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Adaptive Hard Thresholding for Block Matching Three dimension for Denoising Volumetric Data

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Abstract: BM3D is a recent state of art patch based denoising algorithm .It works on the fact that an image has a locally sparse representation in transform domain.It is composed of two stages i)hard thresholding and ii)weiner filtering This paper provides a mechanism that incorporates an improved version of BM3D which combines the digital image characteristic with added noise pollution levels, and adaptively selects block-matching threshold in grouping stage for an extended BM3D to four dimension so as to denoise volumetric data corrupted by Gaussian and rician noise. Experimental results demonstrate it outperforms not only in terms of objective criteria of PSNR, but also in improving the visual quality.
Keywords: Image denoising, adaptive thresholding, Patches, Volumetric data

I. INTRODUCTION

Noise is an inevitable that gets added while capturing or transmission in electronics devices. Several approaches have been devised in literature to remove the noise .Recently patch based approach has attracted research community and gained enormous popularity .They have been applied and incorporated in various machine learning ideas. Two most powerful approaches are NLMeans, BM3D and powerful enhancement of Patch based approach that is non local means. In past decades patch based has been employed to denoise medical images such as MRI.

Noise in MRI can be gaussian or rician noise .Numerous approaches exists in literature to denoise MRI images . Few approaches follow filtering, transform domain , or statistical approach . In particular, nonlocal means (NLM) filter [1] has been used to denoise MRI image, achieving notable results [4][5][6]. NLM exploits the redundancy of the neighborhood pixel to remove the noise. The restored pixel is considered as the weighted average of the intensities of all pixels within the neighborhood area. Since MRI image has multichannel nature, NLM has been modified to denoise MRI data where the similarity measure can be considered to combine the relative information between different slices. Pierric and et al proposed a series of methods in [12] Magonni proposed an approach and later extended for varying variance estimation rather than fixed[4][5].Recently Muhammad Aksam Iftikhar and et al [6] [8]proposed an extension to Non local Means for MRI and obtained promising results. Hosein M. Golshan and et al determined a method for MRI denoising using LLMSE[7].in[17]authors proposed an approach for modification of BM3D with adaptive threshold.

The paper is organized as follows. In Section 1 we provide introduction in section 2 depicts methodology followed by mathematical model in section 3 and results in section 4

II. METHODOLOGY

This approach selects the digital image characteristic with added noise pollution levels, and adaptively selects block-matching threshold in grouping stage. The proposed algorithm makes use of voxels instead of fragments. The result is a formation of group which is created by stacking similar cubes, and hence a 4D hyper rectangle is formed. As observed in BM3D [6], the grouping is highly sparse and hence this type of grouping allows effective segmentation of signal and noise using threshold method or filtering process. Inverse transformation is estimated for each grouped cube which are then aggregated to original co-ordinates by adaptive weights and this acts as a regularize operator, Hence reconstructing incomplete volumetric data.

Reconstruction is performed iteratively, where in every iteration the missing part of the spectrum is excited with random noise.It attenuates the noise present in both magnitude and phase, thus disclosing even the minute details[4].

A. MBM3D Algorithm Steps

1) Algorithm Step1: Estimation of Adaptive Hard Thresholding

Read a Noisy Image

For each voxels in the noisy image do the following

a) Block matching grouping
b) Adaptive hard thersholding
c) Inverse 4D transform
d) Aggregate to reconstruct the image

End

2) *Algorithm Step 2:* Wiener Filtering Estimate

Read an Adaptive hard threshold Image from previous step1

For every voxels of noisy image do the following

a) Block match grouping
b) Wiener Filtering Estimate
c) Inverse 4D transform
d) Aggregate to reconstruct the image

End

III. MATHEMATICAL MODEL

The noise model can be considered as Z which can be mathematical equation of the form

$$Z(k) = y(k) + \eta(k) \text{ and } k \,\varepsilon\, X \quad (1)$$

Where y is the original unknown volumetric image and k is a 3-D coordinate and η(k) is noise variance with value $(0,\sigma^2)$which is independent and identically distributed.

