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Enhanced rough set theory for Denoising Brain MR Images using bilateral filter design.

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ABSTRACT

In this paper, we developed an enhanced Rough Set Theory approach to show the self-similarity of an image for patch based image analysis systems. The motivation of this work is to search for a similar set of pixels from a given image for each pixel or patch present in the image. Still, the image searched by similarity exploration is a time consuming and some of the local search space access is restricted in the previous works. The proposed method explores the image space globally for each given patch using Improved Rough Set Theory (RST) in a better way. A predefined set of attributes of the image is used to explore the similarity of the image. The applicability of denoising methods has been shown on the medical image domain and evaluated quantitatively using various statistical measures. The performance of proposed method was found to be comparable and satisfactory.

Keywords: Rough Set Theory, Image analysis, patch based systems, similarity and medical images.

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INTRODUCTION

Denoising is one of the introductory preprocessing assignments for medical image investigation. The learning procedure of medical images is highly sensitive to noise or unnecessary signals. All in all, the noise related techniques are forecasted to be Gaussian in nature. On the other hand, it has been shown that the noise in Magnetic Resonance (MR) Image could be Rician in nature [1]. However, presumption of having Gaussian noise in set up of Rician noise, in low Signal to Noise Ratio (SNR), the MRI still holds. Be it Gaussian or Rician, expulsion of noise from MR images is crucial for further investigation.

The basic work in the field of denoising includes Mean and Median channels, Isotropic channel, anisotropic channel [2–4], robust statistics [5] and [6]. Besides, non-iterative and edge preserving Bilateral Filter (BF) [7] proposed a great revolutionized in the field of denoising. The basic task of BF has been demonstrated form anisotropic dissemination strategies under Bayesian approach in [8]. BF utilizes two parts, one on spatial area and another on intensity values at the same time. Since its commencement, there have been numerous adjustments of Bilateral Filter as recommended in [9–13]. However, its steady time adaptation, as far as computational complexity, has been proposed as of late in [14, 15]. And it also extended the service to the trilateral filters [16] [17]. The third segment which is utilized in BF with advent of existing technique is planned in different ways. It appears that more data could prompt better execution. In the present article, the channel proposed is trilateral by nature. The third component utilizes the edge data and neighborhood data. Different edge finders, for example, Canny system [18] or division strategies and inclination based techniques, for example, Active Contour Methods [19, 20], could be used for getting edge points of interest.

In addition, the technique, for example, Active Contour neglects to get object limits where number of items is not in power limit of two. The present work is the combination of the Rough Set Theory (RST) in clustering and fuzzy logic with classification. In real applications, the edge map and class names are obtained simultaneously. There are couples of strategies accessible which utilize pair of images to denoise under respective structure, for example, cross reciprocal filter and double two-sided channels [19]. The proposed channel serves as a joint structure for image segmentation and denoising issue, where the lack of traditional bilateral filters. The channel has been connected to a vast arrangement of images with different quality measures like Peak to Signal (PSNR) ratio, Root Mean Squared Error (RMSE), Structural Similarity Index (SSIM) in [18] and Feature Similarity Index (FSIM) in [16]. The execution of proposed channel is observed to be practically identical with the routine techniques for denoising utilizing existing Bilateral and trilateral filters in with the use of filters. Subsequently, the technique is contrasted and strategies under the two-sided structure.

This paper is unionized as follows: Section I depicts the definition, advantages and application of denoising in medical image analysis. Section II portrays the various techniques studied by various researchers. Section 3 involves proposed work. This proposed work is evaluated in terms of performance validation is presented in Section 4 and in Section 5 concluded.

