BM3D MRI DENOISING EQUIPPED WITH NOISE INVALIDATION TECHNIQUE

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ABSTRACT

Block-matching and 3D filtering (BM3D) has shown a great success in image denoising. In this work we propose a new denoising approach for Magnetic Resonance Imaging (MRI) based on a modified BM3D algorithm. BM3D is a combination of nonlocal approach, 3D wavelet shrinkage, and 3D Wiener filtering. We improve the wavelet thresholding stage of BM3D using Noise Invalidation Denoising (NIDe) technique. The new approach provides the optimum wavelet threshold automatically and adaptive to the statistical characteristics of the available data. This is an advantage over the existing denoising stage of BM3D that currently uses an adhoc thresholding value. Combining the proposed BM3D approach with Variance Stabilization Transformation (VST) enables the use of the proposed method for Magnetic Resonance (MR) Image denoising. In our Simulations, the proposed method outperforms the state of the art BM3D based MRI denoising methods in the sense of PSNR and SSIM for T1, T2 and PD weighted MR images.

Index Terms— BM3D filtering, Magnetic Resonance Imaging, Variance Stabilization Transformation, Wavelet Transform Function, Noise Invalidation Denoising

1. INTRODUCTION

MRI is one of the most effective imaging modalities that has been used for soft tissue imaging, such as brain and muscles. Since the acquisition time in MRI is limited, the signal to noise ratio (SNR) of the MR images are usually low. The quality of the MRI images are usually degraded with several artifact and noises that is adequately modeled Rician noise. Under the Rician noise model, the observed MR image intensities are non-linear function of the true image intensities, which adds a bias to the images denoised by conventional denoising methods. Consequently, a denoising technique that removes noise while preserves the image details is an important step of MR image processing. MRI denoising is the focus of many researches to provide images with both good spatial resolution and high SNR. Several filtering methods have been developed in the past decades to address denoising problem in MRI images. Anisotropic Diffusion filter for MR images keeps edges by averaging pixels in the orthogonal dimension of the local gradient [1]. However, it still eliminates small features and generates unnatural images by altering image statistics [2]. Recent methods focus on Non-Local Mean filtering (NLM) [3]. NLM takes advantage of repeated structures in natural images and uses a weighted averaging method based on the similarities between different neighborhoods in the image. Since its introduction, NLM has been modified to be compatible with MR images [2], to be applicable for specific applications with spatially varying noise levels [4], and to be more efficient [5]. Another common class of MR image denoising methods is domain transform filters. These filters are applied to the image data transformed in another domain. Examples of such methods are wavelet domain filtering on the complex valued data with Gaussian additive noise [6] or on Rician distributed magnitude data [7, 8], Principal Component Analysis (PCA) [9] and Discrete Cosine Transform (DCT) filters[10]. These methods still remove some detailed information and create artifacts. BM3D filtering was introduced as an extension to NLM and wavelet domain transform filtering [11, 12]. It is an improved version of NLM filtering that groups similar patches in 3D stacks, transforms them in another domain, shrinks the coefficients and returns them into the original domain by inverse transformation. Applying the transformation on the grouped similar patches considerably increases the sparsity of the data compared to the use of original image. Therefore, the denoising method can attenuate the noise easier and more effectively. BM3D denoising method has demonstrated advantages in denoising images with additive Gaussian noise [12, 13, 14]. It has also been applied to MR images and represented competitive results comparing to the existing methods [15, 16, 17]. The goal in BM3D is to denoise the 3D stacks of similar patches with Wiener filter. However, Wiener filtering requires prior estimate of the patches. This estimate is found in the first stage of BM3D that applies a 3D wavelet hard thresholding on the stacks of similar patches formed by the noisy image. This first stage estimation is then used in the second block matching, which finds the similar patches for the Wiener filtering stage. Optimal use of BM3D requires adjustment of some parameters, including the threshold value used in the first denoising step. Currently, the value of this threshold is found on the basis of heuristic search approach [12]. Here we propose using our newly proposed Noise Invalidation Denoising (NIDe) method instead of the hard thresholding. Unlike the current adhoc hard thresholding, the new approach denoises the data adaptive to the available noisy image. The optimum value of threshold in the latter approach adapts to the data itself and is found automatically [18]. Application of the BM3D denoising approach in MRI denoising is possible by preprocessing the image with a variance stabilization approach [16, 17], which stabilizes the noise variance¹ in the Rician distributed MR image. The performance of the proposed method in denoising the MR images is compared with state of the art BM3D approaches used for MR images using VST [17] and using a bias correction algorithm [15]. Our simulation results illustrate superiority of the proposed method over the existing ones in improving the PSNR and having a better SSIM. The paper is organized as follows: Section 2 briefly reviews the BM3D approach and elaborates on the role of wavelet denoising in the first stage. Section 3 proposes alternative adaptive denoising approach for the first stage and implements the new method for MRI denoising. Simulation results are provided in Section 4, and finally Section 5 includes the concluding remarks.