A. Adaptive Hard Thresholding stage

Let C^z_{xi} denote a cube of LxLxL voxels, with $L^3 \,\varepsilon\, N$, extracted from z at the 3-D coordinate $x_R \,\varepsilon\, X$. In Hard-thresholding stage, four-dimensional groups are formed by stacking together. The resemblance between two cubes is measured via the distance d[17].

$$d\left(C^z_{xi}, C^z_{xj}\right) = \frac{\left\|C^z_{xi} - C^z_{xj}\right\|_2^2}{(L)^3} \quad (2)$$

A group consisting of mutually similar cubes is extracted from z which is built for every (reference) cube C^z_{xi} .Two cubes are considered similar if their distance is smaller than or equal to a predefined threshold τ^{ht}_{match} which thus controls the minimum accepted cube-similarity. Formally, first define a set containing the indices of the cubes similar to C^z_{xi} as

$$S^z_{x_R} = \left\{xi \in X : d\left(C^z_{xi}, C^z_{xj}\right) \leq \tau^{ht}_{match}\right\} \quad (3)$$

Transform, which can be denoted as a joint four-dimensional transform T_{ht} .The obtained 4-D group spectrum is then shrunk into coefficient by coefficient by using a **Adaptive** Hard Thresholding operator

$$\gamma^{ht}\left(\tau^{ht}_{4D}\left(G^z_{Sx^z_r}\right)\right) \quad (4)$$

IV. RESULTS AND DISCUSSION

Phantom image is considered for conducting the experiment. The results obtained for the proposed approach on MRI phantoms based on volumetric data are tabulated in this section. Here for different values of standard deviation, ranging from 1% to 15% of the maximum value, PSNR is computed.The objective quality of the denoising is measured through its PSNR. The execution time of Rician and Gaussian noise for phantom are shown in Tables 1 and 2. Tables 3 and 4 compares proposed algorithm results with state of art algorithms OBNLM3D, PRIBM3D and ODCT3D.The test data of the experiment is the Brain Web and 3-D Shepp-Logan phantom of size 128x128x128 voxels.

TABLE 1 PSNR in dB and Execution Time of the proposed Algorithm for Gaussian Noise

Sigma	1%	3%	5%	7%	9%	11%	13%	15%
Time(in secs)	13.9	14.8	14.8	14.4	14.5	13.9	14.4	15.0

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TABLE 2 PSNR in dB and Execution Time of the proposed Algorithm for Rician Noise

Sigma	1%	3%	5%	7%	9%	11%	13%	15%
Time(in secs)	14.41	14.60	13.9	14.5	14.2	14.3	15.7	14.7

Table 3 Comparison of the proposed MBM3D Algorithm for Gaussian Noise

Sigma	1%	3%	5%	7%	9%	11%	13%	15%
OBNLM3D	42.47	37.51	34.73	32.82	31.42	30.32	29.40	28.61
PRIBM3D	44.04	38.20	35.51	33.67	32.37	31.29	30.40	29.65
ODCT3D	43.78	37.53	35.01	33.13	31.91	30.90	30.07	29.35
MBM3D	44.17	37.51	35.59	33.84	32.54	31.51	30.67	29.26

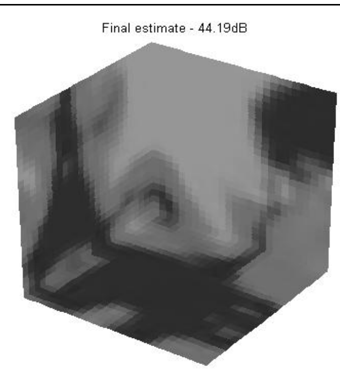
Table 3 shows the comparison of proposed algorithm with various denoising algorithm. From the above comparison it can be observed that MBM3D outperforms OBNLM3D[11], PRIBM3D[18], ODCT3D[11] for all sigma values except 3% and 15%.

