International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Comparative Analysis of Various Denoising Techniques for MRI Images

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Abstract: ***Magnetic Resonance Imaging (MRI) has become a widely used method for diagnosing diseases related to soft tissue organs like heart, brain, and uterus. But this technique is fraught with problems related to noise addition during image acquisition, which degrades the quality of MR images for further study. This paper does a comparative study of different filtering methods that is applied to MR images.***

Keywords: Magnetic Resonance Imaging, Rician Noise, Normalized Absolute Error, Structured Similarity Index, Gaussian Noise

1. Introduction

Magnetic Resonance Imaging (MRI) has become a widely used method of high quality medical imaging, especially brain imaging where MRI's soft tissue contrast and non-invasiveness is a clear advantage [1]. MRI provides a perfect view inside the human body. The level of details we can see is remarkable on being evaluated with other imaging modality. MRI is a medical imaging technique that measures the response of atomic nuclei of body tissues to high frequency radio waves when placed in a strong magnetic field and that produces images of the internal organs [2]. MRI differs from other modalities like X-ray, Computed Tomography in such manner that it can characterize and discriminate among tissues using their biochemical and physical properties. Also, without moving patient it can produce sectional image of equivalent resolution. This adds to its flexibility and diagnostic utility which gives it special advantage for surgical treatment planning [3]. MRI is primarily used to demonstrate pathological or other physiological variations of living tissues and is a commonly used form of medical imaging. Because of the resolution of MRI and the technology being essentially harmless it has emerged as the most accurate and desirable imaging technology. MRI imaging is often used when treating brain, prostrate cancers, ankle and foot. It can also be used for identifying diseases such as Parkinson's, Alzheimer's, brain tumors and stroke [4][5]. Despite significant improvements in recent years, magnetic resonance (MR) images often suffer from low Signal to Noise Ratio (SNR) especially in brain imaging.

2. Problems Encountered In MRI Technique

MRI images may have noises in it. Sources of MR noise include thermal noise (from the conductivity of the system's hardware), inductive noise (from the conductivity of the object being imaged), sample resolution and field of view (among others) [6]. Noises are also induced due to the random distribution of electron devices, the influence of ambient environment and human factors during the imaging process [9]. Noise present in the images will degrade the contrast of the image and creates problems in the diagnostic phase [7]. Noise in MRI negatively affects image processing and analysis works, such as registration, feature extraction, segmentation, classification and visualization [5][10]. Noises occur usually during image acquisition and transmission [8].

Types of Noises in MR images:

Salt-and-pepper noise: This noise is caused by errors in data transmissions and disturbances in the images [11]. It is randomly occurring black or white (or both) pixels over the images. Good noise filtering approach is to use median filters or morphological filters.

Gaussian noise: This type of noise arises during image acquisition. For example, sensor noise caused by poor illumination or high temperature or transmission for example, electron circuit noise. This is a statistical noise having a probability density function (PDF) equal to that of normal distribution which is also known as the Gaussian distribution. Gaussian noise can be filtered using spatial filters like mean and median filters and Gaussian filters [11].

Rician noise: It is a signal dependent noise and hence noise removal is difficult. It causes random fluctuations in the data and introduces a bias to the MR image that reduces image contrast [12]. In low intensity regions of the magnitude image the noise distribution tends to the Rayleigh distribution. In regions of high intensity, the noise tends to a Gaussian distribution. This noise degrades images in both qualitative and quantitative sense and hinders image analysis, interpretation and feature detection. Filters used to remove Rician noise are Non-Local Means (NLM) filter [5][18], Iterative Bilateral filter, Genetic programming based composite filter, Rician Bias Correction Filters etc.

Thermal Noise: Source of thermal noise is the subject or object to be imaged, followed by the electronics noise during the acquisition of the signal in the receiver chain. It is produced by stochastic motion of free electrons in the RF coil, which is a conductor and by eddy current losses in the patient, which are inductively coupled to the RF coil [13]. To remove Thermal noise NLM filters are commonly used.