2. BM3D AND DENOISING STAGE

Let $\overline{Y} = \{\overline{y}(x) | x \in \Omega\}$ be a greyscale image defined in a spatial domain $\Omega \subset \mathbb{R}^2$ where x is the coordinate of each pixel in the image. This image is corrupted with an additive Gaussian noise w that has a zero mean and variance of σ^2 . The noisy image y can be represented as:

$$y(x) = \overline{y}(x) + w(x) \tag{1}$$

Image denoising goal is to eliminate the effects of w(x) as much as possible. BM3D [11] is one of the state of art denoising methods. BM3D is composed of two major filtering steps as shown in Figure 1. In both stages collaborative filtering is utilized. Collaborative filtering itself has four stages: 1) grouping similar patches with a reference patch, 2) 3D wavelet transformation of each stack of patches, 3) denoising the wavelet coefficients (thresholding or Wiener filtering) and 4) inverse 3D transformation. BM3D aims to denoise the patches by Wiener filter, which is done in step 2. This requires a reliable block matching to select the similar patches. This is the main purpose of using hard thresholding in the first step to find the best initial estimate of the noiseless image, which is used in the second stage to select the best patches for the Wiener filtering. The input of the thresholding block is the 3D noisy wavelet coefficients of the similar patches located by block matching applied to the available noisy image. The denoising stage of the first step denoises the following wavelet coefficients of the image:

$$\theta(x) = \bar{\theta}(x) + v(x) \tag{2}$$



Fig. 1. Schematic representation of conventional BM3D hard thresholding (BM3D-HT).

where $\bar{\theta}(x)$ and v(x) are noiseless and noisy coefficients, respectively. This stage conventionally uses hard thresholding with a threshold value of 2.7σ , found heuristically in [12]. The resulted denoised coefficients $\hat{\theta}$ are then transformed back to spatial domain \hat{y} to be used as initial estimates of the noiseless data in calculation of the Wiener filter coefficients. Due to the use of Hard thresholding in the first stage, we denote the conventional BM3D as (BM3D-HT).

3. BM3D AND PROPOSED ADAPTIVE DENOISING STAGE (NIDE)

We propose a new adaptive wavelet thresholding method to be used in the first step of BM3D, in which the threshold is conventionally found and optimized based on a trial and error method on a dozen of samples. Here we replace this critical stage with Noise Invalidation Denoising (NIDe) method, a recently developed algorithm that finds its optimum threshold based on the data and noise characteristics. NIDe relies on statistical analysis of the sorted version of the noisy signal. The denoising procedure discards part of the signal that follows the statistics associated with the additive noise. Lets denote the sorted version (in ascending order) of absolute value of θ coefficients in (2) as z:

$$\theta \to z$$
 (3)

