NOISE REMOVAL ON MRI IMAGE USING ANT COLONY OPTIMIZATION

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Abstract: *The main objective of this work is to automatically minimizing the noise level and increase the quality of the DICOM MRI brain images.Image processing normally discharges the function of processing images in digital form. MRI, X-Ray, CT scan, microscope, and Ultrasound medical images are different modalities. These images have various types of noises such as Gaussian noise, Salt and pepper noise, impulse noise, speckle noise, mixed noise, and so on. De-noising is the process of lowering the amount of noise while preserving as many signal properties as possible. These noises are making it difficult to visualization of the images and occupy more space in memory. Therefore, preprocessing approaches are used to remove the noise and enhance the quality of an image. The main objective of this work is to automatically minimizing the noise level and increase the quality of the DICOM MRI brain images. In this research work proposed the ACO algorithm to minimizing the noise level and provides quality output. The proposed algorithms were compared with widely used existing algorithms and their performances are evaluated. The experimental results analysis showed that the proposed ACO algorithm performs efficiently than existing algorithms.*

Keywords: Image processing, Medical Images, Noise, Pre-processing, Filters.

I. Introduction

Recent innovations in the field of healthcare have been significantly accelerated by improvements in information technology and telecommunications. Medical imaging is a method or procedure for examining bodily organs, tissues, and body parts to identify disease. These images are an exchange is made easier and free of imaging equipment manufacturers with the help of DICOM (Digital Imaging and Communication in Medicine). An international standard known as DICOM is used to store, exchange, and communicate advanced medical images as well as other relevant digital data. DICOM is supported and used extensively by contemporary medical imaging frameworks and apparatus like X-rays, ultrasounds, computed tomography (CT), and magnetic resonance imaging (MRI). Each and every medical image is saved in DICOM format. DICOM records are created by medical imaging technology. The fact is that each DICOM document in the medical area contains a significant amount of difficult-to-store information.

Due to flaws in the electronic equipment, environmental factors, and human error during the procedure, the DICOM images are frequently distorted by noise and speckles. Depending on the noise model, various algorithms are employed. It is assumed that the majority of natural images contain additive random noise, which is represented by a Gaussian distribution. MRI images are affected by Rician noise, whereas ultrasound images show speckle noise. Inference from photos with noise may result in an inaccurate diagnosis and take up more space. In these situations, medical image processing plays a significant role in providing clear images. Image enhancement improves the quality of the image. It is used for compression to provideexact reconstruction output. Filtering techniques are employed to remove the noise in an image. In this research work, existing filtering techniques such as median filter, adaptive filter, and bilateral filter are used to enhance the DICOM

MRI brain images. Pre-processing is the most significant step in medical image analysis and it improves the image quality process. Noise removal is a process of cleaning or removing unwanted noise from the image.

II. Related works

Hanafy M. Ali (2018) [17] described fundamental filters to remove the salt and pepper and Gaussian noise in MRI brain images. Proposed methods were adaptive median filter, median filter and adaptive wiener filter. All these three methods were compared. Computational time and memory for the median filter algorithm higher than adaptive wiener and adaptive median filter.

Nair et al. (2014) [7] estimated the by concentrating on preserving edges and tissue boundaries, one may extract noise-free data from MR magnitude images. The suggested technique for reducing Rician noise in MR images was an improvement over the non-local means maximum likelihood approach. Based on the PSNR ratio, visual quality comparison, and SSIM values, Nair et al. focused on a robust estimator function (Geman-McClure function) for calculating weights.

Sotiriou-Xanthopoulos et al. (2014) [12] proposed a The Riciandenoising technique is implemented in hardware, allowing pipelined processing of the MR image segments without further processing of the picture's denoised pixels. The proposed method, when compared to a software-only approach, increased speed by 6.8X while maintaining equivalent picture quality using a synthetic MRI scan divided into 16 segments.

