Grenze Int. J. of Engineering and Technology, Vol. 1, No. 1, January 2015

A Novel and Efficient Method for Denoising and Compression of MR Images for Telemedicine Applications

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***Abstract*— The presence of Rician noise is the major drawback of MR images for data storage, transmission and analysis for medical applications especially for diagnostic applications at remote locations. This work demonstrates an efficient method for removing the Rician noise and compression of MR image for data storage and transmission applications by preserving useful details. The method demonstrates a fast algorithm based on non local means and DCT based compression scheme for effective storage and transmission applications. This method was tested for 20 sets of MRI data for different noise level and its Peak signal to noise ratio (PSNR) value found acceptable for further applications. This algorithm was effectively degraded the presence of Rician noise which reduced the number of computations and thus by minimising the computational complexity and time of the system. The performance of the method is evaluated and compared by means of mean square error and Peak Signal to Noise Ratio of existing algorithm and it is observed that these parameters were outperformed with respect to existing algorithm which is acceptable for further analysis of MRI Image.**

***Index Terms*— Rician Noise, Image denoising, Image compression, Fast Non local means, DCT, Magnetic resonance image.**

I. INTRODUCTION

The main purpose of telemedicine technology is to enhance health care delivery to a wider population, which provides transfer of pathological and imaging reports of patients across the telemedicine networks, so as to provide consultation by expert from distant locations. This application is very efficient since patient records, stored electronically, can be made available through the internet for consultation, diagnosis, treatment, education, training, monitoring etc resulting in the elimination of the need for physical storage and transfer of records [1]. The medical images which are transmitting across telemedicine network to remote medical centres for multipurpose application have to be pre-processed for eliminating noise present in the images and effective loss-less compression algorithms are necessary for saving storage space and better utilization of bandwidth to increase speed of data transmission[2,3]. Hence the existing image compression algorithms and noise cancellation methods have to be analyzed over several parameters and its constraints.
Magnetic resonance imaging (MRI) is a very effective medical imaging technique for examination of the soft

Grenze ID: 01.GIJET.1.1.13

tissues in the body (such as brain). In this imaging technique, magnetic field in-homogeneities cause distortions in images that are reconstructed by conventional fast Fourier transform (FFT) methods. Since the FFT is a unitary transform, the white Gaussian noise on the measured quadrature signals is converted into white Gaussian noise on the two orthogonal R-space signals. The magnitude of this complex signal corrupted by Gaussian noise then exhibits Rician distributed noise [3]. There exist some techniques that are adapted to eliminate Rician noise. It has been shown that Rician noise is approximated very well by Gaussian noise in the case of high SNR (bright regions) [4]. Several non-iterative image reconstruction methods are used currently to compensate for field in-homogeneities, but these methods assume that the field map that characterizes the off-resonance frequencies is spatially smooth [5]. Particularly, in medical imaging, denoising is challenging because quality of image should be increased, that is measured in terms of signal to noise ratio (SNR) must be high. As an image pre processing procedure, noise removal has been extensively studied and many denoising schemes have been proposed, from the earlier smoothing filters and frequency domain denoising methods to the lately developed wavelet using correlation [6,7], curvelet, and ridgelet based methods, shape adaptive transform [8], bilateral filtering, Non local means (NLM) based methods, Linear minimum mean square error (LMMSE) estimator [9] and more recently proposed nonlinear variational methods like the total variation minimization [10]

Medical image data which is to be used for diagnostic applications should have high SNR so the compression mechanism involved should not be lossy [11]. This is partially due to legal reasons (depending on the corresponding country's laws) and partially due to the fear of misdiagnosis because of lost data in the compression procedure [1]. A possible solution to this problem is to use selective compression where parts of the image that contain crucial information (e.g. micro calcifications in mammograms) are compressed in a lossless way whereas regions containing unimportant information are compressed in a lossy manner [12]. In any case, we will restrict the discussion to lossless data formats [2]. A number of methods are available in literature. Transform coding is a widely used method of compressing medical images. 2-D images from the spatial domain are mapped to the frequency domain and concentrates vital information into few transform coefficients. Examples of such a transform operation are cosine transform [13] and wavelet transform [13, 14].

