DENOISING MRI IMAGES USING FSNLM

Anubha, Dr. Amandeep Kaur

Researcher, Associate Professor
Computer Science & Technology
Central University of Punjab, Bathinda, India.

Abstract: MRI images are very useful source of information for the doctors to diagnose the symptoms. Due to the presence of noise in images hides the important information. Hence we need to preserve the quality of image which can be done by removing the noise. Hence denoising is very necessary to get precise images to simplify the accurate observations. For the estimation of noise-free pixels, FSNLM (Fuzzy Similarity based Non-Local Means) filter is used to select homogeneous pixels. In MRI images, Rician noise is present which introduces bias which further corrupts MRI images. The bias correction has been suggested for the removal of bias which increases PSNR and contrast. The Suggested scheme has been tested on simulated data sets and compared with existing method.

Keywords— dB, FSNLM, IEF, MAE, MRI, NLM, PD, PSNR, SBD, SSIM .

I. INTRODUCTION

Magnetic resonance imaging is a powerful diagnostic technique which is used in radiology to create a picture detailed of the human body as well as based on the principles of nuclear magnetic resonance. MRI images encompass some degree of noise. Noise is a random variation of image Intensity which may produce at the time of capturing or image transmission. It refers to the pixels in the image which show different intensity values instead of true pixel values.

There is an uncertainty in several aspects of image processing. The methodology of Fuzzy Logic emulates the way of decision making in humans which contains all possibilities between values yes and no. It works on the ranges of possibilities like certainly yes, possibly yes, cannot say, possibly no and certainly no of input to attain the definite output. Its main advantages are-:-

- Easy to understand
- Flexible
- Tolerant of imprecise data

There are broadly two filters to denoised images i.e. linear and non-linear filters. Mean filter, Gaussian filter are the linear filters whose advantage is the speed but they are not able to preserve edges. Non-linear models can tackle edges in a better way like non local means filter. It takes the mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. This results in much less loss of detail in the image compared with local mean algorithms. NLM based filters use all the non-local neighbours for the assessment of noise free value without region analysis. It is highly probable that non-local neighbours belonging to different regions (foreground or background) than the central noisy pixel near the image edge information, can disturb the accurate assessment of noise free value. The non-local means algorithm does not make any assumptions about noisy image as other denoising methods. The assumptions are the noise contained in the image is white noise and the true image (image without the noise) is smooth. It assumes that image contains an intensive amount of self-similarity. It is highly feasible that near the image edge information, non-local neighbours belonging to different regions can disturb the accurate estimation of noise free value than the central noisy pixel. Hence by using fuzzy based similarity mechanism non local regions are being analyzed for the estimation noise free pixels.

In existing work, fuzzy similarity based NLM methods had been used for the elimination of Ricain noise. The technique analyses the non-local regions by employing the concept of fuzzy logic based similarity mechanism, and identifies the similar and non-similar regions present around the non-local neighbourhood of the noisy pixel. Based on similarity, non-local pixels present only in the homogeneous regions are used for the estimation of noise-free value. FSNLM computes the weighted average of the surrounding similar pixels, to restore a noisy pixel in the image and hence ignore the pixels present in the non-homogeneous regions. But bias correction is not considered which can be helpful to improve the quality of image. Also, different membership functions like triangular, sigma & S-shape etc. can be applied with fuzzy sets for better results.

In proposed method to overcome the drawbacks of previous work following modifications have been done.

- Non-parametric membership function is used instead of trapezoidal membership function for fuzzification.
- Bias correction method is used to remove bias which improve contrast and PSNR.

