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Improved Segmentation of MRI Brain Images by Denoising and Contrast Enhancement

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Abstract

Background/Objectives: The Rician noise in MRI (Magnetic Resonance Image) degrades the image quality and thus, accuracy in segmentation is reduced and localization of tumour may not be precise. In this paper, a robust approach is proposed which estimates and removes the Rician noise of 2D MRI for improving segmentation and detection of tumours. **Methods/Statistical analysis:** First, a robust Rician noise estimation algorithm is employed to identify all the pixels with high Rician noise. Second, a bilateral filter based denoising algorithm is employed to filter image in the wavelet domain. Successively a bilateral filter parameter optimization method is adopted, which uses the noise, contrast and frequency components in MRI to select suitable filter parameters for Bilateral Filter (BF). It is suitable for edge preserving and for adaptive denoising to segment image correctly. Further, after denoising the image, the contrast of the image is improved as a pre-processing step before the image segmentation. Next, SVM-based image segmentation algorithm is employed to segment the 2D MRI. **Findings:** The algorithm is tested both in synthetic and real-time clinical images of tumour affected human brain. The simulation tests show that the denoising and contrast enhancement improves the segmentation of images. The performance of the proposed approach is improved by 29% in segmentation of synthetic images compared to the existing similar techniques. Similarly, an improvement of 22% in segmentation is observed for real-time images. **Application/Improvements:** This approach shows comparable improvement in with respect to processing of MRI. The same procedure may be adopted for other imaging techniques.

Keywords: Denoising, MRI, Noise Estimation, Rician Noise, Segmentation, SVM

1. Introduction

The MRI images are normally affected by a type of noise called Rician Noise. The presence of noise hampers diagnosis. For this, a few pre-processing and post processing techniques are adopted depending upon a type of application. This improves segmentation results. Also, a fully automated or semi-automated segmentation is desirable in clinical studies to improve the quality of diagnosis. First big challenge is related to an isolation of certain region on MRI affected by noise degradations.

Accuracy in identification of certain regions and tissues affected by diseases is the first step in proper diagnosis. It is now established that an MRI imaging is better option for medical diagnosis because it has better contrast ratio compared to the Computer Tomography (CT) based images. In this work, authors have focused on developing a fully automated imaging procedure in which denoising and contrast enhancement are performed for segmentation followed by extracting parameters for further processing of image.

1.2 A Few Challenges in Segmentation of MRI

The segmentation of brain MRI is difficult owing to the artifacts and in-homogeneities in the image acquisition[1]. The major cause of it is noise which also prevents an automated segmentation. Additionally, intensity in-homogeneity and partial volume effects also cause hurdles[2]. The noise found in magnetic resonance imaging system has a Rician noise distribution. It, however, can

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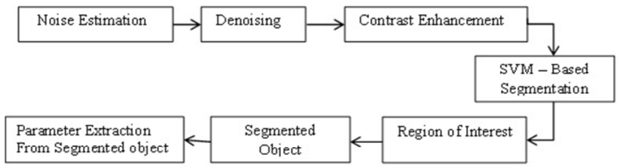


Figure 1. Complete Segmentation Framework.

be eliminated by suitable use of denoising algorithms[3]. The radio frequency field is not homogeneous due to which data acquisition results in shading. This is called intensity in-homogeneity. A few pixels called mixels are occupied by more than one class of tissues often termed as partial volume effect. A complete framework adapted in this paper is given in Figure 1. for achieving better segmentation results.

For better segmentation of the noise affected MRI, initially the denoising algorithm is applied to estimate and remove the noise if any present in the image. Further the contrast of the image is enhanced to have better segmentation. After the pre-processing steps, SVM algorithm is employed to segment the region of interest. Thus these steps are performed to achieve better segmentation results.

2. Noise in MRI

The motion of free electrons is main source of noise in MRI. The motion of electrons can further cause collision with stationary atoms leading to secondary free electron. The random motion of electrons causes noise in receiver coil. The noise presence in MRI should be early estimated and removed before further processing at higher stages. For this research work, a wavelet domain based bilateral filter is used for removing Rician noise.

