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NLM based magnetic resonance image denoising – A review

Hemalata V. Bhujle*, Basavaraj H. Vadavadagi

SDM College of Engineering & Technology, Dharwad, India

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ABSTRACT

Denoising Magnetic Resonance (MR) image is a challenging task. These images usually comprise more features and structural details when compared to other types of images. These structural details in MR images provide additional information to physicians for better diagnoses and hence there is a need to preserve these details. Over the past few years, various MR image denoising techniques have been evolved. Among them, the techniques based on Non-Local Means (NLM) have achieved excellent performance by exploiting similarity and/or sparseness among the patches. The evolution of NLM filter has changed the paradigm of research in the area of MR imaging. Many variants of NLM algorithms have been developed till today which in addition to retaining the edge/structural features, improve the signal to noise ratio and computational efficiency. The aim of this paper is to provide an exhaustive review of the published literature on NLM based MR image denoising techniques. A critical review and discussion on the advantages and limitations of these techniques are provided with quantitative result analysis.

1. Introduction

Magnetic Resonance Imaging (MRI) has emerged as a powerful technology which enables mankind a detailed and extensive study of structural features and functional characteristics of the internal organ. Information provided by MRI technique differs from other imaging modalities like ultrasound and computed tomography scanning. The ability of this technique to obtain images in multiple planes without moving the patient and its potential to characterize and discriminate among tissues based on their physical and biochemical properties offer special advantages in clinical diagnoses and surgical treatment. The application of MRI ranges from imaging static anatomy to many clinical tasks such as imaging blood vessels, cardiac imaging, measuring tissue temperature and fixing retinal disorders. The only limitation of this technique is being its spatial resolution and long acquisition time. The accuracy of the clinical diagnosis depends on the visual quality of MR images which may be seriously degraded by noise during the acquisition process. The acquisition process of MR image gets affected by different kinds of noises. In a single channel acquisition, MR signals are reconstructed by computing inverse discrete Fourier transform. The sampling of MR images is done in the frequency domain and images are extracted from both real and imaginary channels. Signals in these channels are corrupted with additive white Gaussian noise. Since magnitude computation is a nonlinear process, MRI signal follows Rician distribution [1]. Noise distribution in multi-channel signal acquisition system can be described as non-central chi distribution [2,3] since MR image is reconstructed by combining complex images. In parallel imaging system, amplitude of the noise changes with the spatial location of the image and hence tends to introduce chi or Rician distributed noise [4].

Noise removal in MR images can be dealt with two ways. One way is to acquire multiple images of the same data and average them. However, this procedure is quite slow and some time introduces motion artifacts. In the second approach, suitable image denoising techniques are applied after image acquisitions which provide reliable and fast results. Various denoising filters have been proposed for MR images in the past as a post-acquisition process. A few of them include Gaussian filtering [5,6], anisotropic diffusion filtering [7,8], wavelet thresholding [9,10], bilateral [11,12] and statistical approaches [13,14]. Manjón et al. [15] were the first among to apply NLM filter [16] for MR images perturbed with Rician noise. This filter performed superior to all aforementioned filters and was treated one of the state of the art filters at that time for MR image denoising. However high computational cost of this filter has lead many researchers for future work. Presently, abundant quantities of papers can be found on NLM based MR image denoising. This paper provides the reader the review of all such recently developed techniques pertaining to MR images with critical analysis, advantages, and limitations of each technique.

The organization of the remainder of this paper is as follows. In Section 2, characteristic of noise in MRI and its estimation is given.

* Corresponding author.
E-mail address: hemalatabhujle@gmail.com (H.V. Bhujle).

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In Section 3, a complete review on NLM based MR image denoising techniques are provided. In Section 4, comparative results among various published literature are provided. Section 5 concludes the paper.

2. Distribution of noise in MR data

An image is usually assumed to be corrupted with an additive white Gaussian noise, which is quite simple to deal with. However, noise in MR image is signal dependent and signal formation model changes it to Rician. Rician noise degrades the quality of the image qualitatively and quantitatively. Detectability of MR image gets drastically reduced due to bias introduced by Rician noise. In this section, we provide the reader the rationale behind Rician noise assumption.

The complex MR datum X is given by

$$X = X_{Re} + jX_{Im} \tag{1}$$

where X_{Re} and X_{Im} are real and imaginary components of the data. These components are affected by ξ_1 and ξ_2, where ξ_1 and ξ_2 are additive white Gaussian noise with zero mean and standard deviation σ.

$$X_{Re} = Scos\theta + \xi_1 \tag{2}$$

$$X_{Im} = Ssin\theta + \xi_2 \tag{3}$$

Here S is the original MR image and θ is the phase. A noisy MR image when represented as the magnitude of the noisy raw data, given by

$$\left|X\right| = \sqrt{(Scos\theta + \xi_1)^2 + (Ssin\theta + \xi_2)^2} \tag{4}$$