II. LITERATURE REVIEW

Magnetic resonance imaging is a powerful diagnostic technique which is used in radiology to create a picture detailed of the human body as well as based on the principles of nuclear magnetic resonance. MRI images are very useful source of information for the doctors to diagnose the symptoms. Due to the presence of noise in images hides the important information. Few authors have done work in this era. MR simulators are used to construct simulated brain database which includes various features as in noise, modality, slice thickness as well as intensity inhomogeneity. A collection of brain images can be simulated by changing MRI parameters, hence image database is generated to test medical image processing. The generation of SBD provide an environment for determining the effects of MRI parameters on pattern recognition and image processing (Kollokian, 1996). The authors said that MR simulators are used to create simulated brain database which encompasses various features as in noise, intensity inhomogeneity as well as slice thickness. A set of brain images can be simulated by varying MRI parameters, hence image database is created which can be further used to test pattern recognition and medical image processing. The authors said the creation of SBD to provide an environment for measuring the effects of MRI parameters on pattern recognition and image processing (Kollokian, 1996). The authors said that an increased importance of brain mapping automated computer techniques and brain image analysis methods leads to an increased necessity for validation and evaluation of the effect of image acquisition parameters. The validation of analysis method and techniques of in-vivo acquired images is complicated because of the lack of reference data. Moreover, the optimal selection of the MR imaging parameters is difficult because of the large parameter space. Hence, Brain Web makes accessible to the neuroimaging community, online on WWW, a set of simulated brain database, SBD that permits the issues to be examined in a systematic, controlled way (COCOSCO, KOLLOKIAN, KWAN, PIKE, & EVANS, 1997). Uncertainty may arise due to information which is either partial information or not fully reliable. Fuzzy set theory is a tool to handle the uncertainty arising due to vagueness. Vagueness (inexact) is nothing but fuzziness. Fuzzy logic is able tolerate imprecise as well as noisy data. Some of the authors have done work on fuzzy logic. The authors discussed the evaluation of fuzzy logic performed on image in MATLAB environment. The author uses in-built functions of MATLAB which in turn are implemented on image and the resultant images are exhibited using different functions. The author has designed fuzzy inference system for four inputs, one output that tells whether the pixel under consideration is “low”, ”medium” or “high” pixel. The rule base includes of eight rules, which classify the target pixel. The tools which contain different phases of the design process, from the initial description phase to the final implementation phase, construct the Toolbox. The Toolbox's best assets are the capacity to build complex systems and the flexibility that allows the user to expand the availability of functions for working with the use of type-1 fuzzy operators, fuzzy variables, membership functions, de-fuzzification methods and the evaluation of Fuzzy Inference Systems (Kaur & Sethi, 2013). MRI images are very useful source of information for the doctors to diagnose the symptoms. Due to the presence of noise in images hides the important information. Hence we need to preserve the quality of image which can be done by removing the noise. Hence denoising is very necessary to get precise images to simplify the accurate observations. There are broadly two filters to denoised images i.e. linear and non-linear filters. Mean filter, Gaussian filter are the linear filters whose advantage is the speed but they are not able to preserve edges. Non-linear models can tackle edges in a better way like non local means filter. The denoising is very essential but at the same time it is very challenging task. The authors said that neighbourhood filters reduce noise by averaging similar pixels which are nonlocal image and movie filters. The authors proposed neighbourhood filters comprising image and movie denoising methods and further more discussing a recently introduced NLM neighbourhood filter. Three principles will be discussed to compare denoising methods. These are “method noise”, “noise to noise” and “statistical optimality”. They use NLM filter as a segmentation tool (Buades, Coll, & Morel, 2005). The authors said that estimation of the noise level in images is very significant to evaluate the quality of the procurement and to permit an efficient analysis. They said that it is a fundamental step a necessary procedure for many type of denoised and image processing. They proposed a new method to estimate the noise level in MR images and evaluated. The advantage of this is the easiness for utilization during image acquisition and of course the adaptability of the idea of other areas of body. The accuracy of the assessment is addressed by comparison of Atlas noise free images where the level of Rician noise was artificially added and known. The main concept is the matching of same slices after registration in order to assess the level of noise. For assessment of the range of noise in an image we used the signal noise ratio – SNR and a set of MRI with increasing levels of Rician noise. However, others metrics like the normalized cross correlation - NCC or the Root Mean Squared Error (RMSE) could be used as well (Pereza, Concib, Morenoc, Andaluz, & Hernández, 2014). The authors said that Magnitude Magnetic Resonance (MR) data are Rician distributed. They proposed new method to estimate the image noise variance for this type of data distribution. This method is based on a double image acquisition, thus manipulating the knowledge of the Rice distribution moments. When it comes to assessment of the image noise variance, methods related on a double acquisition are far higher to single image techniques in terms of precision. However, existing double acquisition techniques become useless when different phase variations are exist in the two images. To get rid of this problem, a noise variance estimation method has been suggested based on two magnitude images. In case of geometrical registration, the proposed noise variance estimator has been verified to be extremely precise and accurate (Sijbers J. , Dekker, Audekerke, Verhoye , & Dyck, 2014). Magnetic Resonance imaging has become a very powerful imaging technique which provides accurate information about human internal structure. Basically it is a test which uses magnetic field and pulse of radio wave energy to create pictures of structures and organs inside body. As MRI images may contain noise which introduce bias. Hence one major drawback of MRI is that it suffer from intensity inhomogeneity or intensity non uniformity or bias which is need to be reduced or eliminated as it improves contrast and increases PSNR. Some of the authors have done work related to removal of bias. The authors said that Homomorphic un-sharp masking and its variations have been usually used as a post-processing method to eradicate inhomogeneities. Though, little data is available in the literature evaluating the relative efficiency of these algorithms to remove inhomogeneities or explaining how these algorithms can affect image data. The results demonstrate that mean-based filtering is more effective than median based algorithms for removing inhomogeneities and that artefacts are commonly introduced into images at most frequently used window sizes. The results show improvement in the efficiency of the algorithms with larger windows. (Brinkmann, Manduca, & Robb, 1998). The authors addressed the problem of parameter estimation from Rician distributed data. The authors discussed and compared conventional estimation methods with maximum-likelihood (ML) estimation which yield optimal results. ML estimation is proven to be unbiased for high SNR and yield relevant results for low SNR (Sijbers, Dekker, Scheunders, & Dyck, 1998). The authors presented a new method Parametric Bias field Correction to the correction of intensity inhomogeneity’s which improves intensity-based tissue segmentation. The distortion of the image brightness values hinders visual inspection and segmentation by using a low-frequency bias field.. The authors assumed that the image is comprised of pixels assigned to a small number of categories having a priori known statistics. Moreover, the authors assumed that the image is corrupted by noise and a low-frequency inhomogeneity field. The estimation of the parametric bias field is expressed as a non-linear energy minimization problem. They said PABIC can correct bias distortions much larger than the image contrast (Styner, Brechbu¨hler , Szekely, & Gerig, 2000). The authors said that bias field signal corrupts MRI images which is a low-frequency and very smooth signal. The algorithms such as segmentation, classification or texture analysis that use the grey level values of image pixels will not produce acceptable results. Before submitting corrupted MRI images to such algorithms, a pre-processing step is required to correct for the bias field signal. The authors discussed two approaches to tackle with bias field corruption. The first approach can be used as a pre-processing step where-ever the corrupted MRI image is replaced by dividing it by an estimated bias field signal using a surface fitting approach. The second approach shows how to change the fuzzy c-means algorithm so as to it can be employed to segment an MRI image corrupted by a bias field signal (Juntu, Sijbers, Dyck, & Gielen, 2015).

