Modified Restricted Local Maximum Likelihood Method Based Magnetic Resonance Image Denoising

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***Abstract*— MRI Denoising is the process of removing the noise elements from a mri input data. The major challenge present in this field is to denoise the MRI without removing the finer details in the input image. Proper estimation and denoising MR images is important for medical diagnosis. The principal source of noise in MRI is thermal in origin which is produced electrons. The source of noise in MRI is these randomly fluctuating currents in the sample (imaged object) and in the receiver coil. The estimation of noise level in the MRI is by local maximum likelihood estimation of the input image. After estimating the noise levels in the MRI image the denoising can be performed. In this paper the restricted local neighbourhoods denoising can be improved by using the adaptive nonlocal algorithm. In the existing system the restricted local neighbourhoods uses a reference image created by using nonlocal maximum likelihood estimation method. In the proposed system the reference image creation algorithm is replaced by the adaptive nonlocal method.**

Keywords—MRI denoising, Noise, Nonlocal methods.

I. INTRODUCTION

The phenomenon of Nuclear Magnetic Resonance was discovered in bulk matter in the 1950s and for many years its major application was in the field of spectroscopy. In 1970s Lauter bur introduced the concept of magnetic field gradients, so that an image based on magnetic resonance could be produced. By the 1980s whole body magnets were being produced in England permitting the images of human anatomy. Today the technique is known as MR imaging. It provides images with excellent soft-tissue contrast which can be acquired in any imaging plane, and unlike CT it does not involve the use of ionising radiation. The principal source of noise in MRI is thermal in origin which is produced by the stochastic motion of free electrons. These free electrons collide with atoms, resulting in an exchange of energy and generate random electrical fluctuations. This creates the noise in the MR images. Effective denoising is vital for proper analysis and accurate quantitative measurements from Magnetic Resonance (MR) images. Apart from following the general criteria for denoising, the algorithms that deal with MR images should also take into account the bias generated due to the Rician nature of the noise in the magnitude MR images. Maximum Likelihood (ML) estimation methods were proved to be very effective in denoising MR images. However, one drawback of the existing non local ML estimation method is the usage of a fixed sample size for ML estimation. As a result, optimal results cannot be achieved because of over or under smoothing. In this work an adaptive non local ML estimation method is used for the reference image creation. This filtered image can be further used to performs the maximum likelihood based restricted local neighbourhoods denoising algorithm.

II. NOISE IN MRI

The principal source of noise in MRI is thermal in origin which is produced by the stochastic motion of free electrons. These free electrons collide with atoms, resulting in an exchange of energy and generate random electrical fluctuations. The sources of noise in MRI are these randomly fluctuating currents in the sample (imaged object) and in the receiver coil. The acquired raw complex MR data in the presence of thermal noise in the k - space is characterized by a Gaussian probability density function (PDF). The k - space data is then Fourier transformed to obtain the magnetization distribution. The data distribution in the real and imaginary components will still be Gaussian due to the linearity and the orthogonality of the Fourier transform. However, a complex image as such is not used for any analysis. To use both parts of the complex data values, we calculate magnitude images and phase images. Since the computation of magnitude image is a non linear operation the noise distribution in the magnitude image will be no longer Gaussian but Rician distributed.

III. RELATED WORK

A. Noise estimation

The estimated noise variance also gives a measure of the quality of the MR data and could potentially help in improving the design ofscanners[5]. Magnitude MR data in the presence of noise can be well modeled by a Rician distribution when the images are acquired using single coil. Most of the methods proposed earlier estimate the noise level from the background area of the magnitude MR images where the noise follows Rayleigh distribution due to the absence of signal[8]. These methods cannot be used for images where no background information is available. For MR images other than the brain, like cardiac or lung images, background data may not be available. For example, in case the field of view (FoV) is small, such that noise assumptions based on Rayleigh distribution fail[7]. Also, the new scanning techniques and software eliminates most part of the noisy background, which in fact affect the methods based on Rayleigh model that need a certain amount of background pixels to perform proper estimation[9]. The above mentioned issues with the methods based on the Rayleigh model drives the need to develop methods that doesn't depend on the background region for noise estimation. When enough background region is present in the image, noise level can be directly estimated from the pixels in these regions. Even though it is a straightforward and simple approach, the drawback of this approach is the requirement of an explicit segmentation algorithm for extracting the background. In addition, conventional segmentation methods might not work properly when the noise level is too high and/or in diffusion weighted MR images, where the scalp regions are sometimes misclassified as background regions[10]. Many methods were proposed to estimate the noise variance from the image background without explicit segmentation. In some of them the noise variance were estimated from the background mode of the image histogram[11,12]. These methods are based on the observation that the regions representing the background and signal can be easily distinguishable from the image histogram. These methods work well at reasonable noise levels. However when the noise is too high, estimation with these methods will be a problem since it becomes difficult to distinguish the background and the signal region from the histogram. In this work the noise estimation is based on the measurement of local skewness.

