Review on: Image De-noising using Bilateral Filter with Multilinear Discriminant Analysis and SVM

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ABSTRACT
Noise removal from magnetic resonance images is important for further processing and visional analysis. Bilateral filter is known for its effective performance in edge-preserved image denoising. Here, an iterative bilateral filter is proposed for filtering the Rician noise in the magnitude magnetic resonance images. It improves the denoising efficiency. It also preserves the fine structures of the image. It also reduces the bias due to Rician noise. Thus we can preserve the quality of image. The quantitative analysis based on the standard metrics like peak signal-to-noise ratio and mean structural similarity index matrix. It shows the proposed method which performs better than the other recently proposed denoising methods for MRI.

Index terms: Bilateral filtering · Magnetic resonance imaging · Rician noise · Image denoising Search Vector Machine. Multilinear Discriminant Analysis

1. INTRODUCTION
Magnetic resonance (MR) images are generally corrupted by several artifacts and noise sources[1]. The dominant source of noise in the MR image is the patient's body. The body, being a conductive medium, generates fluctuating fields that will be picked up by the receiver coil[2] the whole measurement chain of the MR scanner (coil, electronics, etc.) also contributes to the noise. Computer aided analysis and visual inspection of the images became impossible due to presence of noise in MRI. Therefore, denoising is required for better results.In the early days, many authors applied the conventional classical denoising techniques to denoise MRI. These methods assumed the noise in the MRI as Gaussian. The major drawback of these methods is that the biasing effects of Rician noise, which characterizes magnitude MR images, were not taken into account. This bias increases with decreasing SNR. Later many methods were proposed to denoise MR images. The most popular family of methods proposed for denoising MR images are the non-local means (NLM), partial differential equations (PDE), wavelets and maximum likelihood (ML) estimation methods. NLM- based methods were proposed in [3–5] for denoising magnitude MR Images. Sijbers et al.[6] and Samsonov and Johnson in[7] proposed adaptive anisotropic diffusion methods for denoising MR images. These methods were based on the classical second-order Perona–Malik[8] anisotropic diffusion. However [9] it is mentioned that the anisotropic diffusion Methods based on second-order Perona–Malik can cause staircase effects in the filtered images. To reduce this effect, a fourth-order PDE was suggested by Lysaker et al[10]. Thus main advantage of this method is its capability to compute signals with a smooth change in the intensity value. Basu et al[11]. used a data likelihood term combined with Perona–Malik Anisotropic diffusion to effectively denoise an MR image.Aja-Fernández et al.[12] proposed a linear minimum mean square error (LMMSE) approach to denoise Rician distributed data. Recently, Krissian and Aja-Fernández proposed a noise-driven anisotropic diffusion filter for denoising MR images.ML-based methods were proposed in to denoise magnitude MR images. In this paper, we propose an iterative bilateral filter for denoising magnitude MR images. Bilateral filter is a popular nonlinear filter employed in spatial domain for edge-preserved denoising. The proposed denoising method accounts for the Rician characteristics of the data and also preserves the relevant edge features.

2. NOISE CHARACTERISTICS IN MRI
The main source of noise in MRI is thermal in origin which is produced by the stochastic motion of free electrons. This noise is considered to be white, additive and follows a Gaussian distribution with a variance σ and mean zero. As a result, the acquired raw complex MR data in the presence of thermal noise in the k-space are characterized by a Gaussian probability density function (PDF). The k-space data is then Fourier transformed to obtain the magnetization distribution. However, due to the linearity and the orthogonality of the Fourier transform, the data distribution in real and imaginary components will still be Gaussian. Even though, the magnitude of the reconstructed MR image is commonly used for automatic computer analysis and visual inspection. Therefore, the magnitude reconstruction is basically the square root of the sum of two independent Gaussian random variables and Rican distribution describe the magnitude image data.

