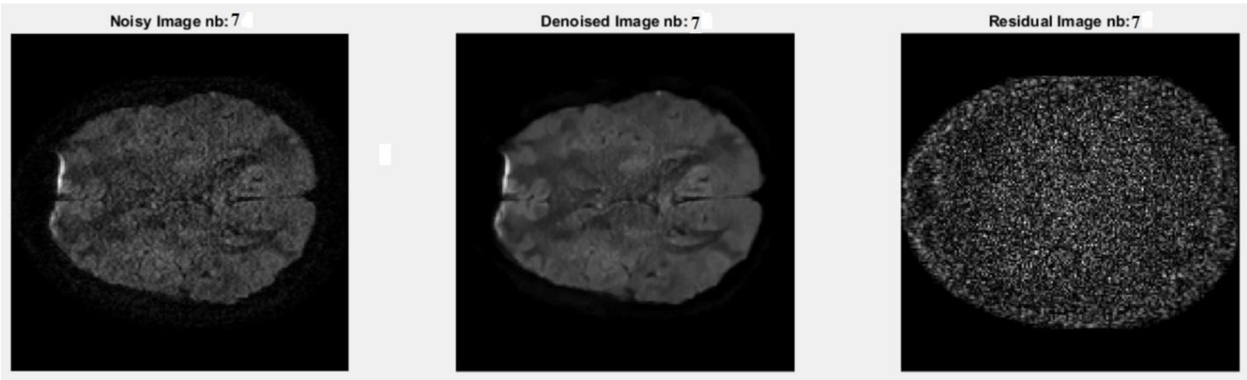
(j) (k) (l)



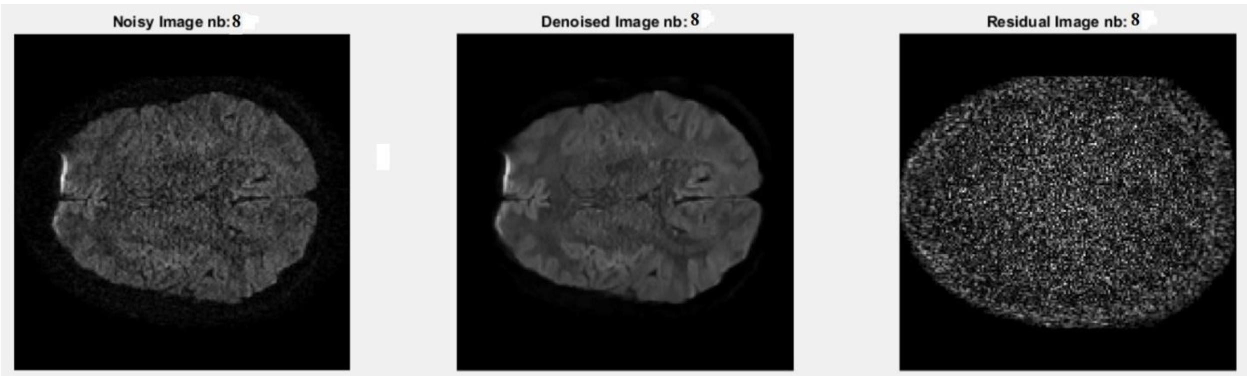
(m) (n) (o)



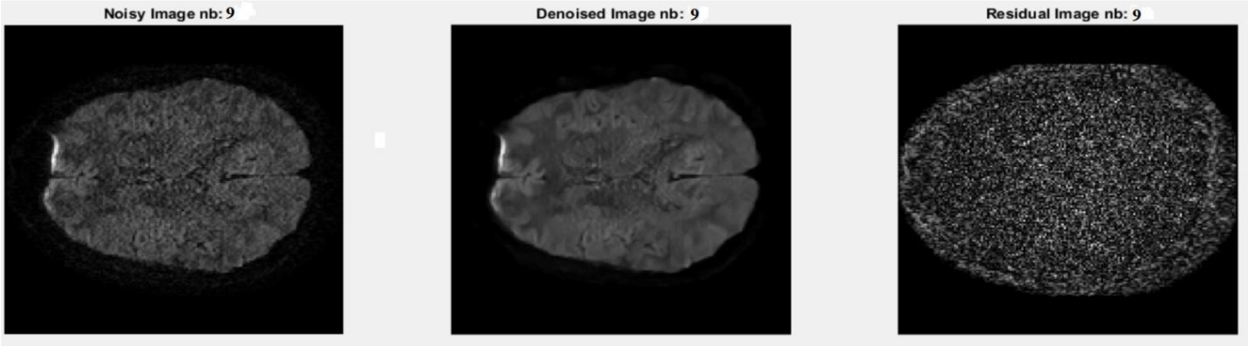
(p) (q) (r)