LITERATURE SURVEY

The Bilateral Filter (BF) intrinsically characterizes spatial and range (photometric) channel to denoise a picture as per spatial domain and power area individually [7]. The last channel uses the result of weights of both the channels for a neighboring pixel. Mathematically, BF can be characterized as

$$\Delta(i, j) = \Psi(i, j)\zeta(i, j) \qquad (1)$$

Where Ψ and ζ are monotonically diminishing non-negative functions for spatial and intensity degree, i is the pixel location placed at the center and area j is in neighborhood of i, i.e. j ∈ N(i), within window w × w.

$$\psi(i, j) = G_{\sigma_\psi}(\|\mathrm{i}-\mathrm{j}\|) \qquad (2)$$

$$\zeta(\mathrm{i}, \mathrm{j}) = \mathrm{G}_{\sigma_\zeta}(\|Y(i)-Y(j)\|) \qquad (3)$$

Where Y(i) represent intensity at location i. The denoised pixel intensity Y (i) at the location i given by

$$Y(i) = \frac{\sum_{j \in N(i)} \Delta(i,j) Y(j)}{\sum_{j \in N(i)} \Delta(i,j)} \quad (4)$$

The scaled respective channel proposed in [10], is one of cutting edge methodology proposed on customary BF system. The key idea behind this is consider the closeness in the scale-space domain where clamor will get stifled by some sum. In this approach, input is initially convolved with a Gaussian bit of suitable size. In its intensity channel, the distinction is considered between scaled versions of information picture at area p with data picture at area q. But this obscuring may prompt a loss of edge data. The selection of suitable scale for examination reason for existing was not suggested. The spatial channel is kept same. The intensity filter is defined as:

$$\zeta(p,q) = G_{\sigma_\xi}(\| I_G(\mathrm{p}) - \mathrm{I}(\mathrm{q}) \|) \quad (5)$$

$$\mathrm{I}_G(p) = \sum_{q \in N(p)} G_{scale}(\| p - q \|) I(q) \quad (6)$$

Here, I_G is the scaled version of input image I, p and q are positions in the image and N (p) is the neighborhood considered around position p.

A Wavelet based bilateral filter has been proposed in [13] in multi-determination system. A data input is deteriorated into its approximation (LL band) and point of interest sub-groups (LH, HL, HH bands) through wavelet decay at two levels utilizing "db8" channel. The BF is connected on appropriate sub-band at both level and wavelet thresholding is connected on point of interest sub-groups.

In BF, a pixel is assessed utilizing weighted normal of pixels in the given neighborhood space. The idea of non neighborhood implies [21] methodology composed for image denoising. Non-Local closeness concentrates on the range channel by leveraging the impact of spatial channel in predefined neighborhood. However, for computationally proficient procedure, an adequately large window is considered around every pixel to look for comparable pixels in terms of intensity. The non local means is regularly considered as a generalization of reciprocal channel.

IMPROVED ROUGH SET THEORY TECHNQIUE

The significant approach of this work is to give more information from boisterous image in the bilateral system to enhance the performance. Under BF, edge data can be accustomed to stop denoising procedure over the limits. However, the vicinity of noise makes it harder to get real edges. The present approach is based on Rough Set Theory using fuzzy classification techniques. The granule data preparing of RST serves to imagine the possible presence of edge or heterogeneity in the granules. Granules are defined as modest picture of size 2 × 1, 1 × 2 or 2 × 2 etc. The RST based methodology, with the assistance of granules, gives standard tuitions in the picture to make lower and upper approximation of the object. These are known as object lower and upper approximation set. Note that, lower estimate set will be contained in upper rough approximation set.