Let x and y represents the real and imaginary parts of the noisy complex MR data (corrupted with zero mean Gaussian and stationary noise with the standard deviation d) with mean values Tx and Ty, respectively. Then the Probability distribution function (PDF) of the magnitude data will be Rician distribution will be like this:

$$P_{mag}(M) \; = \frac{M}{d^2} e^{-\frac{M^2 + A^2}{2a^2}} H_0 \left(\frac{AM}{d^2}\right), M_{0 \geq} 0$$

Where $M = \sqrt{x^2 + y^2}$, $A = \sqrt{T^2x + T^2y}$ and H_0 is the modified Bessel function of the first kind with order zero. The first two moments of the Rice PDF are given below:

$$E\,[M] = d\sqrt{\tfrac{\pi}{2}} e^{-\frac{A^2}{4d^2}} \left[\left(1+\frac{A^2}{2d^2}\right) H_0 \left(\frac{A^2}{4d^2}\right) + \frac{A^2}{2d^2} H_1 \left(\frac{A^2}{4d^2}\right)\right]$$

$$E\,[M^2] = A^2 + 2d^2$$

When the SNR goes to zero Rician distribution likely to become Rayleigh distribution

$P_{mag}(M) = \frac{M}{d^2} e^{-\frac{M^2}{2a^2}}, \quad M \geq 0$

And when SNR goes to high

$P\text{mag}(M) = \frac{1}{\sqrt{2\pi d^2}} e^{\frac{\left(M-\sqrt{A^2+d^2}\right)^2}{2d^2}}$

So shape of the Rician distribution depends on the SNR, which is the ratio of $\frac{A}{d}$.

3. LITERATURE SURVEY

A lot of research has been done in the field of image de-noising but yet the area of image de-noising, especially for the medical images remains to be a hot area of research. Stress has been laid to summarize the concept of different authors who has worked in this field.

[S.Zhang, E.Salari 2005] presented a neural network based de-noising method implemented in the wavelet transform domain. In this, a noisy image is first of all wavelet transformed into four sub bands further. After this, a trained layered neural network is applied to each sub band to generate noise-removed wavelet coefficients from the noisy ones. Then de-noised image is obtained .This is very productive method in removal of the noise. To obtain very good de-noising results, it needs only one level of signal decomposition.

[Sudha2009] have discussed that in medical image processing; image de-noising has become a very important exercise throughout the diagnosis. Arbitration between the perpetuation of useful diagnostic information and noise suppression has been treasured in medical images. In general controlling the quality of processed images has been relying on the intervention of a proficient. If we take the example of ultrasound images, the noise has been restraining information which is valuable for the general practitioner. Consequently, if medical images are used, they have been very inconsistent, and it has been crucial to operate case to case. They have presented a wavelet-based thresholding scheme for noise suppression in ultrasound images. The results obtained with this proposed method and the results achieved from other speckle noise reduction techniques have demonstrated that it is higher performance for speckle reduction.

[Ratnaparkhe, 2009] have discussed that human vision system has limitations in distinguishing the broad range of gray level values. Pixel intensities up to 15-30 gray levels can be discriminated by human eye. This restricts the qualitative analysis of radiological images. The quantitative analysis has been preferred to reveal more information from the image. Texture feature based approach has also presented by them. Images produced as an output from Computerized Tomography (CT) scan machine used for the work. A Method based on Ridgelet transformation called as texture feature extraction has been reported. In the first step work involves determination of texture features from Region of Interest (ROI). Energy and entropy in partitions of Ridgelet transform images represent texture features. During the next step of work two-class and multiclass classification has been carried out. Percentage Correct Classification for Ridgelet based energy and entropy features and comparative analysis of performance measures for different organ images have been reported.