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3. Quality Metrics for Judging the Noise Level in Images

For image quality management there are basically two approaches: subjective measurements and objective measurements [14]. Subjective measurements are the result of human experts providing their opinion of the image quality and objective measurements are performed with mathematical algorithms. Subjective measurements are too inconvenient, time consuming and expensive. An objective image quality metric can play a variety of roles in image processing applications. It can be used to dynamically adjust and monitor image quality, to optimize algorithms and parameter settings of image processing systems and to benchmark image processing systems and algorithms. Objective image quality metrics are classified according to the availability of an original (distortion-free) image, with which the distorted image is compared. It has three approaches: Full-reference approach, No-reference approach and Reduced-reference approach. In Full-reference approach, a complete reference image is assumed to be known. In No-reference or "blind" approach, the reference image is not available and in Reduced-reference approach, reference image is only partially available, in the form of set of extracted features. The metrics used for comparison of images in this paper are Full-reference approach. These metrics have clear physical meanings, and are mathematically convenient in the context of optimization, but they are not well matched to perceived visual quality. Some of the metrics are discussed here.

Mean-Squared Error (MSE): MSE is computed by averaging the squared intensity differences of distorted and reference image pixels [15].

$$\mathrm{MSE} = \frac{1}{\mathrm{MN}} \sum_{\mathrm{i}=0}^{\mathrm{M}-1} \sum_{\mathrm{j}=0}^{\mathrm{N}-1} [\mathrm{I}(\mathrm{i},\mathrm{j}) - \mathrm{K}(\mathrm{i},\mathrm{j})]^2 \qquad (1)$$

Where I and K are reference image and distorted image respectively.

Peak Signal-to-Noise Ratio (PSNR): PSNR is the ratio between maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Higher PSNR shows greater resemblance between images [15].

$$\mathrm{PSNR} = 20\ \log_{10} \mathrm{Max}_{\mathrm{i}} - 10 \log_{10} \mathrm{MSE} \qquad (2)$$

PSNR is biased towards over smoothed (=blurry) results, i.e. an algorithm that removes not only the noise but also a part of textures will have a good score.

Signal-to-Noise Ratio (SNR): SNR is used in imaging as a physical measure of the sensitivity of a (digital or film) imaging system [2].

$$\mathrm{SNR} = 10\log10 \left(\frac{\mathrm{var}\ (\mathrm{x})}{\mathrm{var}\ (\mathrm{x}' - \mathrm{x})} \right) \qquad (3)$$

Where, μ_{sig} is the average signal value and σ_{bg} is the standard deviation of background.

Structured Similarity Index Method (SSIM): This is a full reference metric for measuring the similarity between two images. It considers image degradation as perceived change in structural information. Structural information depends on the idea that pixels have strong inter-dependencies when they are spatially close. These inter-dependencies carry information about the structure of the objects in visual scene. The SSIM is calculated on various windows of an image. The measure between two windows x and y of common size N x N is [16]:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (4)$$

With μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y, $c_1 = (\mathrm{K_1L})^2$, $c_2 = (\mathrm{K_2L})^2$ are two variables to stabilize the division with weak denominator, L is the dynamic range of the pixel-values ($2^{\#\ \text{bits-per pixel}} - 1$), $\mathrm{K_1}$=0.01 and $\mathrm{K_2}$=0.03 by default. The resultant SSIM index is a decimal value between -1 and 1; it is calculated on a window size of 8 x 8. This is a better quality measure but more complicated to compute.

Normalized Absolute Error (NAE): It's the numerical difference between the original and reconstructed image. For an image of size M x N, NAE is calculated as below [17]:

$$NAE = \frac{\sum_{j=1}^{M} \sum_{k=1}^{N} |x_{j,k} - x'_{j,k}|}{\sum_{j=1}^{M} \sum_{k=1}^{N} |x_{j,k}|} \qquad (5)$$

For poor image quality NAE will give a larger value.