The novel approach of RST is the merge of Rough Set Theory in clustering and fuzzy logic with classification. In RST clustering, the data with similar attributes are contributed to be cluster and the data with dissimilar attributes are gathered to be another cluster. This methodology is applicable to handle uncertainty and incomplete information. The data is divided into different groups. Based on the attributes, the cluster is divided into similar and dissimilar clusters. The similar cluster contains the group of data with similar properties. The dissimilar cluster contains the group of data with different in properties. The fewer number of clusters will lose the details. The unsupervised learning methodology is used to find any label of the cluster. The advantage of this improved RST is the simplification of the process. The cluster is divided into three types:

- Exclusive clusters: Any categories or objects belong to only one cluster.
- Overlapping clusters: Category or an object may belong to many clusters.
- Probabilistic clusters: A category or an object belongs to each cluster with a certain probability.
  The proposed architecture is as follows:

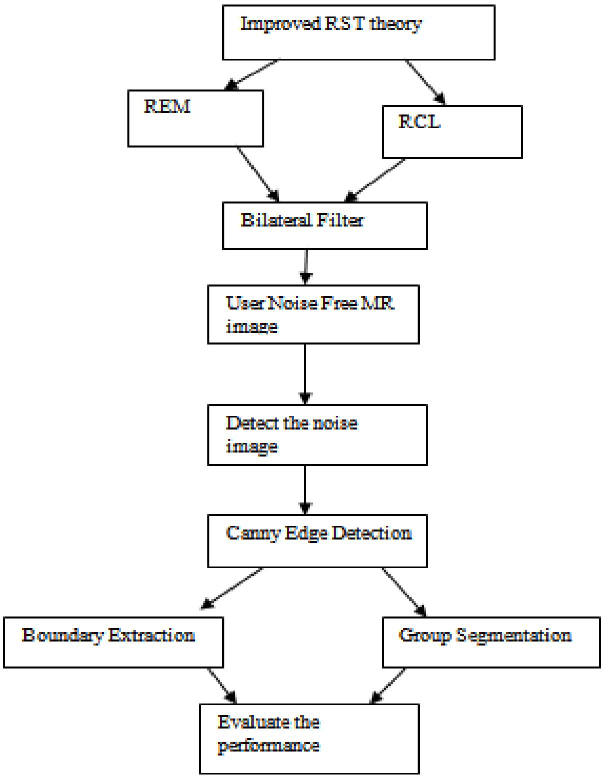

Fig 3.1: Proposed Architecture

EXPERIMENTAL ISSUES AND ANALYSIS

Fig 4.1 Preprocessing Stage

- Fig 4.1 shows that the multiple images are given as input from the brain MR image dataset.

- The noise in the image is denoised using bilateral filter. The bilateral process has rough edge map and rough class label.
- In preprocessing stage the slicing method is used to display the images in different forms such as arial, sagittal and coronal.

