Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 1786 - 1792
Received 25 April 2021; Accepted 08 May 2021.

Fuzzy Based Mean Filtering Techniques Using Nlm Algorithm

R.Sivakami [1], Dr.S.Angel Latha Mary [2], Dr.A.Usha Ruby [3], Dr.S.Yasotha[4], P.Matheswaran [5], Dr.M.Deivakani [6], S.Gowdhamkumar [7]

[1] Associate Professor, Department of Computer Science and Engineering, Sona College of Technology, Salem, Tamilnadu. Email Id: shivasona07@gmail.com

[2] Professor and Head, Department of Computer Science and Engineering, Karpagam College of Engineering, Coimbatore. Email id: xavierangellatha@gmail.com

[3] Associate Professor, Department of Computer Science and Engineering, GITAM School of Technology, Bangalore Campus, GITAM University. Email id: uruby@gitam.edu

[4] Assistant Professor, Department of Mathematics, M.Kumarasamy College of Engineering (Autonomous), Karur. Email Id: shanmugam.yaso08pm16@gmail.com

[5] Assistant Professor, Department of Computer Science and Engineering, K.Ramakrishnan College of Technology, Trichy, Tamilnadu. Email Id: mathesh3@gmail.com

[6] Associate Professor, Department of Electronics and Communication Engineering, PSNA College of Engineering and Technology, Dindugul, TamilNadu-624622. Email Id: mdeivakani82@gmail.com

[7] PSG Industrial Institute (PSGCT), Peelamedu, Coimbatore-641004, Tamilnadu, India Email id:saigowdham@gmail.com

ABSTRACT:

In this paper, a new Fuzzy based Fast Non Local Mean algorithm is proposed to denoise Rician noise from MRI images, when an image is acquired by a camera or other imaging system, often the vision system for which it is intended is unable to use it directly. The image may be corrupted by random variations in intensity, variations in illumination, or poor contrast that must be dealt with in the early stages of vision processing. Many images contain unevenly distributed gray values. It is common to find images in which all intensity values lie within a small range, such as the image with poor contrast shown in Fig.1. Histogram equalization is a method for stretching the contrast of such images by uniformly redistributing the gray values. This step may make threshold selection approaches more effective. In general, histogram modification enhances the subjective quality of an image and is useful when the image is intended for viewing by a human observer

Recently non-local means has been extended to other image processing applications such as deinterlacing, view interpolation, and depth maps regularization. The proposed method gave better result than existing Fast NLM technique with high and density Rician noise in the image and it is Fast than NLM.

Keywords: Image Denoising, Fuzzy Based Non Local Mean, Rician Noise.

1 Introduction

X-ray pictures assume a significant part to analyze different kinds of infections in human body. X-ray pictures are debased with various kinds of commotions, yet principle clamor is Rician commotion. To denoise Rician clamor from MRI picture is troublesome on the grounds that Rician commotion is an intricate clamor. Commotion obscures the significant highlights in the pictures. In this way for additional handling of the picture, clamor expulsion from the picture is required. [1] A denoised picture is needed for precise investigation and finding by clinical experts as it is a significant test in mechanized clinical innovation.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 1786 - 1792
Received 25 April 2021; Accepted 08 May 2021.

A simple example of histogram modification is image scaling: the pixels in the range [a,b] are expanded to fill the range [ZbZk]. The formula for mapping a pixel value z in the original range into a pixel value z' in the new range

$$\begin{aligned} z' &= \frac{z_k - z_1}{b-a}(z-a) + z_1 \\ &= \frac{z_k - z_1}{b-a} z + \frac{z_1 b - z_k a}{b-a}. \end{aligned} \quad (1)$$

The problem with this scheme is that when the histogram is stretched according to this formula, the resulting histogram has gaps between bins. Better methods stretch the histogram while filling all bins in the output histogram continuously. If the desired gray value distribution is known a priori, the following method may be used. Suppose that Pi is the number of pixels at level Zi in the original histogram and qi is the number of pixels at level Zi in the desired histogram. Begin at the left end of the original histogram and find the value k1 such that

$$\sum_{i=1}^{k_1-1} p_i \leq q_1 < \sum_{i=1}^{k_1} p_i. \quad (2)$$

Picture de-noising is perhaps the most crucial issues in picture preparing. Pictures procured utilizing various modalities experience the ill effects of different sorts of commotion. Commotion is added either by the instrument or the imaging climate.