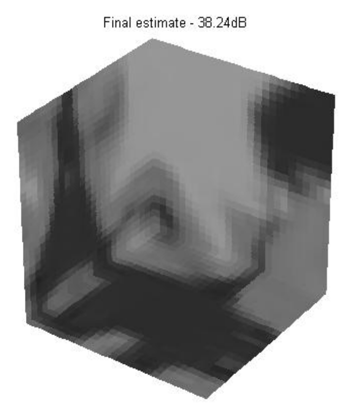
Table 4 Comparison of the proposed MBM3D Algorithm for Rician Noise

Sigma	1%	3%	5%	7%	9%	11%	13%	15%
OBNLM3D	42.40	37.45	34.54	32.71	30.97	29.32	28.62	28.61
PRIBM3D	43.97	38.19	35.54	33.37	31.94	30.74	29.75	28.88
ODCT3D	42.96	37.38	34.70	32.90	31.53	30.41	29.48	28.67
MBM3D	44.19	38.24	35.56	33.78	32.41	31.33	30.44	29.68

Table 4 shows the comparison of proposed algorithm with various denoising algorithm. From the above comparison it can be observed that proposed method outperforms OBNLM3D[11],PRIBM3D[18],ODCT3D[11].

Table 5
Phantom images for different sigma values after denoising





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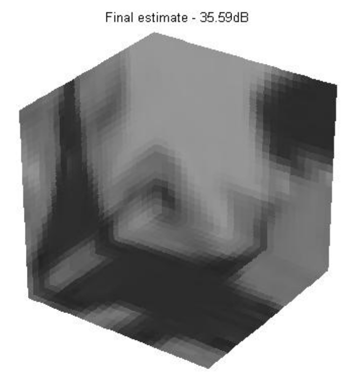
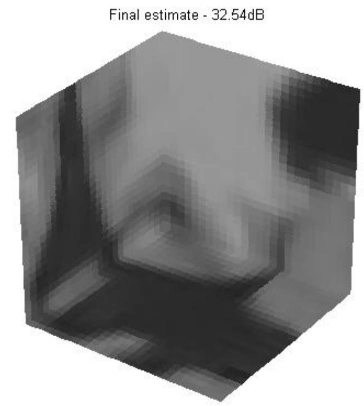
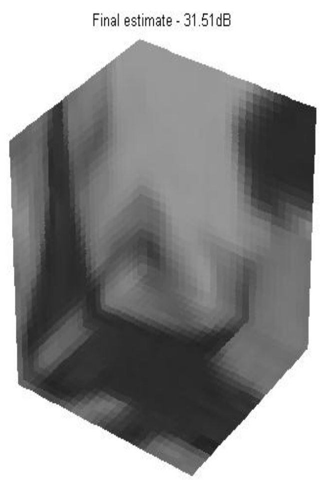
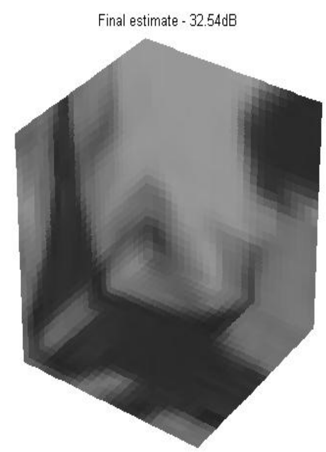
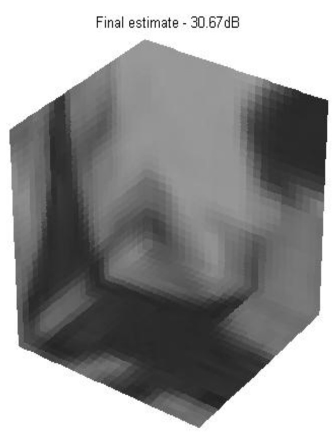
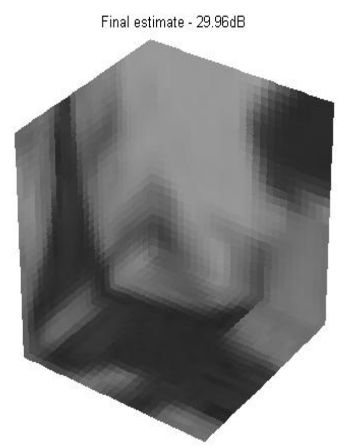
	Sigma=1%	Sigma=3%
		
	Sigma=5%	Sigma=7%
		
	Sigma=9%	Sigma=11%
		
	Sigma=13%	Sigma=15%

Table 5 depicts Noisy phantom for sigma values 1 to15 .It can be observed that de-noised phantom results in the table 5 shows better visual quality.