III. METHODOLOGY

1. Database collection

MR simulators are used to construct simulated brain database which includes various features as in noise, modality, slice thickness as well as intensity inhomogeneity. A collection of brain images can be simulated by changing MRI parameters, hence image database is generated to test medical image processing.

Generation of the Database

It is essential to create the conditions of MRI parameters prior to build the database.

- Assessment of pulse sequence
- Assessment of noise levels
- Assessment of RF inhomogeneity
- Assessment of different levels of slice thickness

2. Fuzzification of Image

Fuzzification is the procedure of converting a crisp quantity fuzzy. By merely identifying that some of the quantities that need to be considered to be crisp and deterministic but are actually not deterministic at all. They have some kind of uncertainty. If the uncertainty happens to arise because of imprecision, ambiguity or vagueness, the variable is perhaps fuzzy which is represented by a membership function. In this step, by applying non-parametric membership function fuzzified values are obtained to get the images in fuzzy domain i.e. pixels having values in the range (0, 1). The process of fuzzification permits us to deal effectively with uncertainties and inexactness present in the images.

Using non-parametric equations

By applying non-parametric membership functions, fuzzified values are obtained. Few steps to be taken:

- Image is read
- Find the minimum and maximum pixel values.
- Divide the whole image with maximum value.

3. Apply Non Local Means Filter with Fuzzy Similarity mechanism

The Basic idea of the NLM filter is considering the data redundancy among the windows of a noisy image and replace the noise free pixel using weighted average of non-local pixels. The weight estimates the similarity between Ni, N1j and N2j neighborhoods which is centered on pixels pi, q1j and q2j called patches or similarity window. The non-local means filter reflects the pixel intensities of the whole image in the weighted average for theoretical reasons while for practical reasons the pixel intensity is restricted to a neighbourhood called search window (Binaee & Hasanzadeh , 2011).