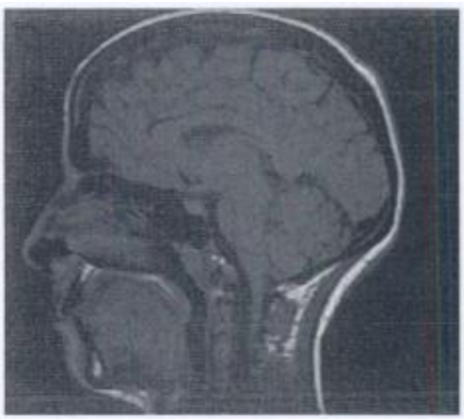


Fig.1 Image with Poor Pixel range

The utilization of loud pixels around pixel for denoising gives significant data to improving the commotion concealment ability are a class of versatile picture channels that consider power data from more inaccessible areas. In this channel weighted amount of all pixels in the picture is utilized for sup-squeezing clamor in every pixel. The heaviness of a pixel relies upon it likeness to the pixel to be reestablished. The dark level force of the pixels is utilized to quantify the closeness between them [2] the spatial distance between the pixels is utilized to figure pixel loads. Yaroslavsky channels give ideal outcomes in homogeneous locales however will in general obscure edges and surfaces presented a straightforward and viable methodology that consolidates dim levels or shades of pixels on both their spatial closeness and their photometric comparability giving lighter loads to approach pixels than the distant ones. Their proposed approach is prominently alluded to as Bilateral Filtering”. A change in outlook in the methodology of picture denoising was proposed by Buades et who presented non-neighborhood implies (NLM) channel. In their methodology, two picture patches are looked at utilizing the dark level layout coordinating. The methodology gives superb de-noising execution over the reciprocal channel strategy in light of the fact that the force of the pixel at the focal point of the reference fix is

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 1786 - 1792
Received 25 April 2021; Accepted 08 May 2021.

changed relying upon weighted normal of the Euclidean distances of the reference and target patches. Albeit the NLM channel favorable to vides great denoising execution, it experiences high computational intricacy. The focal point of this strategy is to propose a quick NLM based technique for commotion concealment in MRI pictures

2 Related Work

A. The Nonlocal Means (NLM) Algorithm

In any digital image, the measurement of the three observed color values at each pixel is subject to some perturbations. These perturbations are due to the random nature of the photon counting process in each sensor. The noise can be amplified by digital corrections of the camera or by any image processing software. For example, tools removing blur from images or increasing the contrast enhance the noise

The principle of the first denoising methods was quite simple: replacing the color of a pixel with an average of the colors of nearby pixels [3].The variance law in probability theory ensures that if nine pixels are averaged, the noise standard deviation of the average is divided by three. Thus, if we can find for each pixel nine other pixels in the image with the same color (up to the fluctuations due to noise) one can divide the noise by three (and by four with 16 similar pixels, and so on). This looks promising, but where can these similar pixels be found? The most similar pixels to a given pixel have no reason to be close at all. Think of the periodic patterns, or the elongated edges which appear in most images. It is therefore licit to scan a vast portion of the image in search of all the pixels that really resemble the pixel one wants to denoise. Denoising is then done by computing the average color of these most resembling pixels. The resemblance is evaluated by comparing a whole window around each pixel, and not just the color. This new filter is called non-local means [1, 2] and it writes