Aarya et al. (2013) [2] proposed a rician noise adaptive filtering method. Rician noise exhibits a variety of distribution features depending on the SNR of the image. Based on the probability distribution function of noise and SNR data gathered from the image, the recommended filter performed de-noising utilizing neighbourhood-specific local statistics contained inside the mask. The filter then applied adaptive de-noising based on the regional SNR of the neighbourhood. The recommended filtering technique had been used on synthetic pictures and T2-weighted MRI images. Researchers were able to validate the efficacy of the proposed filtering approach by comparing the MSSIM, PSNR, and RMSE properties of the de-noised and noisy image to the original image. The suggested de-noising method enhanced the contrast ratio and PSNR of the noisy image.

Sudeep et al. (2013) [13] described a fresh method for eradicating homogeneous Rician noise from magnetic resonance (MR) images. LMMSE estimator was taken as a wise decision for resolving the inverse dilemma. The compressed sensing L1 regularization problem was thought to be solved by de-noising (CS). To reduce the total variation (TV) function, the Split Bregman iteration technique was successfully applied. It was anticipated that de-noising would be enhanced by merging these results in the transform domain. The suggested algorithm outperforms other current approaches in the literature, according to experiments, in terms of Peak Signal Noise Ratio (PSNR).

Foi (2011) [6] developed optimum in both directions variance stabilizing in addition to presenting a stable and quick iterative method for robustly estimating the noise level from a single Rician-distributed image, transformations for the Rice distribution were also presented. These transformations were used to approach the problem of magnetic resonance (MR) image filtering by using standard de-noising algorithms designed for homoskedastic observations. The process uses a homoskedastic variance-estimation technique in combination with variance stabilization at each iteration. The method of Rician noise estimation and elimination by variance stabilization has been shown to be effective through theoretical and experimental testing.

Golshan et al. (2011) [8] proposed an effective method based on the previously proposed method for improving the noisy magnitude MRI LMMSE estimator. To enhance the effectiveness of the unknown signal estimation, the inherent redundancy of the obtained MR data was used. The proposed method was created to cope with 3-D MR volumes since, in actuality, the MR data is primarily 3-D. The new approach's performance was demonstrated and compared to that of several cutting-edge denoising algorithms using both quantitative and qualitative measures. The proposed method conveniently restores delicate structural details while maintaining a low computational cost, according to experimental data.

III. System Methodology

The proposed algorithms were compared with widely used existing algorithms and their performances are evaluated. Peak Signal Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Execution Time are considered performance measures for image preprocessing. The experimental results analysis showed that the proposed ACO algorithm performs efficiently than existing algorithms.The proposed system architecture of this phase is depicted in Figure 1.

