Denoising in Magnetic Resonance Images using Improved Gaussian Smoothing Technique

Beshiba Wilson, Julia Punitha Malar Dhas

Abstract: Magnetic Resonance Images (MRI) are usually prone to noise like Rician and Gaussian noise. It is very difficult to perform image processing functions with the presence of noise. The objective of our work is to investigate the best method for denoising the MRI images. This study included 25 MRI subjects selected from the Open Access Series of Imaging Studies (OASIS) - 3 database. The 25 brain image subjects includes cases of both men and women aged 60 to 80. The input RGB image is first converted to gray scale image in which the contrast, sharpness, shadow and structure of the color of image are preserved. The proposed work uses an improved Gaussian smoothing technique for denoising Magnetic Resonance Images by constructing a modified mask for Gaussian smoothing. The performance of the proposed technique has been compared with various filters like median filter, Gaussian filter and Gabor filter. The performance evaluation was carried out by metrics like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structural Similarity (SSIM) index. The experimental results show that the Improved Gaussian Smoothing Technique (IGST) performs better than other methods. All experiments were conducted using Scikit Learn version 0.20 and Scikit Image version 0.14.1 under Python version 3.6.7.

Index Terms : Denoising, Gaussian noise, Improved Gaussian Smoothing Technique (IGST), Magnetic Resonance Images (MRI), Rician noise, Susceptibility Weighted Images (SWI).

I. INTRODUCTION

Medical images play a vital role in clinical applications for proper diagnosis and treatment of diseases. It is very difficult to analyse lesions in brain using simple MRI techniques. The MRI sequence namely Susceptibility Weighted Imaging (SWI) is recently used in clinical applications related to brain. SWI focuses mainly on the analysis of the images and its visual interpretation by experts in the field of radiology. However, it is very important that the visual quality of the input image is free from noise. The presence of noise in the acquired image can decrease the performance of the computing techniques segmentation and classification [1]. There are various methods existing for removal of noise in an image. The most pervasive method for denoising is the Gaussian noise model [2]. An efficient noise removal algorithm must perform denoising while preserving image details [3]. A method for noise removal using Steering Regression Kernel (SKR) which is signal dependent was proposed by Takeda et al [4]. The performance of the filter was effective as the noise level increases. A NLM based filter to remove noise effectively was developed by Kerverran et al, [5]. Hossein et al,[6] has proposed noise removal technique based on spectra decomposition which uses a patch based model. In the patch based noise removal technique, each pixel is calculated from all pixels of the entire image. A combined method which utilizes spatially adaptive threshold along with wavelets has been proposed by Chang et al, [7] as an effective method for filtering noises from images. A mixture of Gaussians based modeling of wavelet coefficients of images has been proposed by Portilla et al [8]. In the proposed work, an efficient mask for Gaussian Smoothing has been introduced effectively perform denoising in Magnetic Resonance Images. The Gaussian Smooth mask is a discrete approximation to the Gaussian function.

II. CONVERSION OF RGB TO GRAY SCALE IMAGE

The original input MRI image sequence called Susceptibility Weighted Image (SWI) is an RGB image which is converted to gray scale image using a standard function which preserves the contrast, sharpness, shadow and structure of the color image. Fig 1 shows the original image and its gray scale image.

III. NOISE MODELS

Magnetic Resonance Images are mainly affected by two main types of noise namely Rician and Gaussian noise. Fig 2 shows a Gray scale image and its noisy counterpart.
Denoising in Magnetic Resonance Images using Improved Gaussian Smoothing Technique

3.1. Rician Noise:
Magnetic Resonance Images are affected by Rician noise which is easily understandable from the influence of Rician distribution on the image intensity [9]. Signals with less intensities are biased because of noise. This underlying noise can be estimated and the bias factor can be reduced. The Rician noise is formed from complex Gaussian noise based on measurements in original frequency domain.

3.2. Gaussian Noise:
The Gaussian noise is another important additive noise which affects the MR images. This is mainly caused due to the constant noise level produced by image sensor [10]. The probability density function of a Gaussian noise is equal to that of Gaussian distribution. Gaussian noise is used as additive white noise to yield additive white Gaussian noise.

IV. MATERIALS AND METHODS
In this section, the dataset used in the proposed work are discussed.

4.1. Dataset
OASIS-3 dataset is used for the implementation of the proposed work. The Magnetic Resonance Imaging (MRI) slices includes axial view of Susceptibility Weighted Images (SWI) of 3.0 Tesla MR sessions obtained using Siemens TIM Trio 3T MRI Scanner. The brain image subjects includes 25 cases both men and women aged 60 to 80. All experiments were conducted using Scikit Learn version 0.20 and Scikit Image version 0.14.1 under Python version 3.6.7.

4.2. Denoising methods
There are various filters available for performing denoising in MRI images.

4.2.1. Median Filter:
It is a non-linear digital filtering method which effectively removes noise and preserves the edges of an image. A window which represents a pattern of neighbours slides over the image pixel by pixel. Each pixel is replaced with the median value of the neighbouring pixels. It is found to be effective for ‘salt and pepper’ type noise removal.

4.2.2. Gabor Filter:
It is a linear filter which is used mainly for texture analysis. In the spatial domain, the kernel of a Gabor filter represents a Gaussian Kernel function which is modulated by a sinusoidal wave.