The existing medical image compression techniques discussed so far have not presenting any techniques for effectively removing the noise present in the image without affecting quality of the image. This work gives a novel method for Rician noise elimination and compression technique using modified non local means algorithm and discrete cosine transform (DCT). This paper is organized as follows. The Method and material used for this work is discussed is discussed in section II, Section III details the results obtained in this work and a discussion of results followed by conclusion of the work.

II. Methods and Materials

The basic block diagram of entire procedure is shown in fig.1. The method consists of two phases. The first phase is acquisition of MR image data and denoising of this image data. Second phase is compression of denoised MRI data which is in the DICOM format using DCT compression. The performance of the method is evaluated by means of computing SNR on decompressed images for different noise levels of the input image.

A. Image Acquisition and Denoising

MRI images were collected from the Department of Radiology, Sree Chitra Institute of Medical Sciences and Technology (SCIMST) and Regional Cancer Centre, Thiruvananthapuram, Kerala, India. The images were gray scale images. Axial slices of T1 weighted post contrast brain MRI data were considered in this work. Image denoising and compression was done on 20 data sets with each set contains 20 slices. The images acquired contain Rician noise which has to be removed by retaining content of the image. Pre processing steps involved before compression are not sufficient for removing the noise. The method used here is modified method of non local means algorithm. Non Local (NL) means algorithm is based on the natural redundancy of information in images to remove noise. At the pixel i, the non local means denoised pixel, $\widehat{v(i)}$ is the simply the weighted average of all of the pixels within the noisy image as per eqn. (1).

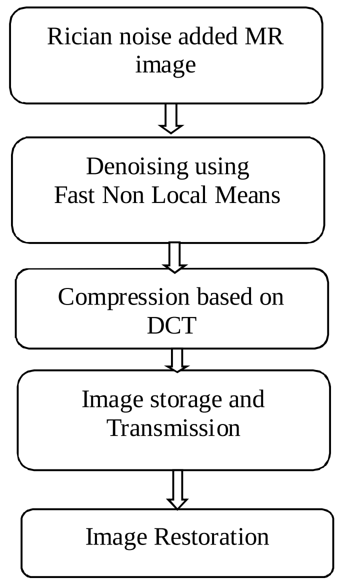


Fig.1 Block diagram of the method

$$\widehat{v(i)} = \sum_j w(i,j)v(j) \tag{1}$$

where the weights w(i, j) depend upon the similarity between the pixels i and j and must satisfy the conditions $0 \leq w(i,\ j) \leq 1$ and $\sum_j w(i,j) = 1$. Note that each pixel i of the image has its own independent weights of the other j pixels within the image. To quantify the similarity between the pixels i and j, a neighbourhood or window, N_i, around the pixel of interest is defined to allow information about local structures and textures to be incorporated.

The similarity between the pixels i and j is then computed using a Gaussian weighted Euclidean distance, D(i, j), between the neighbourhood around the pixel *i*, *v(Ni)*, and the neighbourhood around the pixel *j*, *v(Nj)*,in eqn. (2).

$$D^2(i,j) = \left\|v(N_i) - v(N_j)\right\|_{2,a}^2 = \sum_l^{nl}[G_a\,(l)(v(N_i(l)) - (v(N_j(l)))]^2 \tag{2}$$