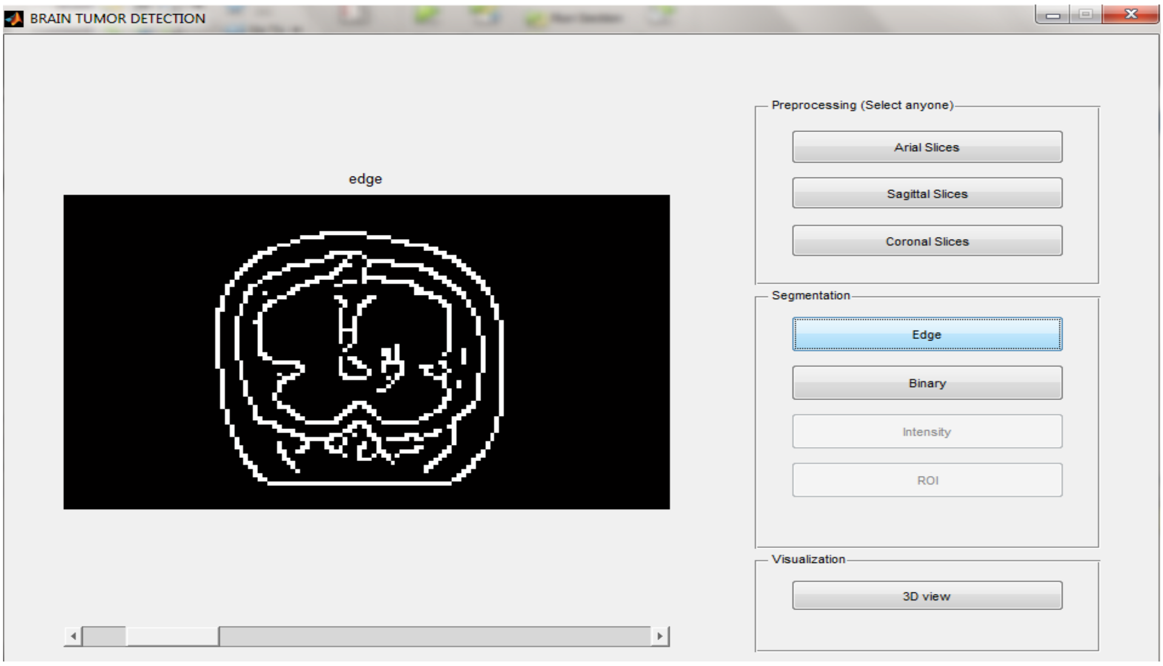

Fig 4.2 Segmentation

- Fig 4.2 shows the segmentation process, the noise from the image has been removed and the edge and boundary regions are highlighted.
- After the images are denoised the damaged regions are displayed in color.
- The sharpness of the images are identified based on their intensity.

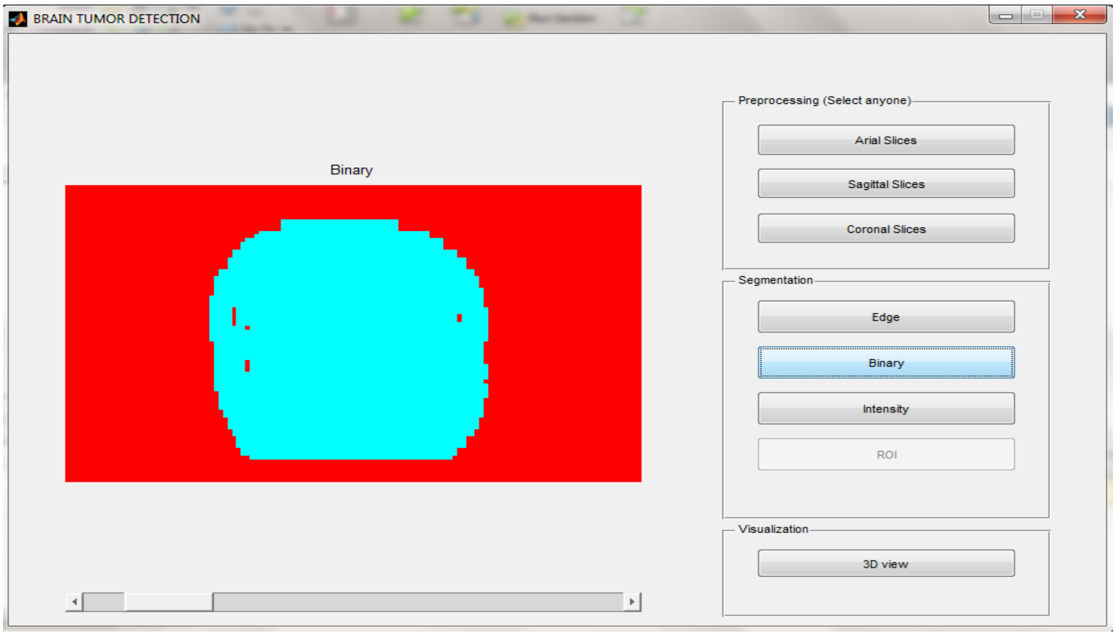

Fig 4.3 Binary

The images are denoised and the damaged regions are displayed in color.