4.2.3. Gaussian Filter:
It is usually used in multi-scale edge detection methods. Gaussian filters are effective in the localization of both spatial and frequency domains. A 2D Gaussian function which is centered at origin is represented as,

$$g(x,y) = e^{-\frac{(x^2 + y^2)}{2\sigma^2}}$$  \hspace{1cm} (1)

where $\sigma$ is the Standard Deviation.

4.3. Proposed Work
In the proposed work, we generate a modified mask for Gaussian smoothing and the process is referred to as Improved Gaussian Smoothing Technique (IGST). When an original image ‘o’ is smoothed by the IGST with impulse response ‘I’, the smoothed image ‘n’ is obtained in the frequency domain using the following expression,

$$N(h,g) = O(h,g) \ast I(h,g)$$  \hspace{1cm} (2)

where $N(h,g)$, $O(h,g)$ and $I(h,g)$ are the frequency domain values of $n(x,y)$, $o(x,y)$ and $i(x,y)$. In the spatial domain, the final smoothed image is represented using the following convolution expression,

$$n(x,y) = o(x,y) \ast i(x,y)$$  \hspace{1cm} (3)

IV. RESULTS AND DISCUSSION
The input images are first converted into Gray Scale images. The performance of Improved Gaussian Smoothing Technique (IGST) is compared with traditional filters like Median filter, Gabor filter and Gaussian Filter. The output obtained after applying all the filters individually to the input image is shown below.

![Fig.3. Output obtained from Median filter, Gabor filter, Gaussian filter and Improved Gaussian Smoothing.](image-url)
For performing improved Gaussian smoothing, all the images were taken from Oasis-3 dataset [11]. The performance metrics used in the work are PSNR, MSE and SSIM. PSNR refers to the Peak Signal to Noise Ratio ratio, MSE refers to Mean Square Error value and SSIM refers to Structural Similarity Index. Tables 1, 2 and 3 illustrates the performance comparison of Median filter, Gabor filter, Gaussian filter and Improved Gaussian Smoothing Technique (IGST) using PSNR for five image samples.

Table 1 : Performance comparison of Median filter, Gabor filter, Gaussian filter and Improved Gaussian Smoothing Technique (IGST) using PSNR for five image samples.

| Sl.No. | Denoising Technique                  | Image 1 | Image 2 | Image 3 | Image 4 | Image 5 |
|-------|--------------------------------------|---------|---------|---------|---------|---------|
| 1.    | Median                               | 20.87   | 20.53   | 20.79   | 20.81   | 20.88   |
| 2.    | Gabor                                | 21.19   | 20.64   | 20.81   | 20.97   | 21.03   |
| 3.    | Gaussian                             | 21.36   | 20.70   | 20.85   | 21.19   | 21.21   |
| 4.    | Improved Gaussian Smoothing Technique| 22.08   | 21.49   | 21.62   | 22.02   | 21.97   |

Table 2 : Performance comparison of Median filter, Gabor filter, Gaussian filter and Improved Gaussian Smoothing Technique (IGST) using MSE for five image samples.

| Sl.No. | Denoising Technique                  | Image 1 | Image 2 | Image 3 | Image 4 | Image 5 |
|-------|--------------------------------------|---------|---------|---------|---------|---------|
| 1.    | Median                               | 39      | 32.61   | 37.74   | 35.72   | 39.10   |
| 2.    | Gabor                                | 37.20   | 32.10   | 37.65   | 34.93   | 38.46   |
| 3.    | Gaussian                             | 36.85   | 31.98   | 37.45   | 34.19   | 37.56   |
| 4.    | Improved Gaussian Smoothing Technique| 33.94   | 29.20   | 34.28   | 31.10   | 34.47   |

Table 3 : Performance comparison of Median filter, Gabor filter, Gaussian filter and Improved Gaussian Smoothing Technique (IGST) using SSIM for five image samples.

| Sl.No. | Denoising Technique                  | Image 1 | Image 2 | Image 3 | Image 4 | Image 5 |
|-------|--------------------------------------|---------|---------|---------|---------|---------|
| 1.    | Median                               | 0.43    | 0.52    | 0.51    | 0.44    | 0.45    |
| 2.    | Gabor                                | 0.47    | 0.48    | 0.48    | 0.47    | 0.47    |
| 3.    | Gaussian                             | 0.54    | 0.56    | 0.56    | 0.54    | 0.54    |
| 4.    | Improved Gaussian Smoothing Technique| 0.60    | 0.62    | 0.62    | 0.60    | 0.60    |

The graphical representation of the performance comparison of various filters using different performance measures is given below.

Fig. 4. A graph representing the comparison of performance of Median filter, Gabor filter, Gaussian filter and IGST for five image samples using PSNR.

Fig. 5. A graph representing the comparison of performance of Median filter, Gabor filter, Gaussian filter and IGST for five image samples using MSE.

Fig. 6. A graph representing the comparison of performance of Median filter, Gabor filter, Gaussian filter and IGST for five image samples using SSIM.

VI. CONCLUSION

Image preprocessing is an important step in various applications of medical image analysis. Though various filters are currently existing, it is very important to choose a filter which effectively removes noise in Magnetic Resonance Images. In this work, we have proposed an Improved Gaussian Smoothing Technique which generates a Gaussian kernel by avoiding errors like Quantization error and average intensity error. The performance evaluation shows that the proposed technique performs better than the traditional filters.
Denoising in Magnetic Resonance Images using Improved Gaussian Smoothing Technique

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