Here the operator $\|.\|_{2,a}^2$ denotes the squared Gaussian weighted Euclidean distance D^2 (i, j), G_a represents the Gaussian kernel with standard deviation *a*, and *l* represents one of the total *nl* elements within a neighbourhood. For a two dimensional image, the Gaussian kernel, G_a, can be defined by eqn. (2),

$$G_a(x,y) = \exp\left(-\frac{(x-x_0)^2 + (y-y_0)^2}{2a}\right) \tag{3}$$

where x_o and y_o denote the center of the Gaussian kernel with x and y corresponding to the coordinates of the element l in eqn (2).Given the Gaussian weighted Euclidean distance, D(i, j), between the pixels i and j, the weights w(i,j) are computed according to eqn.(4)

$$w(i,j) = \frac{1}{Z(i)}\exp\left(\frac{-D^{\,2}(i,j)}{h^2}\right) \tag{4}$$

where Z(i) is the normalizing factor defined by eqn. (5) to ensure$\sum_j w(i,j) = 1$.

$$Z(i) = \sum_j \exp(\frac{-D^{\,2}(i,j)}{h^2}) \tag{5}$$

The parameter h is a constant which controls the decay of the exponential function as a function of the euclidean distance [14]

The main disadvantage of the NL-means algorithm is the computational complexity and its increased computation time. In this work, a modified method of NL algorithm is used to reduce computation time and improve the performance of the method. Weight evaluation using an exponential function is still a time consuming task. To reduce the amount of these evaluations a lookup table can be used for the weight calculations in eqn (4). Since the bandwidth parameter *h* is constant, the weights can be calculated in advance [15]. An improvement of image quality towards the original algorithm is to ignore the contributions from dissimilar windows. Using a pre-classification technique, only weights for the most meaningful pixels are computed. This pre-classification technique is based on the similarity of the mean and the gradient, similar neighbourhoods tend to have close means and close gradients [15, 16]. This technique is a fast way to exclude dissimilar windows, which eventually results in a smaller computation time and even in a better overall denoising quality. The gradient is sensitive to noise level, so the standard deviation is preferable in case of high level of noise. In this way, the local means and local standard deviations are pre-computed in order to avoid repetitive calculations of moments for one same neighbourhood [16].

B. Compression of denoised DICOM Image

The denoised MR image data in DICOM format is compressed using DCT based compression standard. In JPEG compression, subdivide the image into sub-blocks of size 8x8. It is then processed from left to right and top to bottom and 2D- DCT is computed for this block [17, 18]. The resulting coefficients are then quantized in accordance with the transform normalization array. After each block's DCT coefficients are quantized, the elements of the resulting array are recorded in accordance with the zigzag pattern and entropy coding (EC) is performed using Huffman coding [17]. Compressed image could be retrieved using reverse process of compression.

C. Performance Evaluation

There are some quality measures which allow comparing compression algorithm performances. Two error metrics are generally used. Compressed image could be retrieved using reverse process of compression. In medical domain, details loss may cause a loss of useful clinical information leading in some cases to a possible erroneous diagnosis. According to American College of Radiology [12], clinically significant diagnostic information must not be lost during compression process. Thus, finding an acceptable distortion level is a great challenge which is according to [9] dependant on the kind of medical imaging modality used, coding algorithm, image acquisition protocol, explored organ, and pathology. The performance of the denoised and compressed image is measured in terms of mean square error (MSE), Peak signal to noise ratio (PSNR) and its compression ratio.

*Mean Square Error (MSE):*The MSE is the cumulative squared error between the compressed and the original image [3]. This parameter essentially captures the error that has occurred as a result of compressing an image in a lossy manner. Where $I(x, y)$ is the original image , $\check{I}(x, y)$ is the decompressed image.

