# MRI DENOISING USING BM3D EQUIPPED WITH NOISE INVALIDATION DENOISING TECHNIQUE AND VST

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**Abstract**

**Image denoising is very important in medical applications. Magnetic Resonance Imaging (MRI) denoising is the focus of many researches to provide images with both high signal-to-noise ratio and good spatial resolution. In the proposed method, Block-matching and 3D filtering (BM3D) technique is used for MRI denoising. Main steps used in BM3D are Nonlocal approach, 3D wavelet shrinkage and 3D Wiener filtering. In the proposed method, Noise Invalidation Denoising (NIDe) is used instead of hard thresholding. This new approach provides the optimum wavelet threshold automatically based on the data and noise characteristics and adaptive to the statistical characteristics of data. This is the main advantage of NIDe over the hard thresholding. Variance Stabilization Transform (VST) removes the dependency of the noise variance on the MRI image intensities before denoising. Combining the proposed BM3D technique with Variance Stabilization Transformation (VST) enables the use of the proposed method for Magnetic Resonance Image denoising. Performance metrics such as peak signal to noise ratio (PSNR), mean square error (MSE) and structural similarity index (SSIM) are find out for T1, T2 and PD weighted MR images.**

**Keywords: Block-matching and 3D filtering; Magnetic Resonance Imaging; denoising; Noise Invalidation Denoising; Variance Stabilization Transform.**

## I. INTRODUCTION

Medical imaging became an integral part of disease diagnosis in present days. Various medical imaging modalities are developed for different applications since last few decades. These modalities are used to acquire the images of the anatomical structures within the body to be examined without opening the body. X-rays, Computed Tomography, Magnetic resonance Imaging and Ultrasound are the popular medical imaging modalities at present to diagnose the various diseases. However these imaging modalities are suffering with a big problem called noise. Noise means, the intensity values of pixels in the image show different values instead of true pixel values. During image acquisition or transmission, several factors are responsible for introducing noise in the imaging modality such as Quantum noise in X-rays and Nuclear imaging, speckle noise in ultrasound imaging, Rician noise in Magnetic resonance imaging etc. The noise which is present in the image degrades the contrast of the image and creates problems in the diagnostic phase. So denoising is very important step to remove the noise from images [1].

Magnetic resonance imaging (MRI) is imaging technique which provides highly detailed images of tissues and organs in the human body. MRI system is working on the principles of nuclear magnetic resonance (NMR), to map the spatial location and associated properties of specific nuclei in a subject using the interaction between an electromagnetic field and nuclear spin. It detects and processes the signals when hydrogen atoms are placed in strong magnetic field and excited by a resonant magnetic excitation pulse. The human body is largely composed of water molecules and fat. Each water molecule has two hydrogen nuclei. These hydrogen nuclei are imaged to demonstrate the physiological or pathological alterations of human tissues [2]. Acquisition time in MRI is limited. Therefore the signals to noise ratio (SNR) of the MR images are usually low. The qualities of the MRI images are usually degraded with several artifact and noises that is adequately modeled Rician noise. Therefore, denoising techniques that removes noise, while preserve the image details is an important step of MR image processing [3].