It has been shown in [18] that noisy part of z, denoted by n_z has the following expected value and variance:

$$E\left(n_{z}\right) = F\left(n_{z}\right) \tag{4}$$

$$var(n_z) = \frac{1}{N} F(n_z) \left(1 - F(n_z)\right)$$
(5)

where $F(\cdot)$ is the available cumulative distribution function of the Gaussian additive noise v in (2) and N is the number of pixels. The variance of n_z is much smaller than its expected value and it has been shown in [18] that n_z can serve as a unique noise signature for the purpose of invalidation, i.e. any coefficient of z that is inside the confidence boundary of $E(n_z) \pm \lambda \sqrt{var(n_z)}$ is noise and will be discarded. The value of λ is chosen based on the probabilistic

¹A Matlab implementation of VST is available by its author(s) on http://www.cs.tut.fi/~foi/RiceOptVST/#ref



Fig. 2. NIDe process: blue lines indicate the boundaries for the noise confidence area while the red line indicates the sorted absolute value of the signal.

confidence of the normal distribution CDF. For example, the choice of $\lambda = 3$ is known to provide a 99.9% probabilistic confidence. Figure 2 shows an example of how NIDe works. The bounded area between two dashed blue lines is known as the noise confidence area. The sorted absolute value of the wavelet coefficients of the noisy signal are compared to the noise confidence area. Any value that is in the noise confidence area is considered to be the Gaussian noise and should be discarded.

3.1. BM3D-NIDe in MRI Denoising

The noise boundaries in NIDe are defined based on additive Gaussian noise assumption, while the Rician noise involved in the observed MRI images does not match to the zero mean and additive structure assumed in conventional denoising methods. In addition, MRI noise level has a nonlinear dependency on the image intensity. Due to this nonlinearity, many conventional image denoising techniques that are proposed for homoscedastic additive noises, including the BM3D method, would result in biased estimates of the true image if they are applied directly to a MRI image [4, 10, 19, 20]. The magnitude of this bias depends on the observed image intensities such that the bias would be larger at the points with smaller image intensities. This causes the image contrast of the denoised image to be be low [16]. To be able to use the conventional state of the art denoising methods on the MRI images, two approaches have been proposed in the literatures: 1) using bias reduction methods [15] and 2) using Variation Stabilization Transformation (VST) [17]. The first approach concentrates on bias reduction only and can not accommodate the Rician structure of noise and is a postprocessing method (used after BM3D only to reduce the bias term). On the other

hand, VST based methods not only compensates the denoised image by reducing the bias, but also transforms the Rician structure to Gaussian by variance stabilization. Variance stabilization removes the dependency of the noise variance on the MRI image intensities before denoising, which makes the conventional denoising methods, like BM3D, applicable on the transformed images [17]. Therefore, we apply NIDe on MRI images using the VST approach to stabilize the noise variance. BM3D-NIDe denoising method is applied to the MRI images using VST (BM3D-NIDe-VST) with the following three steps: 1) a variance stabilization transform is applied to the MRI image, so it can be treated as a homoscedastic additive Gaussian noise; 2) BM3D-NIDe is employed on the transformed data; and 3) data will be returned to its initial status by applying a corresponding exact unbiased inverse transformations. The schematic of the proposed method is depicted in Figure 3.



Fig. 3. Schematic of the proposed BM3D-NIDe method

4. SIMULATION RESULTS

For simulations, data from Brainweb database [21] is used. The data consist of T1, T2, and PD weighted MRI images of normal brain with resolution of 217×181 . The parameters for BM3D-HT are chosen based on the optimized values proposed in [12] and are as follows: size of the patches k = 7, search window n = 17, maximum number of patches in each group for step 1 is N = 16, and for step 2 is N = 32. Distance threshold to find similar patches for $\sigma \leq 40 \ (\sigma > 40)$ is $\tau_1 = 2500 \ (\tau_1 = 5000)$ in block matching of step 1, for $\sigma \le 40 \ (\sigma > 40), \tau_2 = 400 \ (\tau_2 = 3500)$ used in block matching of step 2. Here, we compare the state of the art BM3D-HT MRI denoising methods using variance stabilization (BM3D-HT-VST) [17] and Bias Correction (BM3D-HT-BC) [15] with our proposed algorithm (BM3D-NIDe-VST), shown in Figure 3. Figure 4 shows the denoising results for T1, T2 and PD weighted MRI images with the three compared methods, when the noise level is 11%. For the purpose of evaluation, Peak Signal to Noise Ratio (PSNR) and Structural Similarity