2.1 Bilateral Filter for Combating Noise

The block diagram shown in Figure 2. demonstrates algorithm execution flow with parameter estimation. The parameter estimation and the wavelet decomposition can be done in parallel processing. Thus it becomes faster. If

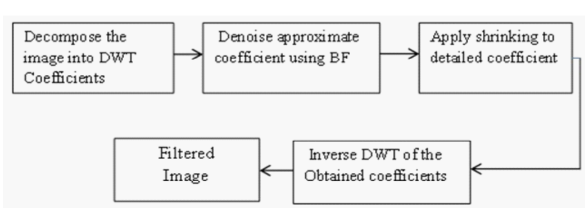


Figure 2. Overall denoising algorithm using Bilateral Filter (BF).

the computational resources are limited, then the same wavelet computational block can be used for calculating the edges, textures and decomposition[4]. Noise estimation is pre-requisite for denoising. The effectiveness of algorithm for denoising also depends on the noise estimation to certain extent[5–10].

The Signal to Noise Ratio (SNR) of an image is given by;

$$SNR = 10\log_{10}\left(\frac{S_{mean}^2}{\sigma_N^2}\right)$$

Where σ_N is the standard deviation. It is estimated for a background and region of interest without signal and S_{mean} is the mean gray level.

3. Contrast Enhancement

The conventional image processing morphological operators like erosion and dilation are used for the enhancement of contrast using algorithm. The Figure 3. shows that algorithm enhancing the contrast of MRI to improve the visual quality of the image. As the MRI is of low contrast image and also the contrast of the MRI is further degraded by presence of Rician noise and thus, noise removing algorithm is a necessary for contrast enhancement.

The contrast is given as

$$C = \frac{S_{\max} - S_{\min}}{S_{\max} + S_{\min}}$$

Here S_{min} and S_{max} are minimum and maximum gray levels respectively. These related to a segment of homogeneous region-of-interest. The same region of interest is received for all images in a given set. C ranges from 0 to 1, 0 being minimum contrast and 1 being maximum contrast. The Figure 3. shows the steps followed in enhancing the contrast of the MRI using the conventional image processing operators. Initially the complement of the image Ac is found while L is the maximum gray level[11]. The disk shaped structuring element SE is applied to the

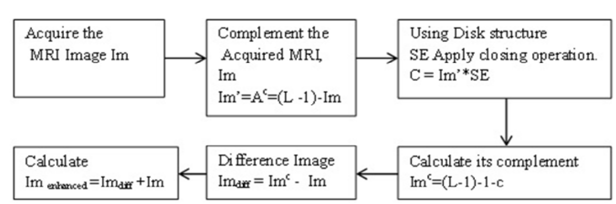
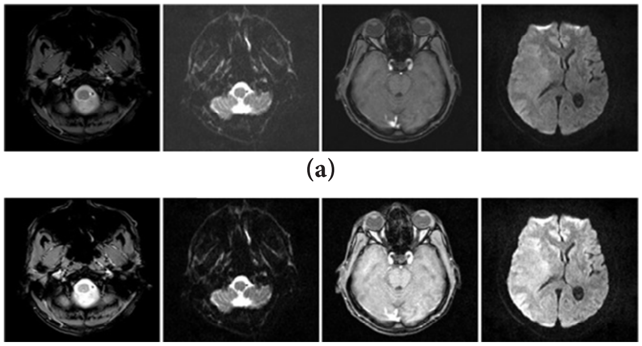


Figure 3. Contrast enhancement algorithm.



(a)

(b)

Figure 4. Output images after Contrast enhancement. **(a)** Original Low-Contrast MRI. **(b)** Contrast enhanced MRI

complement of the image. A difference image is added with the original image to obtain the enhanced image.

The following Figure 4. shows the contrast enhanced image and the original image and the improvement is significant for the images with low contrast ratio.

4. MRI Segmentation Methods

Image segmentation can be broadly classified into different categories. The different algorithms have benefit for a suitable segmentation problem. A Support Vector Machine (SVM) is employed for segmentation of images with brain tumors from the MRI slices. The forthcoming sections are introduced with SVM and SVM based segmentation process for both, synthetic and real-time images. To compare the outputs, an existing works are analyzed for various literatures like Possibilistic C Means (PCM), Fuzzy C-Means Clustering (FCM)[12] and Prior-Information Guided Fuzzy C-Means Clustering (PIGFCM)[13].

The cluster centers are determined using FCM based on iterative adjustments of positions and its objective function. The K-means algorithm variant with prior-information guided algorithm is called PIGFCM algorithm. Noise combating is effective with PCM clustering algorithm. However PCM algorithm is sensitive to initialization process and parameter selection.