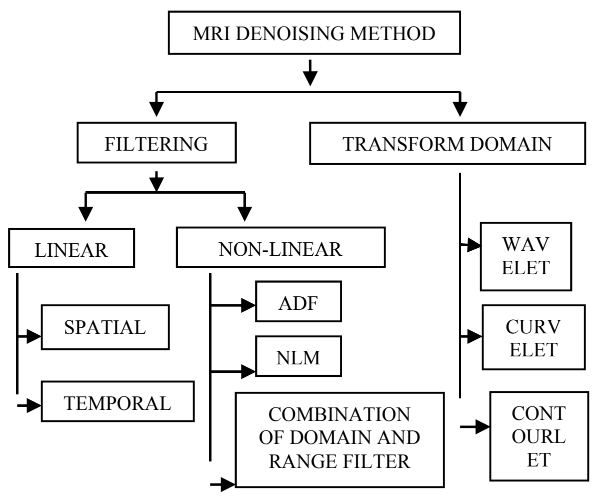


Fig.1 Classification of MRI denoising methods

A variety of techniques have been presented in past on denoising MR images as shown in fig.1 and each technique has its own assumptions, advantages and limitations[4]. The purpose of this literature survey is to present a review of the published paper in dealing with denoising methods in MR images. McVeigh et al. [5] proposed the spatial filter and temporal filter reducing Gaussian noise in MR images. Krissian and Aja-Fernández [6] proposed noise driven anisotropic diffusion filter to remove Rician noise from MRI. Buades et al. [7] depicted the nonlocal means (NLM) filter. Manjon et al. [8] presented the unbiased NLM approach for MRI denoising. Tomasi and Manduchi [9] proposed the bilateral filter as a non-iterative alternative to anisotropic diffusion filter. Wong et al.[10] depicted the trilateral filter for reduction of noise in medical images which works along similar lines to bilateral filtering. Yu and Zhao [11] proposed an iterative scheme based on wavelet shrinkage for reducing Rician noise in the MR images.

BM3D is post acquisition based noise reduction method. BM3D denoising method has demonstrated advantages in denoising images with additive Gaussian noise. The aim of 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 with NIDe on the stacks of similar patches formed by the noisy image. BM3D denoising approach is used in MRI denoising by preprocessing the MR image with a variance stabilization approach [3].

## II. Noise In MRI

Scanner technology has undergone tremendous improvements in spatial resolution, acquisition speed and signal-to-noise ratio (SNR), the diagnostic and visual quality of MR images are still affected by the noise in acquisition. Also, MR images contain varying amount of noise of diverse origins including noise from stochastic variation, numerous physiological processes, and eddy currents, artifacts from the magnetic susceptibilities between neighboring tissues, rigid body motion, non rigid motion and other sources. The main source of noise in MRI is thermal noise that is from the scanned object. In this section, the noise distribution in MR images is explained.

### *A. Characteristic Of Noise In MRI*

The raw data obtained during MRI scanning are complex values that correspond to the Fourier transform of a magnetization distribution of a volume of tissue. Therefore, MRI image is usually reconstructed by computing the IDFT of the raw data. An inverse Fourier transform converts these raw data into magnitude, frequency and phase components that represent the morphological and physiological features of interest in the person which is being scanned. The signal component of the measurements is present in both real channel and imaginary channel. Each of the two orthogonal channels is affected by AWGN. Thus, complex white Gaussian noise is present in the reconstructed complex-valued data. Therefore, noise in the k-space in magnetic resonance (MR) data from coil is assumed to be a zero mean uncorrelated Gaussian process with equal variance in both real part and imaginary part because of the linearity and orthogonality of the Fourier transform [2, 12]. Most frequently, the magnitude of the reconstructed MR image is used for visual inspection and for automatic computer analysis. As the computation of a magnitude (or phase) image is a non-linear operation, the PDF of the MR data changes. since the magnitude of MRI signal is the square root of the sum of squares of the two independent Gaussian variables, it follows a Rician distribution i.e. magnitude data in spatial domain is generated as the Rician distribution and so called Rician noise is locally signal dependent. In low intensity regions i.e. in dark region of the magnitude image, the Rician distribution tends to a Rayleigh distribution and in high intensity i.e. in bright regions it tends to a Gaussian distribution [4].

$$p_M(M|A,\sigma_n) = \frac{M}{\sigma_n^2}\ e^{-(M^2+A^2)/2\sigma_n^2}\ I_0\left(\frac{AM}{\sigma_n^2}\right)u(M) \quad (1)$$

Where $I_0(.)$ is the modified zeroth order Bessel function of the first kind, $\sigma_n^2$ is the noise variance, A the noiseless signal level, M the MR magnitude variable and u(·) is the Heaviside step function.