$$NLu(p) = \frac{1}{C(p)} \int f(d(B(p), B(q)) \, u(q) \, dq, \qquad (3)$$

Where d(B(p), B(q)) is an Euclidean distance between image patches centered respectively at p and q, f is a decreasing function and C(p) is the normalizing factor.Since the search for similar pixels will be made in a larger neighborhood, but still locally, the name “non-local” is somewhat misleading. In fact Fourier methods for example are by far more nonlocal than NL-means. Nevertheless, the term is by now sanctified by usage and for that reason we shall keep it. The term “semi-local” would have been more appropriate, though [4]. The implementation of the current on line demo2 is based on a patch version of the original NL-means. This version is based on a simple observation. When computing the Euclidean distance d(B(p), B(q)), all pixels in the patch B(p) have the same importance, and therefore the weight f(d(B(p), B(q)) can be used to denoise all pixels in the patch B(p) and not only p. For completeness, we shall give both the original (pixelwise) presentation, and the patch wise presentation of the same algorithm, which is somewhat more elegant. The NLM method is computation intensive which grows quadratically with the size of the local window. In this paper, an attempt is made to overcome this limitation by proposing Fuzzy-UNLM for removing Rician noise.

B. NLM Method -1 (PRO)

The drawback of NLM is slow speed; to overcome the drawback of classical NLM various researchers have worked to improve the speed of NLM in median in NLM instead of Mean to improve the performance of NLM and create a dictionary of similar patch and non similar patch to improve the speed of NLM and to find the silent features from the image and then compare these features with local windows pixels instead comparing hole pixels in local windows.

The denoising of a color image u = (u1, u2, u3) and a certain patch B = B(p, f) (centered at p and with size (2f + 1) × (2f + 1)) writes

$$\hat{B}_i = \frac{1}{C} \sum_{Q=Q(q,f)\in B(p,r)} u_i(Q)\, w(B,Q), \qquad C = \sum_{Q=Q(q,f)\in B(p,r)} w(B,Q), \qquad 4)$$

Initially they generated the new image N_{dx} from existing image e using discrete integration and squared differ- ence of image e and its translation d_x by following equation

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 1786 - 1792
Received 25 April 2021; Accepted 08 May 2021.

$$\hat{u}_i(p) = \frac{1}{N^2} \sum_{Q=Q(q,f)|q\in B(p,f)} \hat{Q}_i(p). \tag{5}$$

C. Soft Computing Techniques

Soft computing is defined as a group of computational techniques based on artificial intelligence (human like decision) and natural selection that provides quick and cost effective solution to very complex problems for which analytical (hard computing) formulations do not exist. The term soft computing was coined by Zadeh [Zadeh, 1992]. [5] Soft computing aims at finding precise approximation, which gives a robust, computationally efficient and cost effective solution saving the computational time. Most of these techniques are basically enthused on biological inspired phenomena and societal behavioural patterns. The advent of soft computing into the computing world was marked by research in machine learning, probabilistic reasoning, artificial neural networks (ANN), fuzzy logic [Jang *et al*., 1997] and genetic algorithm (GA). Today, the purview of soft computing has been extended to include swarm intelligence and foraging behaviours of biological populations in algorithms like the particle swarm optimization (PSO) and bacterial foraging algorithm (BFO) [Holland, 1975; Kennedy and Eberhart, 1995; Passino, 2002].

Soft computing methods are associated with certain distinctive advantages. These include the following:

• Since Soft computing methods do not call for wide-ranging mathematical formulation pertaining to the problem, the need for explicit knowledge in a particular domain can be reduced.
• These tools can handle multiple variables simultaneously.
• For optimization problems, the solutions can be prevented from falling into local minima by using global optimization strategies.
• These techniques are mostly cost effective.
• Dependency on expensive traditional simulations packages can be reduced to some degree by efficient hybridization of soft computing methods.
• These methods are generally adaptive in nature and are scalable.

Of late, soft computing techniques have attracted recognition amongst researchers of various branches of engineering in order to arrive at solutions to problem statements the sturdiness of the above techniques has been well tested pertaining to various problems encountered in every sphere of engineering. Indeed, the last decade has seen the implementation of soft computing in microwave applications. This chapter gives a glimpse of the various soft computing techniques that are widely used in the field of electromagnetic.

D. Artificial Neural Networks

Certain features of human brain such as the capability to recognize and perceive, have been studied for decades. The remarkable characteristics of the human brain drove researchers into attempting to emulate these characteristics in computers.[6] First drawback of NLM method to remove Rician noise is, it blurs the edge and second introduces extra bias in pixels. So some advanced methods are required to remove the above said drawbacks.