4.1 Support Vector Machine Based Algorithms

Support Vector Machines are normally used in pattern classification and segmentation process for better results. The segmentation and classification is carried out in a linear or a non-linear separation in a given background space[14].

The separating function $f(x)$ is expressed by

$$f(x) = \sum_{x_j \in S} \alpha_j y_j K(x_j, x) + b$$

Where, x_j indicates the trainings, $y_j \in \{+1,-1\}$ represents class label with S as a set of support vectors. The vectors can be support vector set, error set or well classified set. Depending on the size of the image and the segmentation, the efficiency of the vector set may vary.

The dual formulation of the above expression is given by;

$$\min_{0 \le \alpha_i \le C} W = \frac{1}{2} \sum_{i,j} \alpha_i Q_{ij} \alpha_j - \sum_i \alpha_i + b \sum_i y_i \alpha_i$$

α_i are the coefficients and b is the offset.
$Q_{ij} = y_i y_j K(x_j, x)$: Indicates symmetric kernel matrix and C represents parameters of error points.
Conditions given by Karush-Kuhn-Tucker (KKT) plays a dominant role in the constrained optimization and the KKT conditions for finding an optimal point is given by:

$$g_i = \frac{\partial W}{\delta_{\alpha_i}} = \sum_i Q_{ij} \alpha_j + y_j b - 1 = y_i f(x_i) - 1$$

$$\text{And } \frac{\partial W}{\delta_b} = \Sigma_j \, y_j \alpha_j = 0$$

Thus using the modified kernel function, the SVM can be reduced to linearly separable case.

4.2 Simple SVM Architecture

The authors have used a simple and fast SVM algorithm proposed by Vishwanathan et al[15]. The SVM can have initialization followed by directly convergence of the solution to speed up the processing. The algorithm shown in Figure 5. can store all the vector sets and initializes with the points from opposite classes. It is similar to the direct SVM. The algorithm in its iteration process, add all the candidates with violating points which are either misclassified or are left unclassified. The algorithm halts once all the points are divided. The quadratic penalty formulation is used for better linear separation of the data points in a given space.

Thus the initialization is taken from direct SVM. The simple SVM is a fast iterative approach which converges easily. Till all the points in the segment are valid, the algorithm keeps finding the violators which do not satisfy the

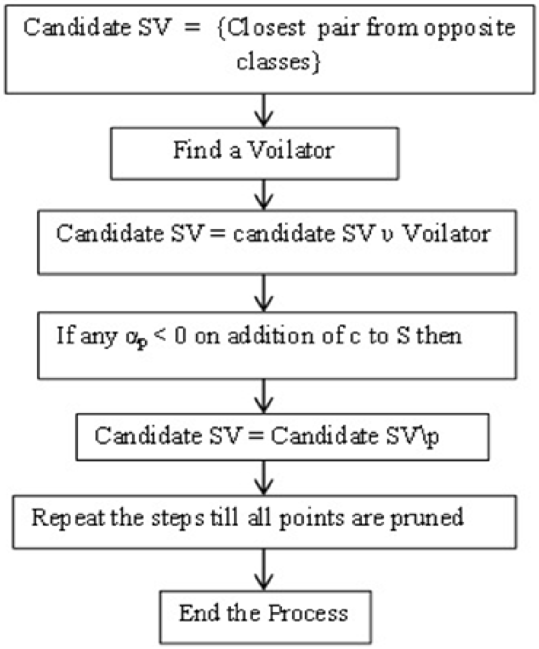


Figure 5. Simple SVM algorithm.

KKT conditions. The additional support vectors are added to C for the existing or initialized support vector S. If no current SV block is included in C to S, then all the S vectors are support vectors. If the value of α_p is less than zero, then the classification of C to S is not needed. The violator is the pixel which is classified wrongly or is not considered as a part of segment where it is supposed to be.

5. Tumor Segmentation

The adopted simple SVM algorithm discussed in section 4 is used for segmentation of the tumour images from given MRI data base. The background and the foreground information can be segregated easily along with type of tissues like gray matter and white matter. For tumour affected brain images, the additional classes for the corresponding tumour type are segmented.