## III. Proposed BM3D-NIDe-VST Method

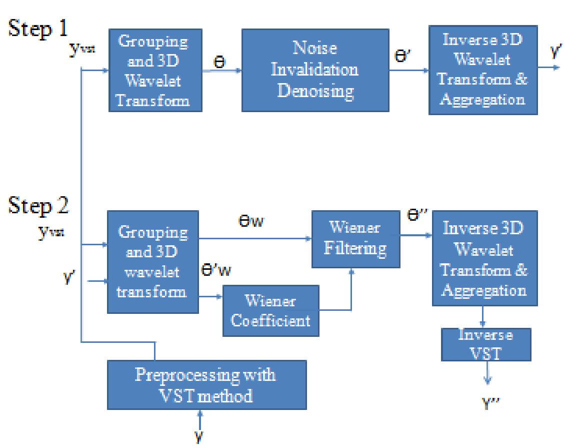


Fig.2 Block diagram of proposed BM3D-NIDe-VST method

BM3D is one of the MRI denoising methods. BM3D is composed of two major filtering steps as shown in Figure 2.

-Denoise the MRI image by using NIDe

-Denoise the MRI image by using Wiener Filtering

In both stages collaborative filtering is utilized. Collaborative filtering itself has four stages [13]:

-Grouping patches similar to the reference patches

-3D wavelet transformation of each stack of patches

-Denoising wavelet coefficients (NIDe or Wiener Filtering)

-Inverse 3D transformation.

BM3D is an improved version of Non Local Mean 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 increases the sparsity of the data compared to the use of original image. So, the denoising method can attenuate the noise easier and more effectively. BM3D denoising method has demonstrated advantages in denoising MRI images with additive white Gaussian noise [14, 15].

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 NIDe 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.

For thresholding purpose newly NIDe method is proposed instead of the hard thresholding. Application of the Block Matching 3-Dimensional Filtering approach in MRI denoising is possible by preprocessing the image with a VST approach [16, 17], which stabilizes the noise variance in the Rician distributed MR image.

### *B. Preprocessing with VST Method*

The noise boundaries in NIDe are defined based on AWGN assumption, while the Rician noise involved in the MRI images does not equivalent to the zero mean and additive structure assumed in denoising methods. Also, MRI noise level has a nonlinear dependency on the image intensity. Due to this nonlinearity result obtained is biased estimates of the true image if they are directly applied to a MRI image [18].VST based methods not only compensates the denoised image by reducing the bias, but also transforms the Rician structure to Gaussian by variance stabilization. Therefore, VST approach is mainly used in proposed BM3D-NIDe-VST method. Final estimate is then obtained by applying an inverse VST to the denoised data.

Anscombe transformation [19] is mostly used VST and considered to be a useful tool due to its simplicity and efficiency. Its expression is as given below,

$$Y_i = T(y_i) = 2\sqrt{y_i + \frac{3}{8}} \qquad (2)$$

Where, $y_i$ is the observed intensity value of noisy image and $Y_i$ is the transformed intensity value .After the Anscombe transformation T, the pixel intensities in image are approximately Gaussian distributed with mean 0 and variance $\sigma^2 = 1$. Thus its variance is assumed to be stationary.

### C. *Noisy Structure of MRI Image*

Let $\{ \overline{Y}(x) | x \in \Omega \}$ be a two dimensional grey scale image defined in a spatial domain $\Omega \subset R^2$, 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 $\sigma^2$ . The noisy image $y$ can be represented as:

$$y(x) = \overline{y}(x) + w(x) \qquad (3)$$

The main goal of BM3D is to eliminate the effects of $w(x)$ as much as possible [3].

### D. *Grouping and 3D Wavelet Transform*

We denominate "grouping" the concept of collecting similar d-dimensional patches of a given signal into a (d+1)–dimensional data structure that we term "group." In the case of 2-dimensional images, patches (signal fragments) are 2-D signal (arbitrary 2-D neighborhoods). First we select one reference patch. According to that reference patch find out all the similar patches and group them together. In the same manner for different reference patches find out the different groups. In this way a group is a 3-D array formed by stacking similar 2-D patches together (image neighborhoods).