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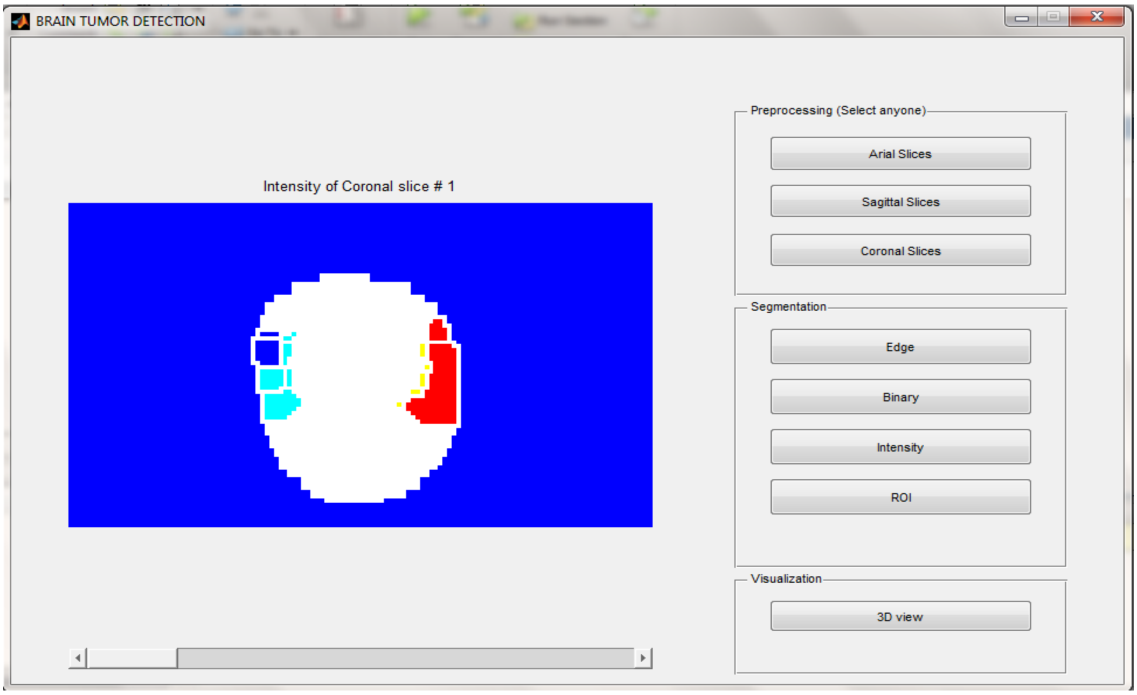

Fig 4.4 Intensity

The sharpness of the images are identified based on their intensity.

- Red – Represents the maximum damaged areas.
- Yellow – Represents the minimum damaged areas.
- Blue – Represents the average damaged areas.