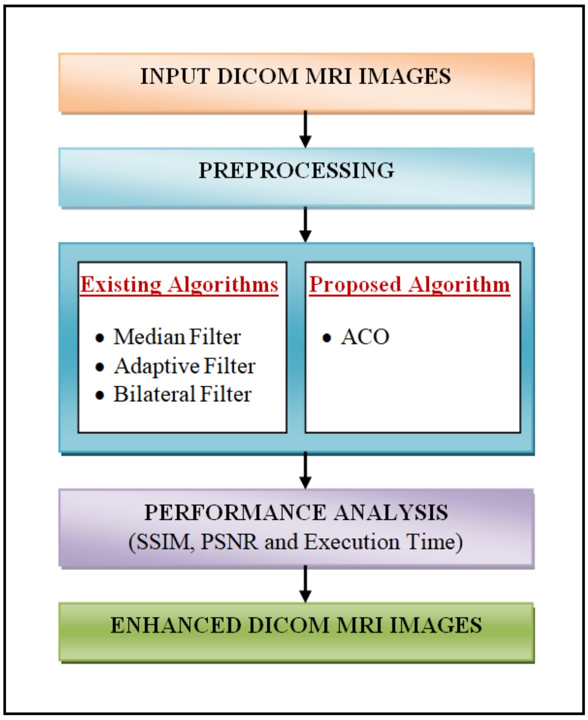


Figure1: Preprocessing System Architecture

3.1 Existing Algorithms

3.1.1 Median Filter

The MR brain images are considered as input and preprocessed by using a median filter. The median filter is capable of reducing the noise deprived by decreasing the sharpness of the image. It is a nonlinear spatial technique, which is used to remove noise from images. It is an effective filtering method that is frequently used to get rid of the noise that gives photos a salty, peppery texture. It is a kind of smoothing technique and removes noise in smooth regions. This filtering is done with an averaging filter and it is best in removing noise with less blurring of edges. In median filtering, every pixel in a picture is changed to have the same value as its closest neighbours. The window size is defined as an odd number of entries i.e., 3 x 3, 5 x 5, 7 x 7, 9 x 9, etc. so that the median can be calculated readily. The pixel values are arranged in ascending order and the median value is identified. Median of series à1, 3, 4, 5, 6, 8, 17, 21, 31 = 6, the center value 1 is replaced by the median value 6. This process is continued until all the pixels are replaced.

3.1.2 Adaptive Filter

Adaptive filter is done by applying a wiener filter to an image. Wiener performs little smoothing. The adaptive filter is more selective in preserving edges. It requires more computation time than median filtering. The grayscale version of the original color image is created. The image is then presented after adding Gaussian noise. First, noise is eliminated, next motion-blurred images are converted with reduced blurring, and finally, the wiener function is used to sharpen the blurred image.

3.1.3 Bilateral Filter

The weights of the bilateral filter, which is a nonlinear weighted averaging filter, rely on both the spatial and the intensity distances from the center pixel. This filter's ability to maintain edges while doing spatial smoothing is its key characteristic. The range weight of the bilateral filter, which uses pixels of various intensities, makes it a strong filter. It ignores outliers and averages out the local tiny details [1]. It applies a range and domain filter to the image. Domain filtering chooses values depending on the required number of pixel combinations, whereas range filtering chooses values depending on the required amount of low pass filtering.

3.2 *Proposed Algorithm*

3.2.1 Ant Colony Optimization (ACO)

ACO technique is optimization technique to solve computation problems. This algorithm motivation of real ant gatherings [19]. ACO is a metaheuristic algorithm that attempts to strike a balance between directing and broadening the search. It draws ants via pheromones. Ants converge more quickly toward a solution when their pheromone sensitivity is increased, but they typically find worse solutions as a result. The ACO-based part bunching is utilized for grouping the picture including vectors dependent on similitude. The kernel clustering which is done through the ideal groups is got utilizing EACO. Initially, the training attribute vectors, mark network, hash works, the fitness function, metrics, and pheromone trails are introduced. At that point for each preparation vector, the bits are dispensed and the portion refreshing is explored. The Eigen esteem issue is overwhelmed through getting the enormous Eigenvector and ascertaining the most similitude esteems. As per these qualities, clustering is accomplished. Anyway, to accomplish ideal clustering, the ACO is used.

The concert of ACO best than other techniques for numerous problems like task scheduling in grid computing [20]. It is also used in protecting unlawful transactions and attacks [21].

In common the ants pick the way dependent on the pheromone fixation on it. The pheromone mindfulness in a way is associated with the quantity of the ant's transient through the way, it figures the plan simply to get into a nearby ideal. To maintain a strategic distance from this downside and improve the combined speed of the subterranean insect settlement calculation the proposed framework is planned using ACO through the pheromone. At each emphasis, the ants which have discovered the briefest way in the cycle are named world-class ants. This way of choice system of subterranean insect settlement calculation is registered through regular ants.