4. Results and Discussions

For comparative purpose we take Mean, Median, Gaussian and Laplacian filters on the noises Salt-and-pepper and Gaussian.

Salt-and-Pepper Noise:

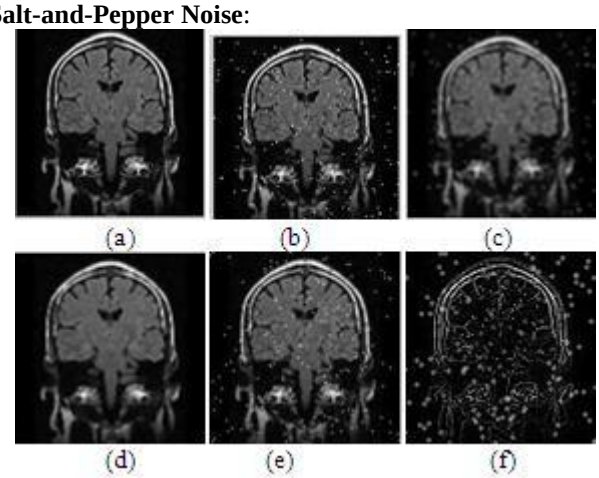


Figure 1: Results of Filters on Salt and Pepper Noise. a) Original Image b) Salt-and-Pepper Noise added c) Mean Filtered d) Median Filtered e) Gaussian Filtered f) Laplacian Filtered

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Gaussian Noise:

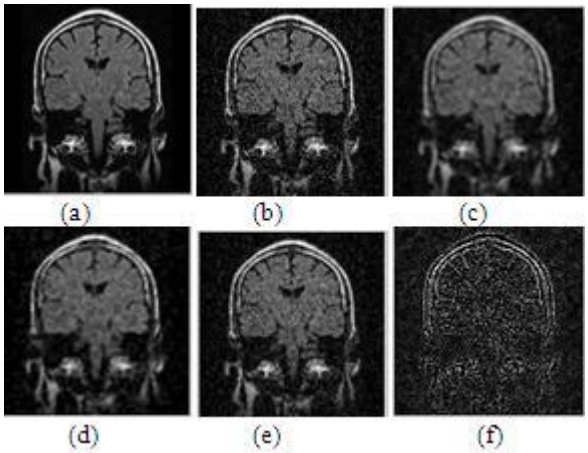


Figure 2: Results of Filters on Gaussian Noise. a) Original Image b) Gaussian Noise added c) Mean Filtered d) Median Filtered e) Gaussian Filtered f) Laplacian Filtered

The comparison metrics used here are MSE, PSNR, SNR and NAE. The results of various filters on Salt-and-Pepper and Gaussian noises are given in Table 1.

Table 1: Comparison of MSE, PSNR, SNR and NAE values for Mean, Median, Gaussian and Laplacian Filters

Noise	Filter	MSE	PSNR	SNR	NAE
Salt-and-Pepper	Mean	370.86	22.47	8.335	0.263
	Median	**219.07**	**24.76**	**10.53**	**0.15**
	Gaussian	257.18	24.06	10.011	0.13
	Laplacian	5201.1	11.00	2.9150	1.146
Gaussian	Mean	392.67	22.22	8.1392	0.331
	Median	**326.74**	**23.02**	**8.78**	**0.281**
	Gaussian	267.91	23.88	10.053	0.299
	Laplacian	5149.98	11.05	-3.185	1.258

As observed from [15] images which have lower MSE, higher PSNR and SNR and lower NAE gives better visual quality. Median filters appear to satisfy these criteria.

5. Conclusion

The effect of various noises on MRI image is taken and the uses of filters on the noises are shown in the Table 1. Observation shows that median filters are better when undergoing filtering on MRI images. Figures 1 and 2 shows that visual quality output image for median filters. Hence median filters are most suitable for filtering MRI images.

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