The distribution of $|X|$ becomes Rician [17] [1], and is represented as

$$P(X|S,\sigma) = \frac{X}{\sigma^2} e^{\frac{-(X^2+S^2)}{2\sigma^2}} I_0\left(\frac{XS}{\sigma^2}\right), \quad X > 0 \tag{5}$$

Here I_0 denotes the modified Bessel function of the first kind with order zero, S is the noiseless signal, σ^2 is the noise variance of Gaussian distribution and X is the observed MR magnitude image. From the above equation it is clearly observed that for low intensity regions i.e., when S approaches zero, the expression leads to a Rayleigh PDF given by

$$P(X|S,\sigma) = \frac{X}{\sigma^2} e^{\frac{-X^2}{2\sigma^2}}, \quad X > 0 \tag{6}$$

wherever the signal intensity is high the above PDF approaches a Gaussian distribution [18].

$$P(XS,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-\left(X-\sqrt{S^2+\sigma^2}\right)^2}{2\sigma^2}} \tag{7}$$

To estimation the noise in a magnitude image $|X|$, Nowak [18] squared the magnitude by which bias in the MR images can be made additive and signal independent.

$$\left|X\right|^2 = (Scos\theta + \xi_1)^2 + (Ssin\theta + \xi_2)^2 \tag{8}$$

Taking the expectation on both the sides yields,

$$E\left[|X|^2\right] = E[\left(Scos\theta + \xi_1\right)^2 + \left(Ssin\theta + \xi_2\right)^2 = \mu_S^2 + 2\sigma^2 \tag{9}$$

where μ_s is the mean value of the pixels. Bias in the squared magnitude domain is observed to be $2\sigma^2$. The noise in the MR image is estimated from the background regions [19]. The estimate of noise in the background is given by $\sigma = \sqrt{\frac{\mu}{2}}$ where μ is the mean value of the pixels from the background. Sijbers et.al [20–22] were the first among to estimate Rician noise in MR images using the statistical approach like Maximum Likelihood Estimation (MLE) prior to signal reconstruction and bias compensation. This work has been extended further to estimate Rician noise from the background mode of MR image histogram [23]. There are numerous recent developments in MRI, as far as fast acquisition and reconstruction of data are concerned. A closed form solution of Linear Minimum Mean Square Error (LMMSE) estimator is proposed [24] for MR images acquired with a single coil that follow a Rician model. Noise estimation in SENsitivity Encoding (SENSE) and GeneRalized Autocalibrating Partially Parallel Acquisitions (GRAPPA) reconstructed image has been discussed in [25]. A high Angular Resolution Diffusion Imaging (HARDI) and HYbrid Diffusion Imaging (HYDI) techniques are usually performed at high b values and hence yield low Signal to Noise Ratio (SNR). A noise correction scheme for such techniques is discussed in [26]. Authors in [27] have devised a scheme to estimate noise from correlated multiple coil MR data, however in [28] noise in single and multiple coil MR data is estimated by statistical models.

3. NLM based MR image denoising

For MR images, there is always a trade-off between the resolution and SNR. High-resolution images lead poor SNR and vice-versa with low resolution images. However, to detect anatomical structures images should possess good resolution with high SNR. Hence dealing with noise to obtain the best possible result is quite difficult. In this regard, NLM filter is a preferred choice as it has good edge preserving capability while denoising.

3.1. NLM filter

A nonlocal means filter [16] exploits redundancy in the image. Each pixel in NLM filtered image is the weighted average of all other pixels in the image. This can be represented as

$$\begin{gathered} NLM(I(i)) = \sum_{j \in N_i} w(N_i, N_j) I(j) \\ 0 \le w\left(N_i, N_j\right) \le, \quad \sum_{j \in N_i} w(N_i, N_j) = 1 \end{gathered} \tag{10}$$

where $I(j)$ is the noisy intensity of the j^{th} pixel, N_i is the neighborhood of i^{th} pixel, $w\left(N_i, N_j\right)$ is the weight function computed based on the similarity between two patches. In [16] authors have limited search window size and patch size to 21×21 and 7×7, respectively. Euclidean distance between two patches is given by

$$d = \left\|I(N_i) - I\left(N_j\right)\right\|^2_{2,\sigma} \tag{11}$$

where σ is the standard deviation of the Gaussian kernel. Further the weights can be computed as

$$w\left(N_i, N_j\right) = \frac{1}{Z(i)} e^{\frac{-d}{h^2}} \tag{12}$$

where h is the filtering parameter and Z is a normalization constant given by

$$Z(i) = \sum_j e^{\frac{-d}{h^2}}. \tag{13}$$

3.2. NLM denoising techniques in MRI

The variants of NLM filter developed for MR image denoising is illustrated in Fig. 1. The NLM denoising for MR image sequences can be broadly classified into four categories. There are various NLM techniques which improve the SNR with better edge preservation however, suffer from high computational cost. 3D processing of