For the k-th exploratory ant the likelihood $p_{ij}^{k}(t)$ of time t to move from i −th grid to j-th grid is depicted via utilizing subsequent condition.

$$p_{ij}^{k}(t) = \begin{Bmatrix} \dfrac{\frac{\eta_{ij}^{\beta}(t)}{\tau_{ij}^{\alpha}(t)}}{\sum_{S\in allowed_k} \frac{\eta_{ij}^{\beta}(t)}{\tau_{ij}^{\alpha}(t)}}, j \in allowed_k \\ 0, otherwise \end{Bmatrix}$$

Where,

$allowedk$-group of the residual possible situation of the k-th exploratory ant

α, β −Weight of $\tau_{ij}^{\alpha}(t)$and $\eta_{ij}^{\beta}(t)$ on the change over possibility, correspondingly

The η_{ij} is the Local heuristic role of visibility , it is defined via below formula

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (2)$$

The best ant's pheromone inform system is distinct as

$$\tau_{ij}(t+n) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}(t) + \alpha + \Delta\tau_{\mathrm{ij}}^{best}(t) \quad (3)$$

Where,

$\Delta\tau_{ij}(t)$- pheromone increment of common ants

The $\Delta\tau_{\mathrm{ij}}^{best}(t)$ is the pheromone growth of elite ants which discharge on the path $< i,j >$ in the present iteration

$$\Delta\tau_{\mathrm{ij}}^{best}(t) = \begin{Bmatrix} \frac{Q}{L_{best}}, i, j, \in L_{best} \\ 0, Otherwise \end{Bmatrix} \quad (4)$$

Where, Q– stable which depicted the quantity of the pheromone addition

L_{best} –length of the path that the k-the lite ant has approved in the present cycle.

Hence the best kernel clustering is achieved which aids in the enhanced recovery of images.

Algorithm 1: Pseudo-code for Ant Colony Optimization (ACO)

Input:DICOM MRI brain images

Output: Enhanced DICOM MRI brain images

Procedure:

Step 1. Initialize the input DICOM MRI brain images
Step 2. Read the pixels from DICOM MRI brain images
Step 1. Position each ant in a starting node
Step 2. For k=1 ; k$\leq r$ do
Step 3. If is updating then
Step 4. $a_k^0 \leftarrow a_k^*$
Step 5. end
Step 6. else
Step 7. Solve the generalized Eigen value problem
Step 8. $K_l^T R_{k-1} K_l a = \lambda K_l^T R_{k-1} K_l$obtaining the largest Eigenvector a_k^0 such that $(a_k^0) K_l^T K_l a_k^0$=1
Step 9. End
Step 10. If $((h^0)^T R_{k-1} h^0 > (h^*)^T R_{k-1} h^*$ then
Step 11. $a_k^* \leftarrow a_k^0 h^* \leftarrow h^0$
Step 12. end
Step 13. if (The ant is a common ant)
Step 14. Chose next node using $p_{\mathrm{ij}}^k(t) = \begin{Bmatrix} \frac{\frac{\eta_{\mathrm{ij}}^{\beta}(t)}{\tau_{\mathrm{ij}}^{\alpha}(t)}}{\sum_{S \in allowed} \frac{\eta_{\mathrm{ij}}^{\beta}(t)}{k\, \tau_{\mathrm{ij}}^{\alpha}(t)}}, if j \in allowed_k \\ 0, otherwise \end{Bmatrix}$
Step 15. end if
Step 16. until (Every ant has build a solution)
Step 17. if (The ant distance is superior than an elite ant distance)
Step 18. Replace the elite ant with the ant
Step 19. end if
Step 20. Update the pheromone
Step 21. Obtained the Enhanced Output Image

Step 22. End

IV. Experimental Results

All the experiments are carried out on a 2.00 GHz Intel CPU with 4 GB of memory and running on windows 8.1. The performance factors of this phase are Structural Similarity Index Measure (SSIM), Peak Signal Noise Ratio (PSNR), and Execution Time.