Noise Level	3%	5%	9%	11%	13%	15%	17%
T1 Input PSNR	29.82	25.27	20.10	18.35	16.90	15.65	14.56
BM3D-HT-VST (T1)	34.44/0.93	31.53/0.88	28.42/ 0.80	27.35/0.76	26.45/0.72	25.64/0.69	24.89/0.65
BM3D-HT-BC (T1)	34.41/0.908	31.49/0.84	28.41/0.75	27.31/0.71	26.46/0.67	25.66/0.64	25.07/0.62
BM3D-NIDe-VST (T1)	34.77/0.93	31.86/0.89	28.80/0.81	27.78/0.77	26.91/0.74	26.15/0.71	25.45/0.69
T2 Input PSNR	30.09	25.57	20.40	18.64	17.19	15.94	14.84
BM3D-HT-VST (T2)	33.46/0.95	30.10/0.90	26.40/0.81	25.15/0.77	24.11/0.74	23.24/0.70	22.47/0.67
BM3D-HT-BC (T2)	33.42/0.94	30.20/0.90	26.43/0.82	25.20/0.78	24.16/0.74	23.22/0.70	22.56/0.67
BM3D-NIDe-VST (T2)	33.65/0.95	30.25/0.90	26.52/0.82	25.25/0.78	24.20/0.75	23.31/0.71	22.60/0.68
PD Input PSNR	30.10	25.58	20.35	18.56	17.07	15.80	14.69
BM3D-HT-VST (PD)	35.28/0.94	32.17/0.89	28.80/0.78	27.71/0.74	26.81/0.70	26.03/0.67	25.36/0.64
BM3D-HT-BC (PD)	35.21/0.93	32.14/0.88	28.75/0.79	27.61/0.75	26.63/0.71	25.74/0.67	25.18/0.64
BM3D-NIDe-VST (PD)	35.41/0.94	32.23/0.89	28.91/0.79	27.87/0.75	27.00/0.71	26.26/0.68	25.60/0.66

Table 1. Comparison Table of PSNR/SSIM values for different noise levels on T1, T2, and PD weighted MRI image



Fig. 4. MRI image denoising when the noise level is 11%. The first column is T1 weighted, the second column is T2 weighted, and third column is PD weighted images. Row one is the noiseless image, second row is the noisy image. Third row, forth row, fifth row are the denoised images with BM3D-HT-VST, BM3D-HT-BC, and BM3D-NIDe-VST respectively.

Index (SSIM) [22]² are calculated for each method. Table 1

shows PSNR/SSIM values with noise levels from 3% to 17% for the three types of T1, T2 and PD weighted images. The results demonstrate that the proposed approach performs better than the existing approaches in all the cases. As table 1 illustrates BM3D-NIDe-VST method seems to be more robust to increase of the noise variance.

5. CONCLUSION

A new denoising method was proposed for MRI that is based on the state of the art BM3D denoising approach. The performance of BM3D was improved by using NIDe denoising method, which improved the wavelet thresholding of the first step compared to heuristic threshold search used in the original work. It is known that the complicated nature of noise in MR images makes the use of conventional denoising methods impossible. Combination of the new BM3D approach and variance stabilization transform (VST) provided an efficient MR image denoising approach. The proposed method, denoted by BM3D-NIDe-VST, was compared with two recently proposed BM3D based MRI denoising techniques. The results demonstrate advantages of the proposed method over the existing ones.

6. REFERENCES

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 $^{^2}A$ Matlab implementation is available online by its author(s) at https://ece.uwaterloo.ca/~z70wang/research/ssim/

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