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A. Image Reconstruction

Kspace with the non-Cartesian trajectories Radial, Spiral, Logarithmic Spiral, Limited Angle and Spherical are used .For each trajectory PSNR and SSIM metrics are used to evaluate the performance. The phantom size is 128x128x128 voxels which is further sliced into cross section of 64x128 voxels. The performance metrics used to evaluate reconstruction mechanism are again the PSNR and SSIM.

Table 6
Trajectories magnitude and phase for sigma 5%

Sigma	Trajectories	Magnitude	SSIM	Phase	SSIM
5%	Radial	25.18	0.77	18.42	0.82
	Spiral	12.42	0.24	11.21	0.24
	Logarthmic Spiral	26.74	0.79	18.92	0.82
	Limited Angle	14.37	0.28	11.92	0.25
	Spherical	28.85	0.87	19.64	0.85

The following depicts the image reconstruction of two trajectories spiral and radial. the objective performance is almost always excellent; Additionally, the results for σ = 5% often approach those obtained in the denoising experiments reported in Table II, that correspond to the ideal conditions of complete sampling and zero phase

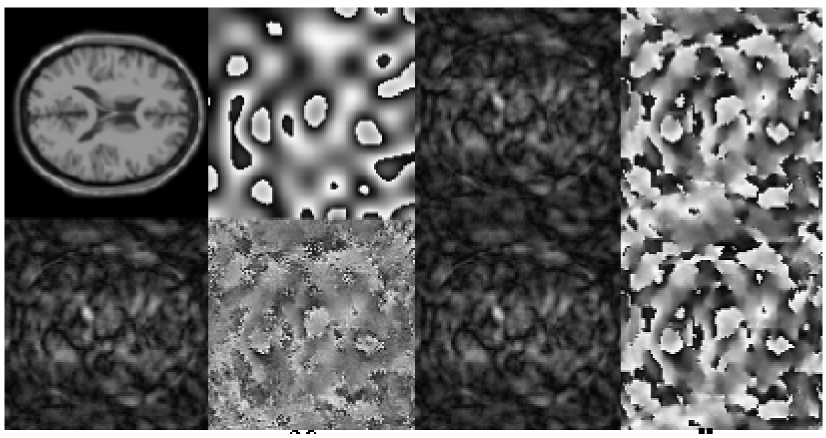

Fig 1 Spiral trajectory of the brain web phantom

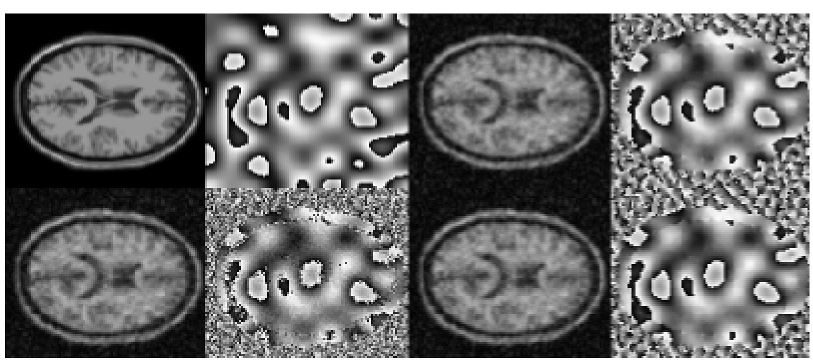

Fig 2 Radial trajectory of the brain web phantom

.Fig 1 and 2 shows the trajectories of radial and spiral for image reconstruction and

V. CONCLUSION

The proposed approach significantly outperforms the current volumetric data denoising method. In particular, the denoising performance on MRI images corrupted by Gaussian and rician noise demonstrates the superiority of the proposed approach in terms of achieving higher PSNR by using adaptive threshold.

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