B. Denoising Methods

As discussed the data acquired by an MRI system are inherently corrupted by noise which has its origin in the thermal Brownian motion of electrons. Noise remains one of the main causes of quality deterioration in MRI and is a subject in a large number of papers in MRI literature. Other than visual analysis, processing techniques such as segmentation, registration or tensor estimation in diffusion tensor MRI (DT-MRI) will be affected or biased due to **noise**[13,14]. Noise can be naturally minimized by averaging images after multiple acquisitions. This, however, may not be feasible in clinical and small animal MR imaging where there is an increasing need for speed . Thus, post processing techniques to remove noise in the acquired data are important. Also, time-sensitive acquisitions in contrast material-enhanced studies, functional studies, diffusion MRI (dMRI) or studies with limited imaging time, experiments cannot be repeated to do averaging. Most of the methods proposed earlier can be mainly classified as either based on Partial Differential Equations (PDEs), wavelets or Non Local Means (NLM).In one of the PDE based **approach**[14,15] they demonstrated that anisotropic diffusion is an effective filtering technique for MRI in the sense that it can significantly decrease the image noise and simultaneously preserve fine details in the image. A major drawback of their method, however, was the incorrect assumption about the noise distribution. The noise was assumed to be Gaussian instead of Rician, as a result of which a bias is introduced in the filtered image. Such a bias becomes particularly important in low SNR MR images, such as diffusion weighted**images**[16]. To account for the Rice distribution, an adaptive anisotropic diffusion method for magnitude MR data was **proposed**[17]. All aforementioned PDE methods are based on classical 2nd order anisotropic **diffusion**[18]. Although such methods are effective in denoising images, they tend to cause staircase effects in the filtered **images**[19]. To reduce this effect, a noise removal algorithm for MRI based on fourth order PDE was **suggested**[20]. The main strength of this method is its ability to process signals with a smooth change in the intensity value. Recently a noise driven anisotropic diffusion filter for denoising MR images, in which the diffusion is controlled by the local statistics in the image derived from the linear minimum mean square error (LMMSE) estimator for the Rician model is **proposed**[21]. A second class of noise filtering schemes are wavelet **based**[22,23,24]. These algorithms exploit the decorrelating properties of the wavelet transform to suppress noise coefficients using statistical inference. However the aforementioned wavelet based filters may introduce characteristic artifacts that can be quite **problematic**[25]. A trilateral filter was proposed to take into account the local structure in the image, in addition to intensity and geometric **features**[26].During the past years, NLM based denoising methods gained much **popularity**[27].

IV. EXISTING SYSTEM

Signal estimation using restricted LML method

To overcome the drawback of the LML estimation method, a restricted LML (RLML) estimation **method**[28] is used. In RLML, only the pixels in the local neighborhood of the noisy pixel $\boldsymbol{m_i}$ that have an underlying gray level value close to the underlying gray level value of $\boldsymbol{m_i}$, will be considered for the true signal estimation. However, the selection of pixels with similar underlying gray value from a noisy image is a difficult problem. To this end, a reference image using the NLM method is created. Now, to denoise a noisy pixel $\boldsymbol{m_i}$ at i, a list $\boldsymbol{l_i}$ is created from the neighbors of $\boldsymbol{l_i}$:

$$\boldsymbol{l_i} = \left\{\boldsymbol{m_j}, (\boldsymbol{j} \in \boldsymbol{\Omega}_{\mathbf{m}}) \mid \boldsymbol{abs}\left(\boldsymbol{f}(\boldsymbol{m_j}) - \boldsymbol{f}(\boldsymbol{m_i})\right) < \boldsymbol{t}\right\}$$

where $\boldsymbol{\Omega}_{\mathbf{m}}$ represents the neighborhood space around $\boldsymbol{m_j}$, $\boldsymbol{f}(\boldsymbol{m_j}) = \boldsymbol{r_j}$ and $\boldsymbol{f}(\boldsymbol{m_i}) = \boldsymbol{r_i}$. The threshold t used for the classification is calculated from the reference image as the range of the intensity dispersion of a uniform area. This intensity dispersion can be automatically calculated from the reference image, *R*, as the mode of all the local distributions of the range calculated around the neighborhood of each pixel:

$$t = mode\{range(R_F)_\omega\}$$

Where R_F represents the foreground region of the reference image and ω is the neighborhood window size. Unlike the complex images, where the noise is Gaussian, in magnitude images the range of intensity dispersion has a dependency on the local SNR due to the non linear operation used to create the magnitude images. Hence, to reduce the error in the classification of pixels in the reference image, the threshold t is computed only from the foreground region of the image. Once a list is created as mentioned before, the denoised pixel $\hat{a}_i$ at location i, can be computed by substituting the values in the list l_i as the Rician distributed magnitude data points in the log likelihood function and then maximizing the log likelihood function. The equations are as follows:

$$\ln L = \sum_{i=1}^{n} \ln\left(\frac{m_i}{\sigma_g^2}\right) - \sum_{i=1}^{n} \frac{m_i^2 + a^2}{2\sigma_g^2} + \sum_{i=1}^{n} \ln I_0\left(\frac{a m_i}{\sigma_g^2}\right)$$

And

$$\hat{a}_{ML} = \arg\{\max_a \ln L\}$$

Applying this procedure to all pixels in the noisy image will give the denoised image.