Gray

σ	Comp. Patch	Res. Block	h
$0 < \sigma \leq 15$	3×3	21×21	0.40σ
$15 < \sigma \leq 30$	5×5	21×21	0.40σ
$30 < \sigma \leq 45$	7×7	35×35	0.35σ
$45 < \sigma \leq 75$	9×9	35×35	0.35σ
$75 < \sigma \leq 100$	11×11	35×35	0.30σ

Color

σ	Comp. Patch	Res. Block	h
$0 < \sigma \leq 25$	3×3	21×21	0.55σ
$25 < \sigma \leq 55$	5×5	35×35	0.40σ
$55 < \sigma \leq 100$	7×7	35×35	0.35σ

Table: 1 Patchwise Parameters Implementation Method

Statistical filters also have limitations such as Non Local filter work better for non- smooth regions when low level ricion noise in MR image. Local statistical work well in smooth region and when high level rician

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 1786 - 1792
Received 25 April 2021; Accepted 08 May 2021.

noise in MRI image.

To overcome this problem Fuzzy based hybrid filters have been proposed by different researchers.. Sharif et. al used fuzzy functions to find the similar windows in NLM and find the difference of central pixel and neighbor pixels in window and then compute the fuzzy membership function and these computed values are used as weights of the pixel to find the denoised central pixel proposed an probability based early termination method in NLM used local and global statistics to construct fuzzy function to estimate the denoise pixels. Fuzzy based filters are also introduced to remove other types of noise such as impulse noise used fuzzy triangular methods to denoise the impulse noise from pixels in local window they find the highest intensity minimum intensity and average intensity of local window and then used fuzzy function and replace the central value of pixel with highest membership value used Fuzzy function to classify corrupted and non corrupted pixels and then used ANN to denoise impulse noise from image proposed a fuzzy based methods which is used to remove the Fixed and Randam Impulse noise in the image. If noise is fixed they used simple array to denoise but if Random Impulse noise then they used fuzzy to denoise image. Many researchers improved NLM methods to suppress Rician noise by using soft computing techniques.

3 Proposed Method

In the Proposed work, Fuzzy based Fast NLM filter is used to denoise Rician noise from image.

A. Reduction in Rician Noise

The results of the proposed method are assessed for Rician noise in magnetic reso- nance imaging (MRI) and the results are compared with unbiased NLM filter (UNLM) and Fast NLM for Rician noise suppression using brain web database. It is a normal perception that the noise in images is independent of the pixel intensity but in many areas of biomedical imaging this is not true. In biomedical images, noise is functionally dependent on image. [7] For example, noise in MRI follows Rician distribution that is signal dependent. In living beings, different tissues have different densities of water molecules. The tissue type can be recognized by an analysis of hydrogen proton density in these tissues. MRI uses this methodology and is widely used in imaging the brain, muscles, heart, etc as it provides good contrast between the different soft tissues of the body. The MRI signal is measured through a quadrature detector that gives the real and the imaginary signals. MRI signal is expressed by