[RathaJeyalakshmi 2010] have discussed that Ultrasound images contain speckle noise which degrades the quality of the images. Eliminating such noise has been an important preprocessing task. They have described and analyzed an algorithm for cleaning speckle noise in Ultra sound medical images. Mathematical Morphological operations have been used in their algorithm. Their algorithm has been based on the Morphological Image Cleaning algorithm (MIC) designed by Richard Alan Peters. The algorithm has used a different technique for reconstructing the features that are lost in noise removal process. It also used arbitrary structuring elements suitable for the ultrasound images which have speckle noise.

[Tanzila SABA, 2010] presented an novel approach based on the Cellular neural networks(CNN) to de- noise an image even in the presence of very high noise. The noises are detected with surrounding information and removed. The proposed algorithm exhibited promising results from qualitative and quantitative point of view. Experimental results of the proposed algorithm exhibit high performance in PSNR and visual effects in color image even in the presence of high ratio of the noise.

4. PROPOSED ITERATIVE BILATERAL FILTER

In this paper, we propose an iterative bilateral filtering scheme for Rician noise removal. Bilateral filter is a nonlinear filter developed by Tomasi and Manduchi and is used for removing noise while preserving edges. The bilateral filter kernel in each neighborhood can be described as product of its two kernels i.e. the domain filter and the range filter. The basic idea lying is that it works in the range of the image. Two pixels can be similar to each other as they are very close to each other. Domain filters weight is directly proportional to the spatial distance of a pixel around its neighborhood. The range filter coefficients are proportional to the radiometric distance around the neighborhood of a pixel. The response of the bilateral filter at a pixel location *j* is given by

$$\hat{H}(j) = \frac{1}{C} \sum_{y \in N(j)} V_S(u,z)\; V_r(u,z)\, H(y)$$

Where *N(j)* represents the neighborhood region around j, *y* is the position in the neighborhood, V_S and V_r are domain and radiometric part of it respectively.

Various parameters (Bilateral filters) are used in this are:

LINEAR FILTER: Linear filters produce output of input signals which are varying with time. They used to smooth an image. The output will change linearly with the change in the input. For Example

MEAN FILTER: It is used to reduce the amount of intensity variation between the pixel and the next. It is used to reduce the noise in the images. It is like convolution filter which is based around the kernel.

WIENER FILTER: It is used to produce an estimate of target random process by linear time invariant filtering of a stationary signal and noise spectra. It minimizes the MSE (Mean Square Error).

NONLINEAR FILTER: These are those filters for which the linearity relationship breaks down.

MEDIAN FILTER: It is a nonlinear filter that removes the outliers and shot noise that is independent of the magnitude.

For comparison analysis quantatively we used two techniques:

SSIM: Structural Similarity Index is method for measuring the similarity between the two images. It is advancement in technique like PSNR (Peak Signal to noise ratio) and MSE (mean square error).

PSNR: it is defined as:

$$\text{PSNR} = \frac{MAXIMUM\ possible\ power\ of\ signal}{power\ of\ corrupting\ noise}$$

5. SUPPORT VECTOR MACHINE

Support vector machines (SVMs) are used for classification and outliers detection.

Various advantages of SVM are:

1. Beneficial in high dimensional spaces.
2. Memory efficient.
3. Versatile.

The disadvantages of support vector machines include:

1. Poor performance if

   Number of features > number of samples.

2. Using an expensive five-fold cross-validation method we can calculate probability estimates, which SVM do not calculate directly.
3. Real world problems can be solved by SVMs :
   a. Text and Hypertext categorization can be made possible by SVMs.
   b. Images can also be classified using SVMs.
   c. Proteins can be classified using SVM.

6. CONCLUSION

An iterative bilateral filter is proposed for denoising magnitude MR images and it improves the denoising efficiency and preserves the edge features and fine structures in the image. For the comparative analysis, experiments were conducted on both synthetic and real MR images, and for the synthetic images, and for the quantitative analysis mean SSIM and PSNR were used. The proposed method is compared with the state-of-the-art methods like UNLM, NLML and LMMSE. The proposed method outperforms the other methods as visual and quantitative analysis is best among all the previous methods used.

7. REFERENCES

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