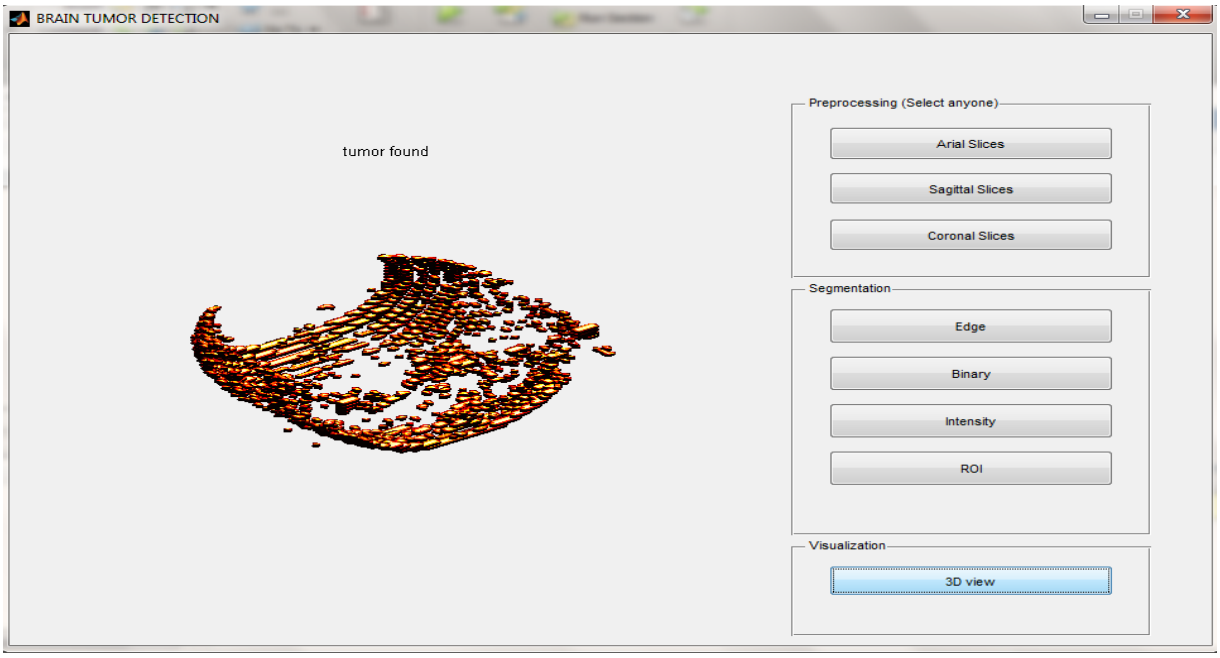

Fig 4.5 Region of Interest

The damaged area in the brain has been clearly detected after the denoising process. It accurately displays the damaged region in the brain image.

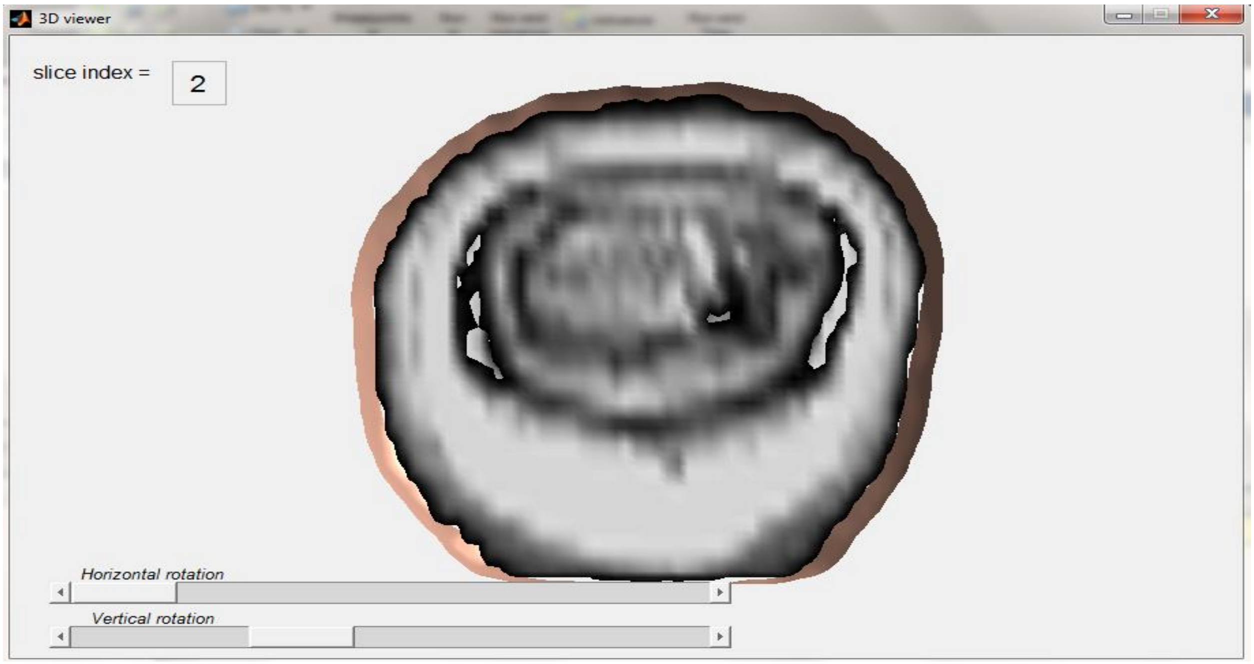

Fig 4.6 3D Visualization

In 3-dimensional form, the tumour affected images can be viewed in horizontal and vertical rotation.