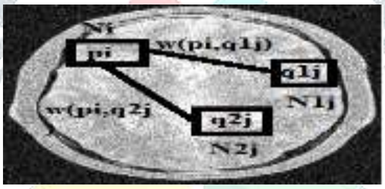


Figure 1: Determining weights for similar windows

The non-local means algorithm has two parameters. The first parameter, Rsim, is the radius of the neighborhoods used to find the similarity between two pixels. No similar neighborhoods will be found if Rsim is too large but too many similar neighborhoods will be found if it is too small.

The second parameter, Rsearch, is the radius of a search window. Due to the inadequacy of calculating the weighted average of every pixel for every pixel, it will be diminished to a weighted average of all pixels in a window.

Fuzzy Similarity Criteria: After getting fuzzified values, next step is to identify the similar windows. Similar windows/patches/regions are identified by using these fuzzified values. Window is a process of selecting a particular part of an image. Windowing is needed as processing the whole image is computationally very expensive. Hence smaller size of area is being used. A better noise free image could be estimated by finding the similar pixels in non-local neighbourhood. Obtaining the similar window is a very-very challenging task due to uncertainty present in MRI images. And that's why fuzzified values are being used to find similar window. Search area is basically used to obtain pixel j similar to pixel i. Out of the whole image, 5*5 and 21*21 windows are taken to obtain similar regions. Consider a region of a gray scale image to explain how similar neighborhoods are evaluated in detail as shown in above figure. Considering pi as the central pixel. The central pixel q1ji and q2j of window N1j and N2j respectively are similar to central pixel pi of window Ni.

The different similarity windows are going to be evaluated by the fuzzy similarity criteria. Search area is used to find a pixel j similar to the pixel i. Rsim represents the radius of local and nonlocal regions or windows Wi and Wj centered at pixel i and pixel j. (Weken, Nachtegael, Witte, Schulte, & Kerre, 2005) The region based comparison is performed to find the similarity of pixel i with all non-local neighboring pixels pixel j separately. The area of radius Rsearch (21* 21), is divided into overlapping windows of radius Rsim (5*5) In order to compute the similarity, if the difference between the fuzzified values of these two windows is less than sim_t,similarity threshold then windows are similar otherwise non-similar. Smaller the differences, greater will be similarity.

$$W_{sim} = F_{ws} - F_{wnl}$$

Where W_{sim}= similar windows

F_{ws} = Fuzzified value of local window

F_{wnl}= Fuzzified values of non-local window

Assigning weights to the pixel and restore the noisy pixel.

The basic principle of the NLM filter is to replace the noisy gray value I (i) of pixel i with a weighted average of the gray-values of all the pixels on the image. The pixel to be denoised is denoted by i and likewise the pixels in the neighbourhood of I by j and use them to denoise i. The NLM algorithm computes a weighted average of non-local pixels and restores the pixels which are in a similar environment. The weight is computed based on the similarity mechanism between the neighbourhood windows of the pixels of interest and contributing pixels. Buades et al. introduced the NLM filter that averages pixel intensities weighted by the similarity of image neighborhoods which are usually defined as 5×5, 7×7 or 9×9 square windows or patches of pixels which has 25, 49 or 81 elements respectively. After computing similar locations firstly calculate the mean of each neighbourhood of entire image. The weight is calculated by using the fuzzified values and mean of those similar windows:

$$weight = \{(1-(F_{ws}-F_{wnl})) * \left(\frac{Ms}{Mnl}\right)\}$$

Where Ms denotes mean of local window, Mnl denotes mean of non-local window

After assigning the weights, calculate the weighted average. The central pixel value is to be replaced by average weighted.

$$\text{Average\_weight} = \frac{\sum_i^n weight * Mnl}{n}$$

Where n= no. of counts weight is assigned.