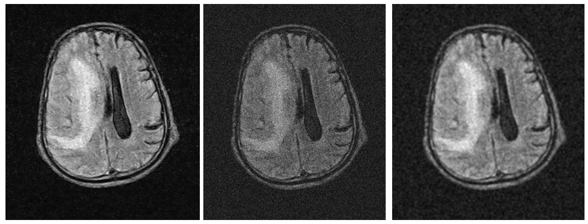
$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[I(x,y) - \check{I}(x,y)\right]^2 \qquad (6)$$

Peak Signal to Noise Ratio: PSNR is a measure of the peak error [18]. PSNR measure the compression efficiency because it is proportional to the quality. PSNR is expressed in decibels. It relates to the mathematical similarity of two images.

$$PSNR = 20log_{10}\left(\frac{255}{MSE}\right) \qquad (7)$$

III. RESULTS AND DISCUSSIONS

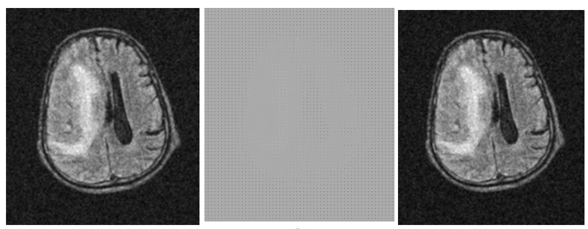
The method was implemented on 20 sets of T1 weighted MRI data. Fig. 2 shows example of a denoised MR image using fast non local means algorithm. The usefulness of the algorithm was tested by adding different levels of Rician noise on same image and repeated for every slice in each dataset.



(a) (b) (c)

Figure.2 shows example for denoising of rician noise added image using fast non local means algorithm for a noise level of 20 db
(a) Original image (b) Rician noise added image (c) Denoised image

Performance of the method was also compared with respect to non local means algorithm. It was observed that, time required Fast NLM is very low compared to existing methods such as Non-Local means. Time required fast non local means is around 8.418seconds and for NLM is 978.04 Seconds.
Denoised MR images were compressed for storage and transmission applications. DCT based compression standard is used here which can eliminate high frequency noise that is channel noise. Using this, a compression ratio of 16 is obtained. Fig. 3 shows the example for compressing a denoised image. Computation time required for NL method and FNLM method, computation time required for compression without denoising and compression after denoising using FNL method are included in table I.



(a) (b) (c)

Figure.3 shows different levels of compression (a) denoised image for compression (b) compressed and encoded image (c) decompressed image

TABLE I. SHOWS COMPARATIVE STUDY ON COMPUTATION TIME FOR EACH METHOD

METHOD	Time Required (Seconds)
Non Local Means	978.042559
Fast Non Local Means	8.418
DCT Compression	2.0419
Denoising (FNLM) and Compression	11.0203

In order to check the robustness of the algorithm, rician noise levels added in the image were varied from 5db to 35db and the corresponding PSNR is measured. Fig.4 shows the graphical plot for Noise level Vs. PSNR. From this graph it can be well observed that this method is very useful for storage and telemedicine applications because PSNR varies from 73 dB to 45dB, medical images having these PSNR values can be used for medical applications.

IV. CONCLUSION

A novel and robust method for denoising and compression of Rician noise added MR image was developed by combining fast Non local means algorithm and DCT based compression technique. The computation time of this method was compared with respect to existing fast non local means algorithm. The novelty of this method is that it is very faster than the existing methods. Using this algorithm, a compression ratio of 16 and a maximum PSNR of 80 db is obtained. The robustness of the method was also tested by varying the noise levels added in the image and proved that this method very effective for storage and telemedicine applications.

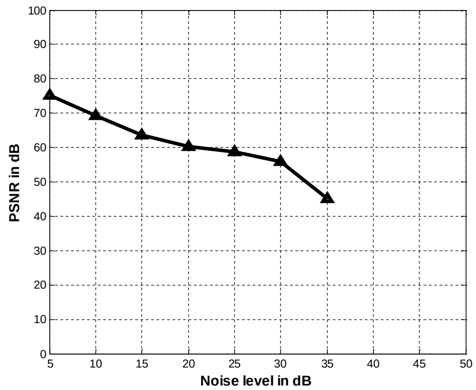


Figure.4 shows the graphical plot of level of rician noise added and PSNR of decompressed image

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