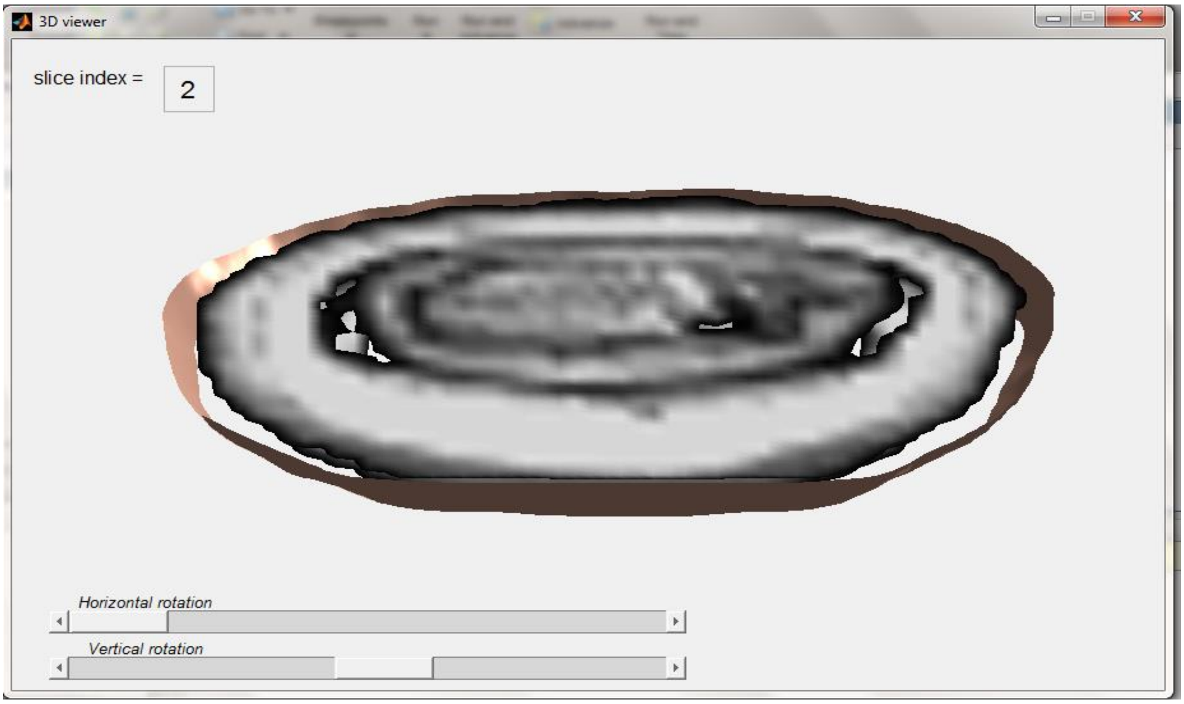

Fig 4.7 Horizontal view

Fig 4.7 shows the tumour affected images are viewed in horizontal form.