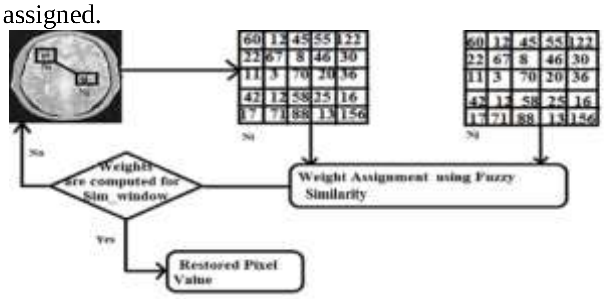


Figure 4: Flow chart of FSNLM

4. Apply bias correction method

After restoring the pixels values, the image we get will be in the de-fuzzy domain. Then apply rician bias estimator to get final denoised image. MRI noise introduces a bias. Bias is a low frequency, smooth and undesirable signal which corrupts MRI images due to the presence of inhomogeneity, change in intensity values of image pixels, in MRI machine. Bias reduction method, a two-step approach is used for post processing of the denoised image obtained by applying Fuzzy similarity based non local means algorithm to improve the denoised image. By such two-step approach edges are preserved in the first step and bias reduction is accomplished in second step. Bias correction is based on variance and variance is calculated by using Bessel correction. Bias is removed by square root of the difference of variance from the result from FSNLM of the image. The bias correction formula:

$m_1(i,j) = \sqrt{m^2(i,j)-\sigma^2}$, CITATION Muk13 \l 1033 (Mukherjee & Qiu, 2013)

Where $m_1(i,j)$ denoted the improved denoised image. Basically MRI images suffer from bias, a signal dependent which reduce contrast.

IV. RESULT AND DISCUSSION

Materials and quantitative metrics

The experiments and comparative analysis are performed on simulated MRI datasets. The simulated MR data is obtained from Brain-Web. These simulated datasets have been used in the comparative analysis.

Simulated MR data

In experiments, three types of modalities T1-weighted, T2-weighted, and PD-weighted of simulated MRI volumes for normal brain are analyzed. The size of each simulated MRI image is 181×181. But for experimental purpose each simulated MRI images are resized to 67×67. The slice thickness of these datasets is kept $1mm^3$.

Quantitative metrics

In order to measure the performance, most widely used qualitative measure is peak signal to noise ratio (PSNR).

PSNR: This term is the ratio between the power i.e. maximum possible value of a signal and the power of corrupting noise which affects the quality. It is expressed in terms of decibel. It is calculated as:

$$\text{PSNR}= 10 * log10\left(\frac{MAX*MAX}{MSE}\right)$$

Where MAX= maximum possible value of the image and MSE is Mean Square Error which is the average of square of errors.

$$\text{MSE}=1/mn\sum_0^{m-1}\sum_0^{n-1}||f(i,j)-g(i,j)||^2$$

Where $f(i,j)$ is the original image, $g(i,j)$ is the degraded image, m represents no of rows and i is index of that row and n represents no of column and j is the index of that column.

MAE: This term is the average difference between reference image or original image and modified image. It is calculated as:

$$MAE = 1/MN\sum_{i=1}^{M}\sum_{j=1}^{N}|x(i,j)-y(i,j)|$$

Where $x(i,j)$ is referenced image and $y(i,j)$ is distorted (modified) image.

IEF: This term is Image Enhancement factor. This factor is an important factor in any subjective evaluation of image quality. It is calculated as"

$$IEF = \sum_{i,j}(n(i,j)-Y(i,j))^2 / \sum_{i,j}(Y1(i,j)-Y(i,j))^2$$

Where $n(i,j)$ is noisy image, $Y(i,j)$ is reference image and $Y1(i,j)$ is modified image.

SSIM: This term is Structural Similarity Index. SSIM measures image quality. It is used to compare the visual quality of image obtained from proposed image and original image. The measure between two windows x and y of common size M*M is:

$$SSIM = (2\mu_x\mu_y + c_1)(2\sigma_{xy}+c_2) / (\mu_x^2+\mu_y^2+c_1)(\sigma_x^2 + \sigma_y^2+c_2)$$

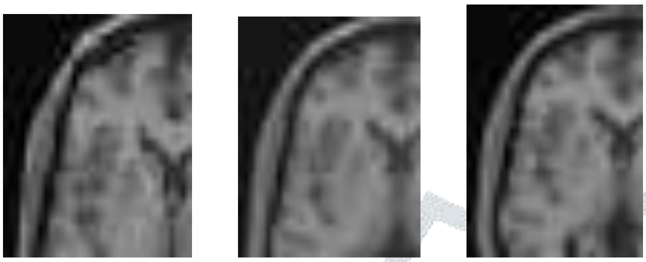
Whereμ_x, μ_y are the average of x and y respectively, σ_x^2 ,σ_y^2 are the variance of x and y respectively. σ_{xy} Is covariance of x and y respectively. c_1 And c_2 are two variables to stabilize the division with weak denominator.