5.1 Simulation Results and Discussion

In this section the performance of the tumour segmentation is analyzed using the adapted simple SVM after the original image is subjected to denoising and contrast enhancement. Segmentation is carried out in a normal way for pathological brain MRI volumetric data. The 3D volumetric data for synthetic MRI is taken from the Brain web resources. The real human brain MRI is taken from the Internet Brain Segmentation Repository (IBSR) and also a few real time samples are taken from the local hospitals. Both synthetic and real human brain MRI is analyzed by using proposed algorithm. The new architecture is better than the existing algorithms available in the literature in terms of accuracy of segmentation and convergence. A Kappa index or Dice Coefficient is used to compare the segmentation performance[1].

$$D = \frac{2|M \cap G|}{(|M| + |G|)}$$

Where M is the segmented tissue and G is ground truth tissue and the Dice coefficient D denotes the amount of spatial overlap. For a perfectly segmented image without any spatial overlap, D = 0. If all the pixels overlap then is unity, then D = 1. The numerator is multiplied by 2 to ensure that the maximum value of D to be unity for a perfect match in segmentation and the expression, and is satisfied.

Table 1. shows the segmentation performance in terms of Dice similarity coefficient and its value is calculated as 1-D.

The values generated in Table 1. is the average values of 100 MR for test images and each of test image is segmented 10 times iteratively by adding noise at random pixel locations. The values in the table indicate a measure of segmentation with 1 being perfect segmentation.

5.2 Evaluation of Segmentation Techniques

The measures of Misclassification Rate (MCR), Root Mean Square Error (RMSE), Under Segmentation (UnS), Over Segmentation (OvS), Incorrect Segmentation (InC) evaluate the segmentation results quantitatively. These are further used to analyze the performance of the segmentation algorithm[16].

Table 1. Comparison of the segmentation performance using Dice on the synthetic image

Method	Dice similarity coefficient for 0-10% noise					
	0	2	4	6	8	10
PCM	0.88096	0.87044	0.85044	0.82054	0.80054	0.74098
FCM	0.96013	0.95040	0.94060	0.93085	0.91095	0.88097
PIGFCM	0.99051	0.97090	0.96057	0.94067	0.91089	0.82024
Simple SVM	0.99098	0.99010	0.98085	0.96015	0.95085	0.94067
Simple SVM with proposed Pre-processing	0.99598	0.99462	0.98604	0.96410	0.96396	0.95292

MCR is defined as ratio of misclassified pixels to available pixels in the object of interest excluding the background pixels in the slice.

$$MCR = \frac{number\ of\ misclassified\ pixels}{total\ number\ of\ pixels}$$

RMSE is widely used to quantify true partial volumes compared to estimated values by algorithm. The RMSE of the proposed estimator is the difference between the original parameter value and its estimation value of θ.

$$RMSE\left(\hat{\theta}\right) = \sqrt{MSE\left(\hat{\theta}\right)} = \sqrt{E\left[\left(\hat{\theta} - \theta\right)\right]^2}$$

The three parameters related to segmentation are important. Under Segmentation, denoted by $UnS = N_{fp}/N_n$. This is called as negative false segmentation. Over Segmentation is indicated as $OvS = N_{fn}/N_p$. This represents a positive false segmentation. The last one is incorrect Segmentation given by $InS = (N_{fp}+N_{fn})/N_n$, which indicates total false segmentation.
Where -
N_{fp} indicated pixels that are segmented wrongly.
N_{fn} indicate pixels that are not segmented into the cluster.
N_p indicates the number of pixels of a cluster.
N_n represents pixels that are not in a cluster.

The Figure 6. shows the brain MRI and the segmented image portions and all possible segments. Also the final ROI is shown separately in the last column.

The Table 2. lists the values of the various performance measures of the proposed segmentation algorithm. It is validated for synthetic MRI. It gives a comparison of other existing methods with the equivalent plot in Figure 7. The experiment is conducted for 100 sample test MRI and each image is added with a random noise. Each of the images is iteratively tested at least 10 times to avoid the positional impact of noise.