V. PROPOSED SYSTEM

In the existing system of denoising the reference image is created by using the nonlocal ML method. An adaptive nonlocal denoising method can outperforms the conventional nonlocal ML algorithm[30]. Hence the existing restricted LML method can be modified by replacing the reference image creation algorithm. The existing system uses the conventional nonlocal ML algorithm for reference image creation. The proposed method uses an adaptive nonlocal method for the reference image creation. The quality of the reference image can be improved by using the adaptive nonlocal estimation method[30].

Algorithm 1 : Algorithm for signal estimation using modified restricted NLML method.

1. Estimate the noise variance $\widehat{\sigma_g}^2$ from the input magnitude image M {refer [33] for noise estimation }
2. Create the reference image υ using adaptive NLML method [34]
3. Compute the threshold t from υ by applying equation (2)
4. **For** every pixel m(i) of M **do**
5. Create a list l_i as mentioned in the equation (1)
6. Substitute the values in the list l_i in the equation (3)
7. Estimate $\hat{a}_i$ by maximizing equation (3) with respect to the unknown true intensity.
8. **End for**

VI. RESULTS AND DISCUSSIONS

To evaluate and compare the proposed modified restricted LML with the existing restricted LML method, experiments were conducted on synthetic MR images. For the experiments on the synthetic data, the standard MR image phantom of the brain obtained from the Brainweb database is used. The phantom image was degraded with Rician noise for a wide range of noise levels and the denoising efficiency of both algorithms were evaluated based on the Peak Signal to Noise Ratio (PSNR), the mean Structural Similarity Index Matrix (SSIM). Fig. 1 shows the visual quality comparison of the image denoised with the existing and the proposed improved version. Table 1 shows the quantitative analysis of Restricted local Maximum Likelihood methods in terms of PSNR, and Table 2 shows the mean SSIM comparison. It can be observed from the plots that quality improvement can be achieved by incorporating the suggested improvement in the restricted LML method.

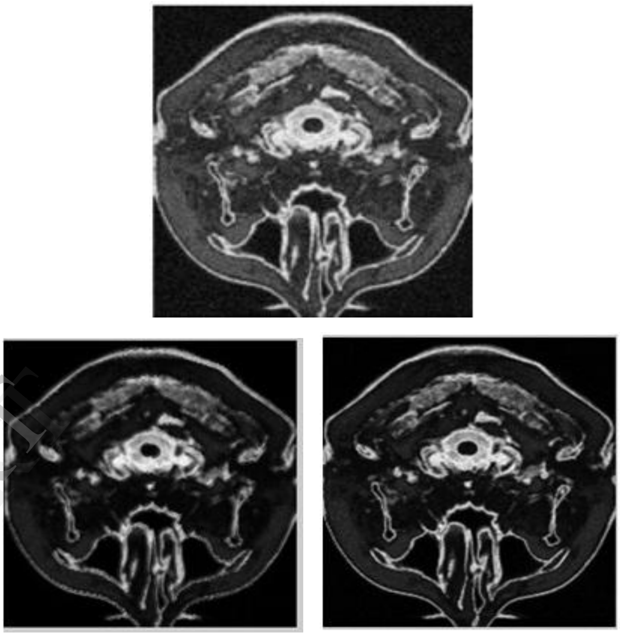

Fig. 1. (a) Noisy Image; (b) Denoised image by existing system; (c) Denoised image by proposed system

Image	Percentage of noise added	Existing System (db)	Proposed system (db)
Image 1	3	40.5342	42.2379
	5	39.8357	41.9367
	7	39.3345	40.8535
	9	38.7266	40.1572
Image 2	3	40.8732	41.3426
	5	40.5356	41.0545
	7	39.9632	40.1345

Table 1. PSNR analysis of methods

Image	**Percentage of noise added**	**Existing System**	**Proposed system**
Image 1	3	0.23345	0.46132
	5	0.22122	0.43352
	7	0.21895	0.41548
	9	0.20989	0.40912
Image 2	3	0.25329	0.44112
	5	0.21193	0.42369
	7	0.20800	0.41532

Table 2. SSIM analysis of methods

VII. CONCLUSION

A method to improve the performance of the restricted LML method is proposed in this paper. The improvement is achieved by adaptively creating the reference image for denoising. Through this approach, the over and under smoothing caused by the existing system can be reduced. Experiments have been carried out on simulated data sets. Quantitative analysis at various noise levels based on the similarity measures, PSNR and SSIM shows that the proposed method is more effective than existing restricted LML.

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