Experimental results

The proposed techniques has been compared with existing method. Three images from simulated data set PD, T1, T2are considered as testing images for experimental usages. These testing images are degraded with noise and quality of restoration as well as quality after bias removal are computed.

a) b) c)

Figure 3: Visual results: comparison of the proposed scheme with existing techniques for simulated PD-weighted MR image, degraded with 3 % Rician noise a Noisy image b Noise removal image c Bias removal image.



a) b) c)

Figure4: Visual results: comparison of the proposed scheme with existing techniques for simulated T1-weighted MR image, degraded with 3% Rician noise, a Noisy image b Noise removal image c Bias removal image.

Figure 3-4 illustrates the comparison between existing and proposed method. In existing method, in order to preserve image details like edges, fuzzy based similarity mechanisms has been presented for the selection of similar pixels of window in non- local window. The existing method calculates the weighted average of the surrounding similar pixels so as to restore a noisy pixel in the image which gives better result. But somehow, rician noise introduce bias which reduces contrast and hence decreases PSNR value as image quality decreases. So the proposed method has been introduced so as to increase the contrast and PSNR value. Each figure includes noisy image, noise removal image and bias removal image by using existing and proposed methods. The proposed method is good at increasing contrast and PSNR values.

To measure the quality of the proposed scheme the detailed experimentation is given on simulated and real MR images. All the experiments were performed using Matlab R2015b.

Table 1: Quality Metric Results Comparison of PD-weighted image

PD-weighted Data sets	PSNR	MAE	IEF	SSIM
Sample Image 1	32.15 dB	3.99	1.42	0.77
Sample Image 2	30.97 dB	6.06	1.11	0.50
Sample Image 3	31.27 dB	4.24	1.48	0.73
Sample Image 4	29.23 dB	4.32	1.49	0.64
Sample Image 5	30.92 dB	6.71	1.43	0.60

Table 1shows the quality measure results for the output obtained from the proposed method of PD-weighted data sets. The PSNR, MAE, IEF and SSIM values of the proposed algorithm are comparing with other existing algorithms by varying noise percent from 3% to 18%. The PSNR value of proposed method is not that up to the mark but it is high as compared with existing method. The MAE value is low as well which shows difference between reference image and test image is low. The IEF value is high which shows image is enhanced. The SSIM value is high which shows both reference image and test image are quite similar.

Table 2: Quality Metric Results Comparison of T1-weighted image

T1-weighted Data sets	PSNR	MAE	IEF	SSIM
Sample Image 1	30.42 dB	5.88	1.08	0.53
Sample Image 2	30.12 dB	8.81	1.33	0.58
Sample Image 3	29.42 dB	7.02	1.08	0.32
Sample Image 4	29.67 dB	4.45	0.97	0.31
Sample Image 5	30.11 dB	3.45	1.04	0.44

Table 2 shows the quality measure results for the output obtained from the proposed method of T1-weighted data sets. The PSNR, MAE, IEF and SSIM values of the proposed algorithm are comparing with other existing algorithms by varying noise percent from 3% to 18%. The PSNR value of proposed method is not that up to the mark but it is high as compared with existing method. The MAE value is low as well which shows difference between reference image and test image is low. The IEF value is high which shows image is enhanced. The SSIM value is high which shows both reference image and test image are quite similar.

IV. CONCLUSION AND FUTURE SCOPE

Fuzzy similarity based NLM filter has been presented which has mainly three components. Firstly Fuzzification has been done. After that fuzzy similarity mechanism is used to identify similar windows or regions for the estimation of noise free pixel. FSNLM calculates the weighted average of the surrounding similar pixels so as to restore a noisy pixel in the image which gives better result. But somehow, rician noise introduce bias which reduces contrast and hence decreases PSNR value as image quality decreases. So the proposed method has been introduced so as to increase the contrast and PSNR value. Experiments results shows that the proposed method is good at increasing contrast and PSNR values. After analyzing the statistical and visual results, it is to be concluded that, the output obtained from proposed method has better visual quality and contrast as compared to the image obtained from existing method.
Future Scope: In this research era, comprehensive experiments on restoration process on images of magnetic resonance imaging has been conducted. The efforts may be made to evaluate the method that can be used to enhance and restore MRI image using Hybrid techniques. In present work, the method is only tested for brain images, so in future other medical images can also be considered.