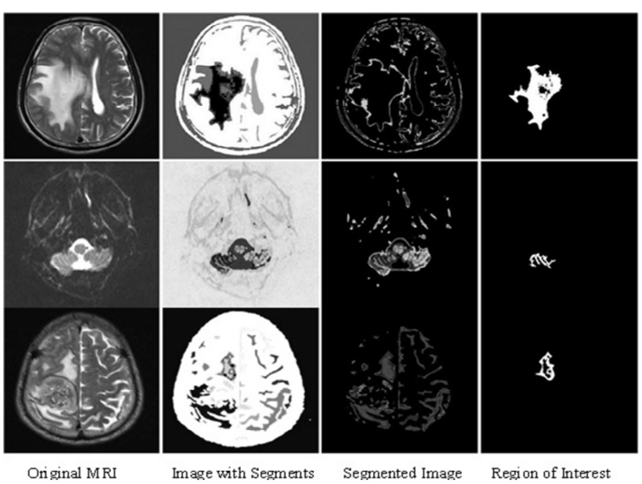


Figure 6. The simulation results of the MRI showing the segmented image and the ROI.

Different test images are considered for finding under segmented, over segmented and incorrectly segmented pixels. Table 2. gives an average value of the results obtained during the simulation run of 100 test samples.

The Table 3. and Figure 8. compares the segmentation performance of various segmentation algorithms for the simulation of human brain MRIs with various levels of noise are introduced as indicated there. For the simulation tests, the noise levels ranging from 0 to 10% is introduced. The data sets consist of a 100 test images for simulation tests.

Table 2. Evaluation of segmentation performance

Evaluation Criterion	PCM	FCM	PIGFCM	Simple SVM	Simple SVM with proposed Pre-processing
UnS (%)	25.20	9.56	6.420	0.023	0.0110
OvS (%)	75.00	23.79	16.22	0.053	0.0358
InC(%)	43.75	14.24	9.88	0.026	0.0143

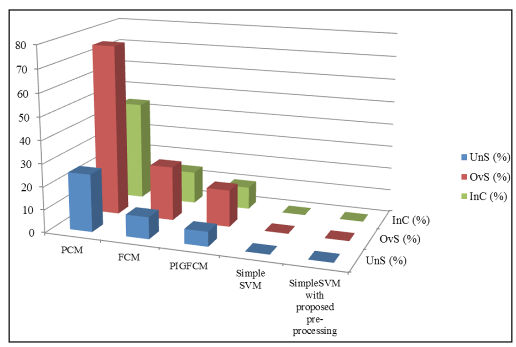


Figure 7. Segmentation performance.

Table 3. Comparison of the segmentation performance using Dice on the real time image

Method	Dice similarity coefficient for 0-10% noise (1-D)					
	0	2	4	6	8	10
PCM	0.88525	0.87510	0.85512	0.82539	0.80571	0.74508
FCM	0.96585	0.95514	0.94500	0.93592	0.91545	0.88594
PIGFCM	0.99552	0.97586	0.96533	0.94554	0.91526	0.82570
Simple SVM	0.99563	0.99553	0.98539	0.96554	0.95553	0.94524
Simple SVM with Proposed Pre-processing	0.99677	0.99948	0.98780	0.96964	0.96889	0.95713

The MCR value for the real time samples are shown in Table 4. As shown in the Figure 9., the MCR value increases for the increase in noise intensity. The improvement in the MCR for the proposed algorithm can be observed graphically in Figure 9.

The RMSE values of the real time image samples are shown in Table 5. and the corresponding plots are illustrated in Figure 10. The values in the table show an increase in the segmentation error if an amount of increasing noise is added. Also the slope of the curve increases quickly if the noise level increases. This behavior can be attributed to the ambiguity in segmentation due to the presence of noisy pixels.

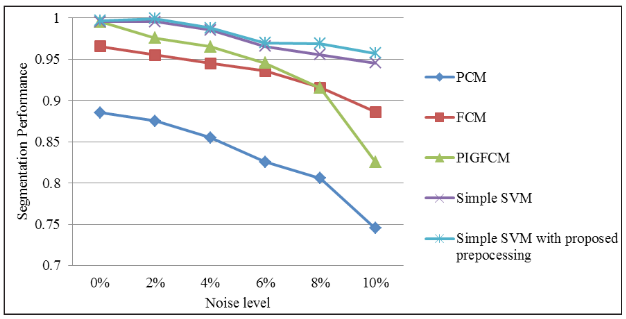


Figure 8. Segmentation performance for various noise intensity.