$$\sum_{i=1}^{k_2-1} p_i \leq q_1 + q_2 < \sum_{i=1}^{k_2} p_i. \qquad (6)$$

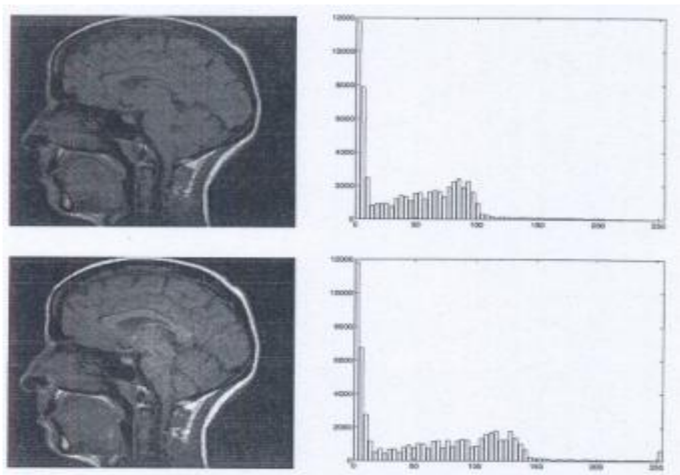
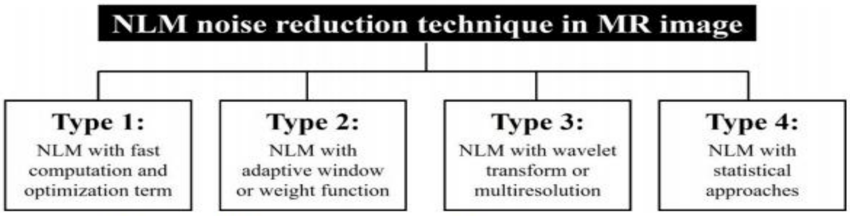


Fig.2 Difference Between the contrast and clarity comparison (Values of graph comparison)

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 1786 - 1792
Received 25 April 2021; Accepted 08 May 2021.



Types of non-local means (NLM)-based noise reduction techniques for magnetic resonance (MR) images.

The performance of the three methods proposed method, UNLM and Fast NLM is compared using T1, T2, and PD weighted MRI images from BrainWeb phantom as used in with noise levels 3%, 6%, 9%, 12%, 15%, and 18%. The original and noisy images with noise level 6%, 18% are shown in Fig. 4. In T1-weighted MRI images, water and fluid-containing tissues are dark and fat-containing tissues are bright. The reverse is true for T2-weighted images. In PD images, there is a marked difference between the brain‟s gray matter and the white matter. The visual results after applying the three denoising methods are shown in Fig. 1. Cut out images are shown in Fig.2. The histogram of normal image without noise with noise and denoise image after applying three methods shown in Fig.3.

The visual results obtained by our proposed method Fuzzy Based Fast-NLM are similar to UNLM and Fast NLM. In terms of PSNR, RMSE, MSSIM, and FOM, UNLM gives best results for pd, T1, T2 weighted MRI images.[8] Fast NLM is the least efficient in suppressing the noise for pd,T1 and T2 weighted images with noise above 9%. But the proposed method gives better results than Fast NLM for pd, T1 and T2 weighted MRI images with noise level higher than 9%.

In terms of computational complexity Fuzzy Based Fast NLM method is faster than the UNLM methods as time taken by this method is less than UNLM. As the computa- tionanal time taken by proposed method is much lesser (approximately 20 time) than the computational time of UNLM and as the computational time is a crucial factor in denoiseing medical images,[9] So the proposed method may be consider better than UNLM and Fast NLM. After ploting the histogram of denoised images using UNLM, Fast NLM and proposed Fuzzy Based Fast NLM it was observed that proposed method preserves the structural information in a better way than the other methods. [10] [11] So from both these observations it can be concluded that the proposed methods is faster than NLM, keeps the originality of the image and gives even better results than Fast NLM.