REFERENCES

[1] Agrawal, N., & Sinha, D. (2015). A Survey on Fuzzy based Image Denoising Methods. International Journal of Engineering Research & Technology (IJERT), 4(5), 528-531.
[2] Adhikari , S. K., Sing, J. K., Bbasu, D. K., Nasipuri , M., & Saha, P. K. (2015). A nonparametric method for intensity inhomogeneity correction in MRI brain images by fusion of Gaussian surfaces. SIViP, 9, pp. 1945–1954.
[3] Aelterman, J., Goossens, B., Pizurica, A., & Philips, W. (2008). REMOVAL OF CORRELATED RICIAN NOISE IN MAGNETIC RESONANCE IMAGING. 16th European Signal Processing Conference (EUSIPCO), (pp. 1-5)
[4] Amza, C. G., & Cicic, D. T. (2015). Industrial Image Processing Using Fuzzy-Logic. 25th DAAAM International Symposium on Intelligent Manufacturing and Automation, DAAAM, 492 – 498.
[5] Binaee , K., & Hasanzadeh , R. P. (2011). A Non Local Means Method Using Fuzzy Similarity Criteria for Restoration of Ultrasound Images. IEEE Machine Vision and Image Processing (MVIP), (pp. 1-5).
[6] Borkar, A. D., & Atulkar, M. (2013). Fuzzy Inference System for Image Processing. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 2(3), 1007-1010.
[7] Brar, A. K., & Wasson, V. (2014). Image Denoising Using Improved Neuro-Fuzzy Based Algorithm: A Review. International Journal of Advanced Research in Computer Science and Software Engineering, 4(4), 1072-1075.
[8] Brinkmann, B., Manduca, A., & Robb, R. (1998). Optimized Homomorphic Unsharp Masking for MR Grayscale Inhomogeneity Correction. IEEE TRANSACTIONS ON MEDICAL IMAGING, 17(2), 161-171.
[9] Buades, A., Coll, B., & Morel, J. M. (2005). A non-local algorithm for image denoising. IEEE Computer Society Conference, 2, pp. 60-65.
[10] Buades, A., coll, B., & Morel, J. M. (2008). Nonlocal Image and Movie Denoising. International journal of computer vision, 76, pp. 123-139.
[11] Chandel, R., & Gupta, G. (2013). Image Filtering Algorithms and Techniques: A Review. International Journal of Advanced Research in Computer Science and Software Engineering, 3(10), 198-202.
[12] COCOSCO, C. A., KOLLOKIAN, V., KWAN, R. K., PIKE, G. B., & EVANS, A. (1997). Brainweb: Online interface to a 3D MRI simulated brain database. In NeuroImage., (pp. 1-1).
[13] D, S. R., M, S., & M.H.M, K. P. (2015). Quality Assesssment parameters for iterative image fusion using fuzzy and neuro-fuzzy logic and applications. 8th International Conference inter Disciplinarity in Engineering, (pp. 889-895).
[14] D, S. R., M, S., & Prasad, K. (2012). Comparison of Fuzzy and Neuro Fuzzy Image Fusion Techniques and its Applications. International Journal of Computer Applications, 31-37.
[15] Juntu, J., Sijbers, J., Dyck, D. V., & Gielen, J. (2015). Bias Field Correction for MRI Images. IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS), (pp. 1-8).
[16] Just, M., & Thelen, M. (1988). Tissue characterization with T1, T2, and proton density values: results in 160 patients with brain tumors. Radiology, (pp. 779-785).
[17] K, M. P., & Rai, D. (2015). Applications of Fuzzy Logic in Image Processing – A Brief Study. An international journal of advanced computer technology, 4(3), 1555-1559.
[18] K, M. P., & Rai, D. S. (2014). Fuzzy Logic – A Comprehensive Study. International Journal of Advance Foundation and Research in Computer (IJAFRC), 1(10), 1-6.
[19] Kaur, A., & Kaur, A. (2012). Comparison of Mamdani-Type and Sugeno-Type Fuzzy Inference Systems for Air Conditioning System. International Journal of Soft Computing and Engineering (IJSCE), 02(02), 323-325
[20] Kaur, J., & Sethi, P. (2013). Evaluation of Fuzzy Inference System in Image Processing. International Journal of Computer Applications, 68, 1-4.
[21] Kollokian, V. (1996). Performance analysis of automatic techniques for tissue classification in magnetic resonance images of the human brain.
[22] Kozlowska, E. (2012, 08 01). Basic principles of fuzzy logic. Retrieved from Access Server: http://access.fel.cvut.cz/rservice.php?akce=tisk&cisloclanku=2012080002
[23] Kumar, B. K. (2013). IMAGE DENOISING BASED ON NON LOCAL-MEANS FILTER AND ITS METHOD NOISE THRESHOLDING. Signal, image and video processing, (pp. 1-12).
[24] Metin Ertas, A. A. (2014). Image Denoising by using Non-Local Means and Total Variation. Signal Processing and Communications Applications Conference (SIU), (pp. 2122-2125).
[25] Narang, S. (n.d.). Applying Fuzzy Logic to Image Processing Applications: A Review.
[26] Narang, S. (n.d.). Applying Fuzzy Logic to Image Processing Applications: A Review.
[27] Nobi, M., & Yousuf, M. (2011). A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images. JOURNAL OF SCIENTIFIC RESEARCH, 81-89.