4.1 Performance Factors

The effectiveness of the proposed and current algorithms is examined using a variety of performance factors. The performance factors of this phase of research work are Peak Signal Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Execution time.

Peak Signal Noise Ratio (PSNR)

The Peak Signal Noise Ratio (PSNR) is used to compare the output and original MRI images for quality. High values gives high quality and low values give low quality of noise removal [18]. The PSNR is defined by

$$PSNR = 10.log_{10} \frac{MAX}{\sqrt{MSE}} \qquad (5)$$

Structural Similarity Index Measure (SSIM)

Structural Similarity Index Measure (SSIM) is the measured similarity between the output image and the original image. The SSIM measure the quality of an image as -1 <= SSIM <= 1, where -1 means undesirable where 1 means an exact match [18]. The SSIM is defined by

$$SSIM\ (x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (6)$$

Execution Time

The required execution time to complete the image pre-processing task is measured.

Table 1 represents Performance Analysis for Preprocessing Algorithms. From the performance analysis, it is found that the proposed ACO algorithm gives high PSNR, SSIM values, and minimum execution time than existing Preprocessing algorithms.

Table 1: Performance Analysis for Preprocessing Algorithms

Algorithms	PSNR	SSIM	Execution Time (Milli Seconds)
Median Filter	27.710236 dB	0.708768	1108.409423 mS
Adaptive Filter	30.173368 dB	0.752128	1025.894500 mS

Bilateral Filter	33.625378 dB	0.662274	941.510596 mS
Ant Colony Optimization (ACO)	37.984224 dB	0.693847	873.637147 mS

Figure 2 shows Performance Analysis for Preprocessing Algorithms using PSNR for MRI DICOM Dataset. From the experimental results, it is observed that the proposed ACO algorithm gives high PSNR values than existing Preprocessing algorithms.

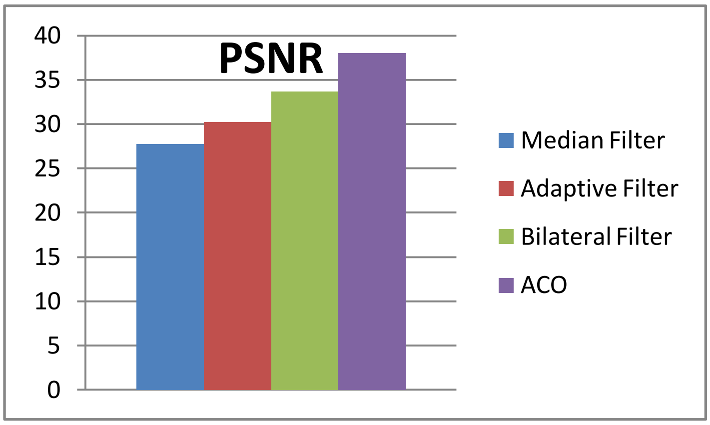


Figure 2: Comparison of PSNR With Preprocessing Algorithms

Figure 3 gives a performance Analysis for Preprocessing Algorithms using SSIM for MRI DICOM Dataset. From the experimental results, it is noticed that the proposed ACO algorithm gives high SSIM values than existing Preprocessing algorithms.

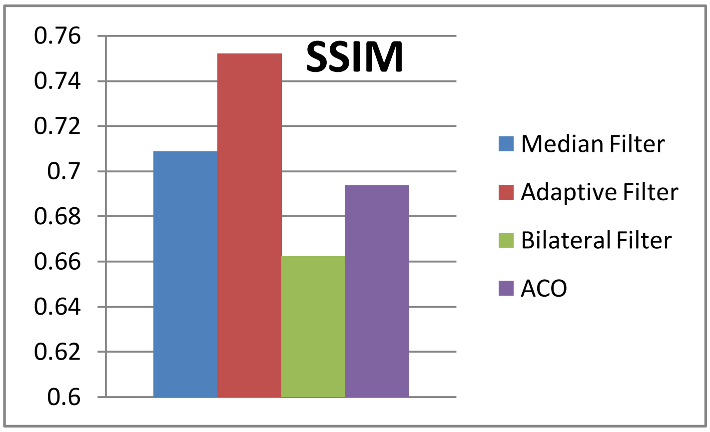


Figure 3: Comparison of SSIM with preprocessing algorithms

Figure 4 depicts the execution time for preprocessing algorithms for MRI DICOM Dataset. From the observation, it is identified that the proposed ACO algorithm takes less execution time than existing preprocessing algorithms.