A 5*5 is fixed in square of patch size. Local search window parameter is pivotal furthermore, sets an exchange off between calculation time and execution of the technique. In real, patch size, p, and look window size, W, are reliant on one another. In this study, we have considered two search windows for assessment purposes. The proposed system selects comparative patches from the image space that evacuates the imperative of neighborhood look window W parameter. The methodology has a canny approach to get

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patches from the entire picture. Henceforth, it is likewise versatile regarding the quantity of patches utilized for every pixel for denoising the present pixel or patch. The evaluation measures such as:

i) Root Mean Square Error (RMSE)

$$\text{MSE: } \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j)-\hat{I}(i,j) \quad (7)$$

$$\text{RMSE}=\sqrt{MSE} \quad (8)$$

ii) Peak to Signal Ratio (PSNR)

$$\text{PSNR} = 10\log_{10}(\frac{L^2}{MSE}) \quad (9)$$

Where L is the maximum intensity level present in the image I and MSE is the same as defined above.

iii) Structural Similarity Index (SSIM)

$$\text{SSIM(x, y)} = \frac{(2\mu_x\mu_y + \epsilon_1)(2\sigma_{xy} + \epsilon_2)}{(\mu_x^2 + \mu_y^2 + \epsilon_1)(\sigma_x^2 + \sigma_y^2 + \epsilon_2)} \quad (10)$$

$$MSSIM = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_i, y_j) \quad (11)$$

Where ϵ1 and ϵ2 ensure the stability $(\sigma_x^2 + \sigma_y^2)$ or $(\mu_x^2 + \mu_y^2)$ when either is close to zero. The SSIM is defined over a local window centered at (x, y) and an average over such windows gives a single measure for the entire image, named as Mean SSIM (MSSIM).

Noise SD	Methods	Slice 70				Slice 100			
		PSNR	RMSE	MSSIM	FSIM	PSNR	RMSE	MSSIM	FISM
3	Noisy	39.00	8.180	0.947	0.975	39.18	7.849	0.934	0.973
	NLM	38.48	9.211	0.973	0.990	40.05	6.427	0.975	0.991
	LPGPCA	42.68	3.500	0.979	0.992	40.14	3.148	0.975	0.992
	Improved RST	43.214	3.102	0.980	0.993	43.67	2.792	0.978	0.993
5	Noisy	34.5663	22.7227	0.8776	0.9409	34.7454	21.8041	0.8541	0.9358
	NLM	37.2108	12.3595	0.9505	0.9842	38.4707	9.2472	0.9415	0.9867
	LPGPCA	39.0903	8.0177	0.9554	0.9837	39.4677	7.3504	0.9459	0.9840
	Improved RST	39.5599	7.1959	0.9585	0.9850	39.9363	6.5985	0.9516	0.9861
7	Noisy	31.6438	44.5353	0.8028	0.9025	31.8229	42.7360	0.7735	0.8947
	NLM	35.9154	16.6547	0.9272	0.9770	37.0060	12.9561	0.9136	0.9811
	LPGPCA	36.0394	16.1862	0.9276	0.9764	37.4026	11.8255	0.9157	0.9831
	Improved RST	37.0354	12.8689	0.9358	0.9760	37.3969	11.8410	0.9246	0.9778
10	Noisy	28.5457	90.8884	0.6971	0.8458	28.7248	87.2163	0.6679	0.8352
	NLM	34.0846	25.3877	0.8949	0.9647	34.9940	12.9561	0.9136	0.9811
	LPGPCA	36.7490	13.7462	0.9307	0.9738	37.0637	12.7853	0.9157	0.9832
	Improved RST	34.4206	23.4976	0.9046	0.9616	34.8828	21.1251	0.8898	0.9647

Table 4.1: Performance comparison of improved RST using brain database under Gaussian noise. (Slice= 70 and 100, modality= T1 and patch size= 5*5)

CONCLUSION

A rigorous framework for the medical image denoising problem using Improved Rough Set Theory has been presented. Under the uproarious environment, uncertain data has been used to denoise the picture and another is the joint system for the image segmentation and denoising issue. The proposed methodology of patch size is more informative in examination to different systems. . Instead of a hard clustering approach, the proposal also considers the adjacent boundary information between objects for getting similar patches. The results are very encouraging and comparable to some of the state-of-the art method. The time complexity is high in existing works if one explores the whole image space for each patch in the image. An improved Rough Set Theory (RST) with the collaboration of denoising and segmentation could be an added advantage.

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