Table 4. Comparison of MCR on the real time image

Method	MCR %					
	Noise = 0%	2%	4%	6%	8%	10%
PCM	2.72	3.58	4.15	4.08	4.78	6.89
FCM	2.28	2.83	3.41	3.28	4.36	6.02
PIGFCM	1.60	1.89	2.43	3.18	3.96	5.09
Simple SVM	1.09	1.56	2.05	2.48	3.67	4.22
Simple SVM with Proposed Pre-processing	0.90	1.23	1.74	2.35	2.83	3.58

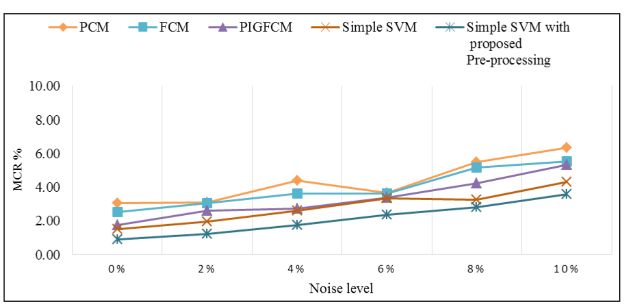


Figure 9. MCR % for various noise intensity.

Table 5. Comparison of RMSE on the real time image

Method	RMSE					
	Noise = 0%	2%	4%	6%	8%	10%
PCM	10.02	11.95	12.56	14.67	19.30	24.27
FCM	8.66	10.30	11.53	13.88	16.33	21.34
PIGFCM	6.98	6.98	10.23	12.10	15.19	21.22
Simple SVM	5.73	5.75	7.48	9.34	12.53	17.83
Simple SVM with Proposed Pre-processing	2.83	4.12	6.44	8.92	9.43	15.43

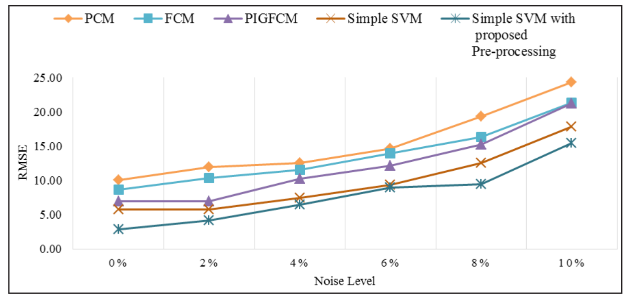


Figure 10. RMSE for various noise intensity.

Also, to simulate the real time MRI scanning process, various uncertainties such as random noise are introduced. Further intensity variations and partial volume effect are introduced. The most of the Rician noise is eliminated by the proposed denoising algorithm. During the acquisition of image, the system may cause a slow change in the intensity and consequently segmentation robustness is degraded by these phenomena. Also across the tissue boundaries, blurring of intensity takes place if multiple tissues possess the same intensity level, which leads to partial volume effect. The proposed pre-processing algorithm removes the noises and enhances the contrast of the image thereby making it suitable for further segmentation process.

6. Conclusion

This paper is presented with a complete framework for accurate and robust segmentation of tumours in human brain MRI by incorporating appropriate pre-processing stages and by adopting the efficient simple SVM algorithm. The proposed segmentation algorithm is better option for the MRI even with image artifacts like rician noise, intensity in-homogeneity and partial volume effect. Further various metrics like UnS, OvS and InC are included for efficiency measurement by the proposed pre-processing and segmentation algorithms. The algorithm is tested in both synthetic and real-time MRI and various performance measures indicate effectiveness and high efficiency of the proposed algorithm. By including suitable pre-processing steps, the segmentation is improved if compared to the existing techniques like PCM, FCM, PIGFCM and SVM. Though the proposed technique has various stages like noise estimation, removal, contrast enhancement and segmentation, it leads to the improved results which show the importance of the individual stages. The evaluation based on the dice coefficient shows a maximum improvement of 29% for the synthetic images and 22% for the real-time images. The algorithm is also good for noise density increasing up to 10%. Also the analysis of the MCR and RMSE value of the segmentation performance in the real time image shows the improvement of the segmentation parameters over the existing methods. The noise level has a significant effect on segmentation performance which is indicated by the values observed for Dice Coefficient, MCR and RMSE. To reduce this effect, the denoising algorithm is applied prior to the segmentation. It has a positive impact on the overall performance of automatic image segmentation system.

The future work involves further improving the efficiency and better segmentation process using algorithms with higher efficiencies and accuracy. The speed of processing images of large size in terms of pixels can be another area of research. Rician noise may be studied for specific applications in medical images for diagnosis. New algorithm development specific to MRI may be undertaken as a future research work.

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