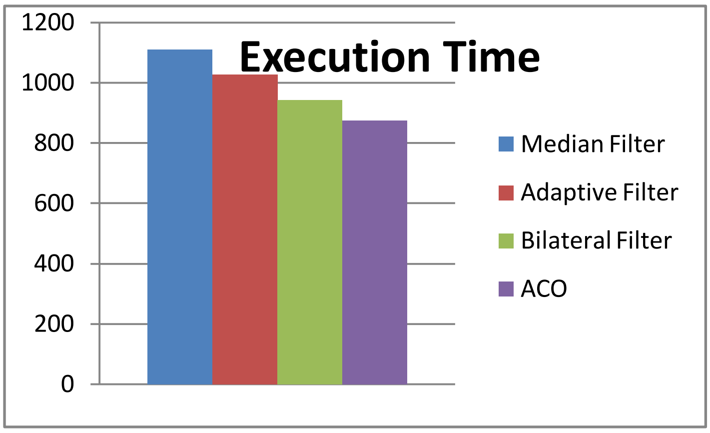
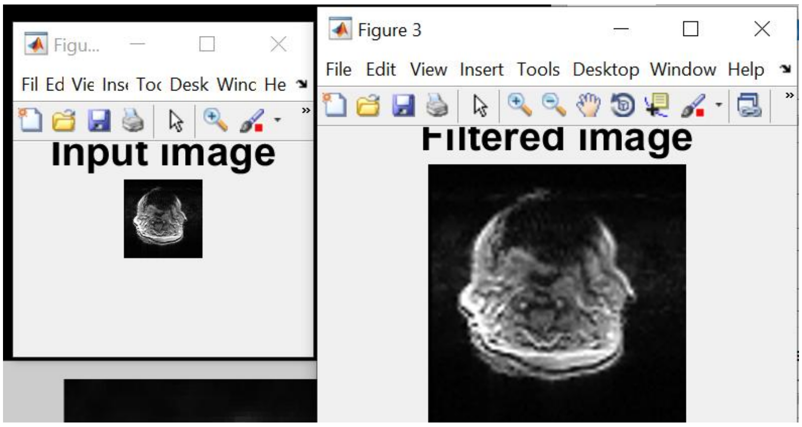
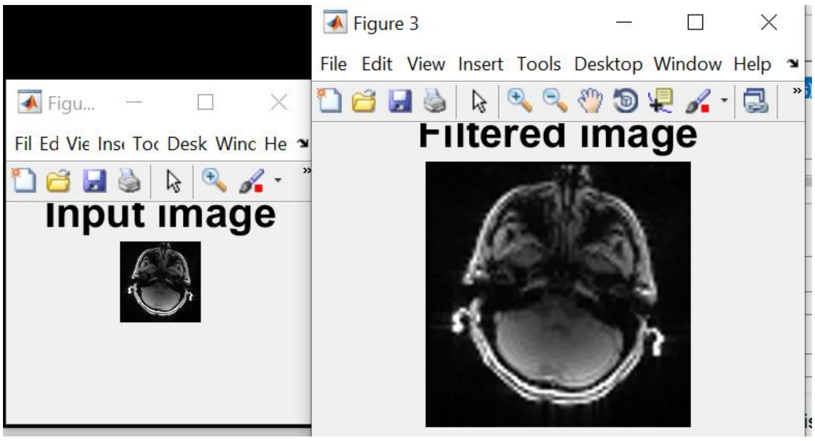


Figure4: Comparison of execution time with preprocessing algorithms

The experiments were done with the DICOM MRI brain image dataset. From the observation, and the experimental results, it was found that the proposed ACO algorithm works well than existing algorithms in all stages. Thus, the preprocessed MRI brain images were fed as input for further processing. The figure 5 represents the input image and filtered image using ACO.