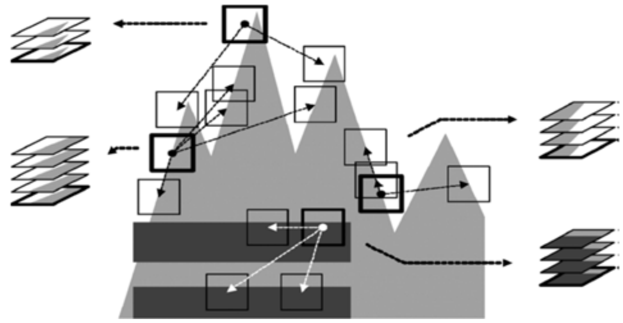

Fig.3 Simple example of grouping in an artificial image

The importance of grouping is to enable the utilize of a higher dimensional filtering of each group, which exploit the potential similarity (correlation, affinity, etc.) between grouped patches in order to find out the true signal in each of them. Similarity between patches (signal fragments) is typically computed as the inverse of some distance measure. Hence, a smaller distance represent higher similarity[13]. Here, $l_p$-norm distance is used to find out distance which is given as,

$$|| x_1 - x_2 ||_2 = \sqrt{\textstyle\sum_i (x_{1i} - x_{2i})^2} \qquad (4)$$

After the grouping (i.e. 3-D array) apply 3-D DWT on the entire 3-D array and get wavelet coefficient.

### E. *Denoising Wavelet Coefficient using NIDe and Wiener Filtering*

The denoising stages denoise the following wavelet coefficients of the image:

$$\theta(x) = \overline{\theta}(x) + v(x) \qquad (5)$$

Where, $\overline{\theta}(x)$ are Noiseless Coefficients and $v(x)$ are Noisy Coefficients.

In the first step, wavelet coefficients of MR images are denoised by using NIDe instead of hard thresholding. In hard thresholding, threshold value 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. This algorithm finds its optimum threshold based on the data and noise characteristics. 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 [20]. 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. After by applying inverse 3D DWT we get estimated image.

This estimated image and VST processed image is used in the second step as input for wiener filtering. Same procedure is repeated in the second step explained above. By applying inverse 3D DWT at the end of second stage we get denoised MR image. Inverse VST is applied on this denoised MR image to get final denoised MR image.

## IV. SIMULATION RESULT

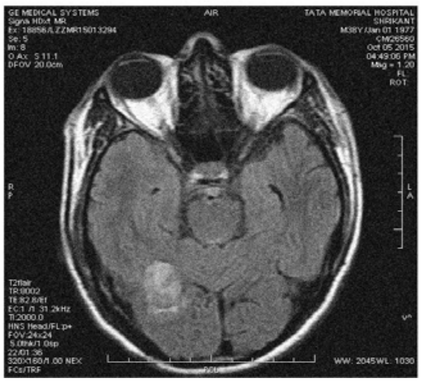

Fig.4.1) Noisy Image(T2-weighted MRI)

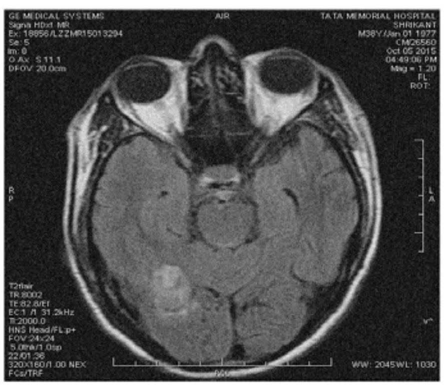

Fig.4.2) VST processed Image

Fig.4.3) Denoised Image (Step-I)

Fig.4.4)Denoised Image(Step-II)

PSNR value of above T-2 weighted MRI image is 34.94 with 3% Noise level.

Table-I

| Noise Level | 3% | 5% | 9% | 11% | 13% |
|---|---|---|---|---|---|
| T1 Input PSNR | 36.12 | 34.89 | 31.52 | 29.86 | 27.60 |
| T2 Input PSNR | 34.16 | 31.54 | 26.48 | 25.12 | 24.55 |
| PD Input PSNR | 35.92 | 34.12 | 30.89 | 29.23 | 27.29 |

Table1.Comparision table of PSNR for different noise levels on T1, T2 and PD weighted MR images

## V. CONCLUSION

A new denoising method proposed for MRI is based on the BM3D denoising approach. The performance of BM3D was improved by using NIDe denoising method. 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. Experiments were performed on T1-weighted, T2-weighted and PD-weighted MRI images to compare the proposed. Performance metrics such as PSNR, MSE and SSIM are found out and results demonstrate advantages of the proposed method over the existing ones in PSNR, MSE and SSIM.

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