[28] Pal, S. K. (2001). Fuzzy image processing and recognition: Uncertainty handling and applications. International Journal of Image and Graphics, 01, pp. 169-195.

[29] Pathak, M., & Sinha, D. (2014). A Survey of Fuzzy Based Image Denoising Techniques. Journal of Electronics and Communication Engineering (IOSR-JECE), 27-36.

[30] Pereza, M. G., Concib, A., Morenoc, A. B., Andaluz, V. H., & Hernández, J. A. (2014). Estimating the Rician Noise Level in Brain MR Image. IEEE, 1-6.

[31] Quality Assessmentnparameternfor iterative image fusion using fuzzy and neuro fuzzy logic and applications. (2015). 8th International Conference inter disciplinarity in Engineering, (pp. 888 – 894).

[32] Sarode, M. V., & Deshmukh, D. R. (2011). Performance Evaluation of Noise Reduction Algorithm in Magnetic Resonance Images. International Journal of Computer Science, 8(3), 198-201.

[33] Sharif, M., Hussain, A., Jaffar, M. A., & Choi, T. S. (2015). Fuzzy similarity based non local means filter for Rician noise removal. Multimedia tools and applications, 5533-5556.

[34] Sijbers, J., Dekker, A. D., Scheunders, P., & Dyck, D. V. (1998). Maximum-Likelihood Estimation of Rician Distribution Parameters. IEEE TRANSACTIONS ON MEDICAL IMAGING, 17(3), 357-361.

[35] Sijbers, J., Dekker, A. d., Audekerke, J. V., Verhoye , M., & Dyck, D. V. (2014). Estimation of the noise in magnitude MR images. IEEE, 87-90.

[36] Styner, M., Brechbu¨hler , C., Szekely, G., & Gerig, G. (2000). Parametric estimate of intensity inhomogeneities applied to MRI. IEEE TRANSACTIONS ON MEDICAL IMAGING, 19(3), 153-165.

[37] Tasdizen, T. (2009). Principal Neighborhood Dictionaries for Non-local Means Image Denoising. IEEE TRANSACTIONS ON IMAGE PROCESSING, (pp. 1-12).

[38] Vaidya, S. D., & Hanchate, V. (2016). Implementation of NLM for Denoising of MRI Images by Using FPGA Mechanism. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 5343 -5352.

[39] Verma, R., & Ali, D. (2013). A Comparative Study of Various Types of Image Noise and Efficient Noise Removal Techniques. International Journal of Advanced Research in Computer Science and Software Engineering, 3(10), 617-622.

[40] Wang, X., Wang, H., Yang, J., & Zhang, Y. (2016). ANewMethodforNonlocalMeansImage DenoisingUsingMultipleImages. PloS one, (pp. 1-9).

[41] Weken, D. d., Nachtegael, M., Witte, V., Schulte, S., & Kerre, E. (2005). A Survey on the Use and the Construction of Fuzzy Similarity Measures in Image processing. IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, (pp. 187-192).