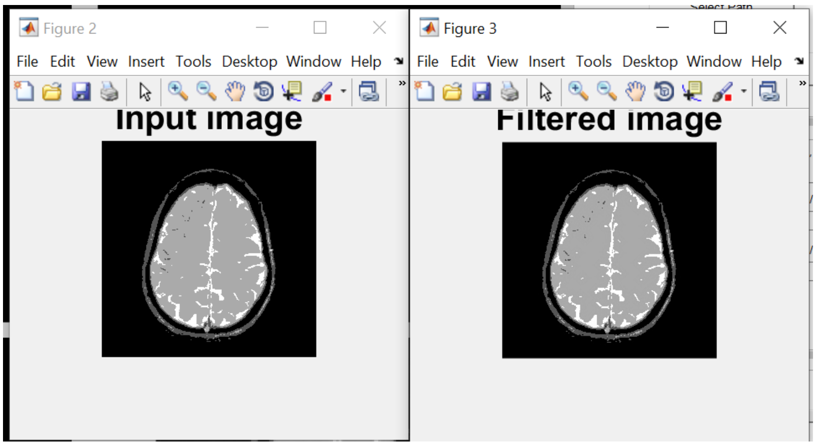


Figure 5: input and output images of various dataset of proposed method.

V. Conclusion

Medical images have various types of noises such as Gaussian noise, Salt and pepper noise, impulse noise, speckle noise, mixed noise, and so on. De-noising is the process of lowering the amount of noise while preserving as many signal properties as possible. These noises are making it difficult to visualization of the images and occupy more space in memory. Therefore, preprocessing approaches are used to remove the noise and enhance the quality of an image. The main objective of this work is to automatically minimizing the noise level and increase the quality of the DICOM MRI brain images. In this research work proposed the ACO algorithm to minimizing the noise level and provides quality output. The proposed algorithms were compared with widely used existing algorithms and their performances are evaluated. The experimental results analysis showed that the proposed ACO algorithm performs efficiently than existing.

References

[1] A. H. Sable and K. C. Jondhale, “Modified Double Bilateral Filter for Sharpness Enhancement and Noise Removal”, in proceedings of International conference, (2010), pp. 295-297.

[2] Aarya, I., Jiang, D., & Gale, T.J. (2013). Adaptive SNR filtering technique for Rician noise denoising in MRI. The 6th 2013 Biomedical Engineering International Conference, 1-5.

[3] Ashour, AS, Samanta, S, Dey, N, Kausar, N, Abdessalemkaraa, WB &Hassanien, AE 2015, „Computed tomography image enhancement using cuckoo search: a log transform based approach‟, Journal of Signal and Information Processing, vol. 6, no. 3, pp. 244-257.

[4] C.-H. Lin, J.-S. Tsai, and C.-T. Chiu, “Switching bilateral filter with a texture/noise detector for universal noise removal”, in the proceedings of IEEE transactions on the image processing, vol. 19, no. 19, (2010), pp. 2307-2320.

[5] Florian Luisier, Thierry Blu, Michael Unser, “Image Denoising in Mixed Poisson–Gaussian Noise”, IEEE transactions on image processing, vol. 20, no. 3, pp. 696-708, march 2011.