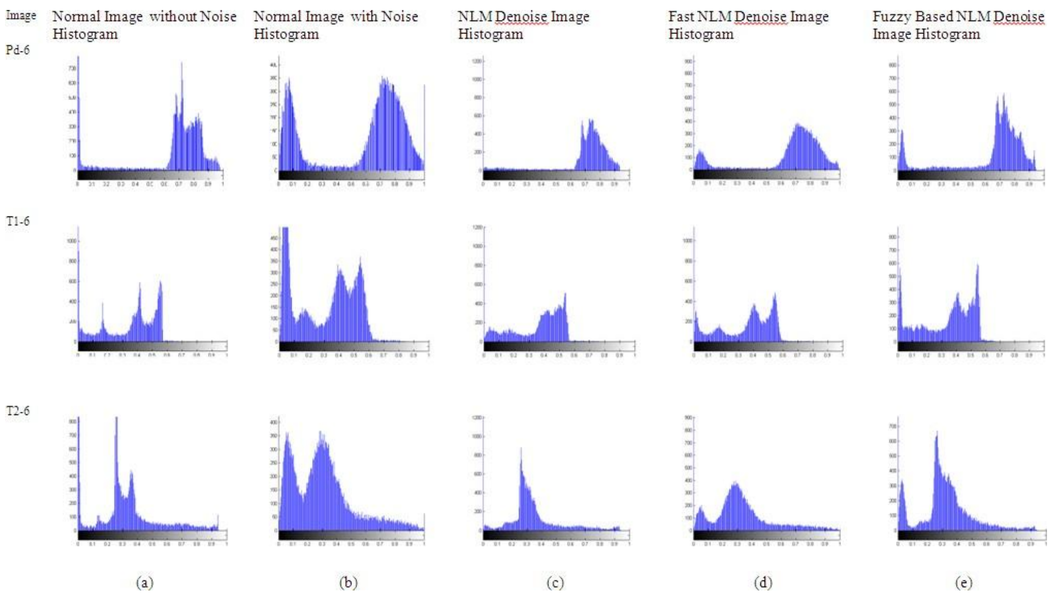


Fig. 3. a) Normal Image without noise Histogram b) Image with Noise Histogram c) NLM Denoise Image Histogram d) Histogram Denoised image using Fast NLM e) Histogram Denoised image using proposed method.

4 Conclusion

It is seen that utilizing Jacords comparability measure improves the denoising brings about pictures with high levels of commotion. In this technique essential picture is utilized to improve the time intricacy. Subsequently, including vital picture, fluffy rationale and Jacords technique brings about better denoising execution. The procedure is computationally less unpredictable than the current UNLM and Fast NLM based comparable methods with improved denoising results.

References

[1] Buades, B. Coll and J. -. Morel, "A non-local algorithm for image denoising," *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, 2005, pp. 60-65 vol. 2, doi: 10.1109/CVPR.2005.38.

[2] L. Alvarez, P.-L. Lions, and J.-M. Morel. Image selective smoothing and edge detection by nonlinear diffusion (ii). Journal of numerical analysis, 29:845-866, 1992.

[3] R. Coifman and D. Donoho. Wavelets and Statistics, chapter Translation-invariant de-noising, pages 125-150. Springer Verlag, 1995.

[4] Donoho. De-noising by soft-thresholding. IEEE Transactions on Information Theory. 41:613-627, 1995.

[5] Ordentlich, G. Seroussi, M. W. S. Verdú, and T. Weissman. A discrete universal denoiser and its application to binary images. In Proc. IEEE ICIP, volume 1, pages 117-120, 2003.

[6] Tomasi and R. Manduchi. Bilateral filtering for gray and color images. In Proceedings of the Sixth Internatmal Conference on Computer Vision, pages 839-846, 1998.

[7] A Manjunathan, A Lakshmi, S Ananthi, A Ramachandran, C Bhuvaneshwari, "Image Processing Based Classification of Energy Sources in Eatables Using Artificial Intelligence", Annals of the Romanian Society for Cell Biology,vol.25, issue.3, pp.7401-7407, 2021.

[8] P Matheswaran, C Navaneethan, S Meenatchi, S Ananthi, K Janaki, A Manjunathan," Image Privacy in Social Network Using Invisible Watermarking Techniques", Annals of the Romanian Society for Cell Biology, vol.25, issue.5, pp.319-327, 2021

[9] M Ramkumar, C Ganesh Babu, K Vinoth Kumar, D Hepsiba, A Manjunathan, R Sarath Kumar, "ECG Cardiac arrhythmias Classification using DWT, ICA and MLP Neural Network",Journal of Physics: Conference Series, vol.1831, issue.1, pp.012015, 2021.

[10] Bhuvaneshwari C, Manjunathan A, "Advanced gesture recognition system using long-term recurrent convolution network", Proc. ICONEEEA, 2019 pp. 1-8.

[11] Dr.A.Vanitha, Dr.N.Balakrishnan. (2020). Data Collection İn Wireless Sensor Network through Hybrid Mac Protocol. International Journal of Advanced Science and Technology, 29(08), 4229-4238. Doi: http://sersc.org/journals/index.php/IJAST/article/view/26243.