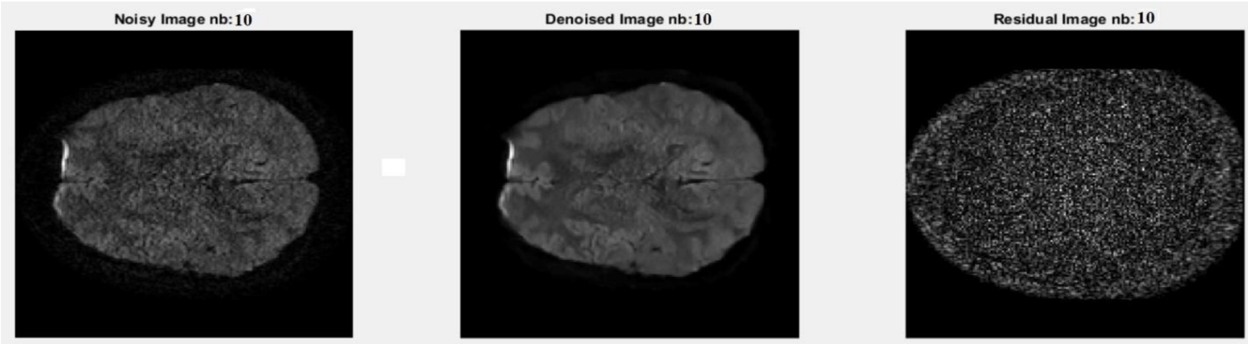
(s) (t) (u)



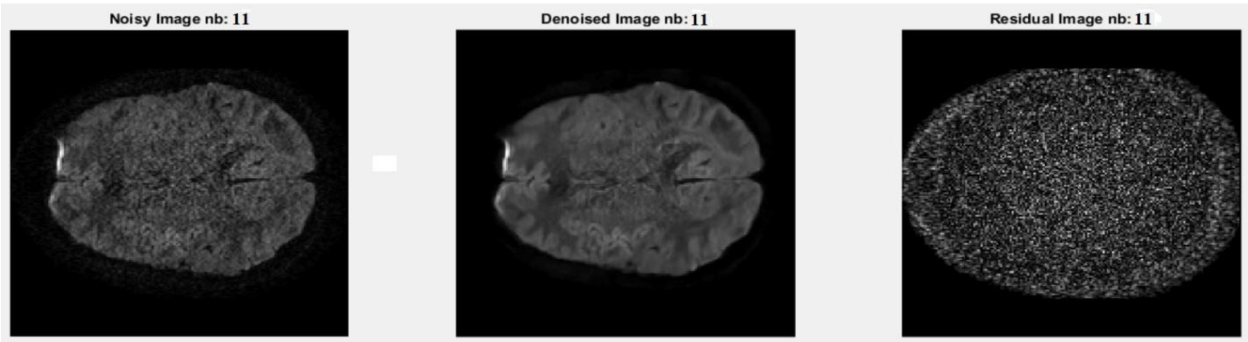
(v) (w) (x)



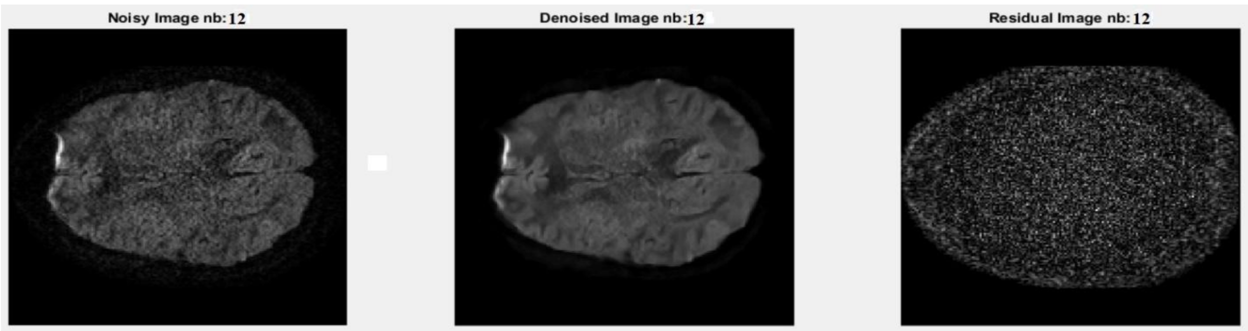
(z) (aa) (bb)



(cc) (dd) (ee)



(ff) (gg) (hh)



(ii) (jj) (kk)

Figure 7: Noisy images (Left side:a,d,g,j,m,p,s,v,z,cc,ff and ii), Denoised images of proposed method (Middle : b,e,h,k,n,q,t,w,aa,dd,gg and jj) and Residual Images (Right side :c,f,I,l,o,r,u,x,bb,ee,hh and kk).

IV. CONCLUSION

An Adaptive Blockwise Approached Non-Local Means Filter for spatially varying Noise Levels for 3Dimensional-Magnetic Resonance image denoising presented in this paper. The soft threshold wavelet coefficient mixing is adapted to the proposed NLM filter to improve its denoising strength to handle spatial and frequency information. The experiments conducted on BrainWeb Magnetic Resonance phantom which shows proposed Adaptive Blockwise Approached NL-means filter reduces the complexity in NL-Means filter with automatic detection of std values present in the noisy MR images.

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