[6] Foi, “Noise Estimation and Removal in MR Imaging: the Variance-Stabilization Approach”, Proc. 2011 IEEE International Symposium on Biomedical Imaging, ISBI 2011, pp. 1809-1814, Chicago (IL), USA, April 2011. DOI doi:10.1109/ISBI.2011.5872758

[7] J. J. Nair and N. Mohan, "A robust non local means maximum likelihood estimation method for Rician noise reduction in MR images," 2014 International Conference on Communication and Signal Processing, 2014, pp. 848-852, doi: 10.1109/ICCSP.2014.6949963.

[8] M. Golshan, Hosein&Hasanzadeh, Reza. (2011). A NonLocalRician Noise Reduction Approach for 3-D Magnitude Magnetic Resonance Images. 2011 7th Iranian Conference on Machine Vision and Image Processing, MVIP 2011 - Proceedings. 10.1109/IranianMVIP.2011.6121559.

[9] M. Heydari and M. -R. Karami, "A new adaptive noise estimator for PDE-based MR images denoising," 2015 23rd Iranian Conference on Electrical Engineering, 2015, pp. 11-16, doi: 10.1109/IranianCEE.2015.7146174.

[10] Raman Maini, Himanshu Aggarwal "A Comprehensive Review of Image Enhancement Techniques" Jounalof Computing, ISSN 2151-9617, VOLUME 2, ISSUE 3, MARCH 2010.

[11] Roman Garnett, Timothy Huegerich, Charles Chui, "A Universal Noise Removal Algorithm With an Impulse Detector", IEEE transactions on image processing, vol. 14, no. 11, pp. 1747-1754, November 2005.

[12] Sotiriou-Xanthopoulos, Efstathios& Xydis, Sotirios&Siozios, Kostas &Economakos, George &Soudris, Dimitrios. (2014). Hardware Accelerated RicianDenoise Algorithm for High Performance Magnetic Resonance Imaging. 10.1109/MOBIHEALTH.2014.7015951.

[13] Sudeep, P. &Ponnusamy, Palanisamy&Rajan, Jeny. (2013). A Hybrid Model for Rician Noise Reduction in MRI. Proceedings - 2nd International Conference on Advanced Computing, Networking and Security, ADCONS 2013. 56-61. 10.1109/ADCONS.2013.29.

[14] V. NivithaVarghees, M. SabarimalaiManikandan and R. Gini, "Adaptive MRI image denoising using total-variation and local noise estimation," IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM -2012), 2012, pp. 506-511.

[15] X. Zeng, L. Yang, "Mixed impulse and Gaussian noise removal using detail-preserving regularization", Optical Engineering vol. 49, no. 9, pp. 097002-1-097002-9, Sep. 2010.

[16] Zhengmao Ye, Habib Mohamadin, Su-Seng Pang, Sitharama Iyengar "Contrast Enhancement and Clustering Segmentation of Gray Level Images with Quantitative Information Evaluation" Weas Transaction on Information Science & Application Vol. 5, pp.181, February 2008.

[17] Hanafy M. Ali "MRI Medical Image Denoising by Fundamental Filters" IntechOpen, High-Resolution Neuroimaging - Basic Physical Principles and Clinical Applications, 2018

[18] Anwar Shah "Comparative analysis of median filter and its variants for removal of impulse noise from gray scale image" Journal of King Saud University – Computer and Information Sciences, 34 (2022) 505–51 Published by Elsevier B.V. on behalf of King Saud University,

[19] S. Kalaivani "Parameter Estimation of Valve Stiction Using Ant Colony Optimization" ICTACT Journal On Soft Computing, July 2012, Volume: 02, Issue: 04.

[20] P. Mathiyalagan "Grid Scheduling Using Enhanced Ant Colony Algorithm" ICTACT Journal on Soft Computing, July 2010, Volume: 01, Issue: 02.

[21] A. Vinodh Kannan "Intrusion Detection in Internet Of Things Using Ant Colony Optimisation" ICTACT Journal On Data Science And Machine Learning, June 2020, Volume: 01, Issue: 03.