An Analysis of NoiseFiltering algorithms for Magnetic Resonance Images

[1]S.Chithra, Shubhi Srivastava[2]
[1,2]Assistant Professor, Department of BCA,
Krupanidhi Degree College, Chikka Bellandur ,

Abstract -Medical images are analyzed for diagnosis of various diseases. In medical image processing, removing noise plays a very important role in the preprocessing modules of the virtual endoscope system. The medical imaging devices particularly X-ray, CT/MRI, and ultrasound are manufacturing overabundant pictures that are utilized by medical practitioners within the method of designation. All medical images contain some visual noise. They are mottled, grainy, textured, or snowy appearance. It is very important to obtain precise images to facilitate accurate observations for the given application. Magnetic Resonance Imaging (MRI) is identified to be conceited by several sources of quality descent, due to limitations in the hardware, scanning times, movement of patients, or even the motion of molecules in the scanning subject. Among them, noise is one source of deprivation that affects acquisitions. The occurrences of noise over the acquired MR signal is a trouble which affects not only the visual quality of the images but also may interfere with further processing techniques such as registration or tensor estimation in Diffusion Tensor MRI. The paper aims to illustrate noise models and investigate noise suppression methods based on image processing techniques in MR images.

Key Words*:* Bilateral, Mean, Median, Magnetic Resonance Image, Noise Models, Wiener

1. Introduction

In Image Processing, the digital images are much sensitive to noise which results due to the image acquisition errors and transmission errors. MRI images play a major role in medical diagnostic. Magnetic Resonance images are normally corrupted by rician noise, random noise, speckle noise, Gaussian noise, salt, and pepper noise etc., as of this reason noise removal methods have been usually applied to improve MR image quality [1]. The entire medical imaging methods generate images with some visual noise. This is generally an undesirable characteristic that reduces the visibility of certain types of objects and structures as illustrated in fig 1.

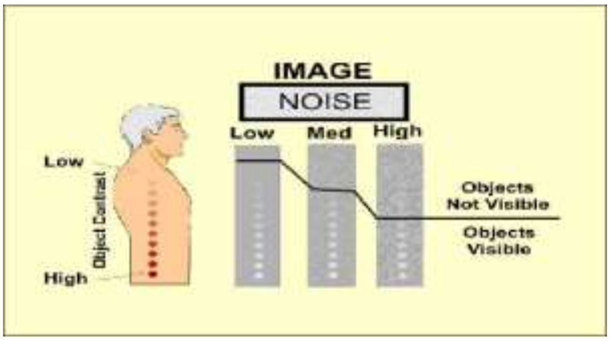

Fig.1. Image Noise Structure

Specifically, noise reduces the visibility of low-contrast objects. This is especially significant in MR images which are often used to image low-contrast differences among tissues. The noise is characteristics that reduce visibility but of different types of objects. Noise reduces the visibility of low-contrast objects, blurring reduces the visibility of small objects or detail. The noise in a MR image can be adjusted with a combination of protocol factors. The complex is that the factors that can be utilized to regulate and decrease noise also have an effect on either image detail [2]. So, the novel imaging techniques utilized to obtain all of these factors into account also present a proper balance. This paper briefly describes the various noise models by which the images are greatly affected and propose different methodologies for noise removing.

2. Noise Models

Noise means needless data in digital images. Noise generate unwanted effects such as artifacts, blurred objects, corners, unrealistic edges, unseen lines, and disturbs background scenes. To reduce these undesirable effects, prior learning of noise models is essential for further processing [3].Digital noise may arise from various kinds of sources such as capturing instrument, data transmission media, image quantization and discrete source of radiation.

a. Rician noise

MR images are degraded by Rician noise that arises from composite Gaussian noise in the new frequency domain measurements. The Rician probability density function for the corrupted image intensity x is given by

$$\mathrm{p}(x) = \frac{x}{\sigma^2}\exp\left(-\frac{x^2+A^2}{2\sigma^2}\right) I_0\left(\frac{xA}{\sigma^2}\right) \qquad (1)$$

Where A is the underlying true intensity, σ is the standard deviation of the noise, and I_0 is the modified zeroth order Bessel function of the first kind [4].

i. Bilateral filtering

MR imaging is corrupted by rician noise, which is image dependent and computed from both real and imaginary images. Rician noise makes image-based quantitative measurement difficult. The Bilateral filter has been proven to be effective against rician noise. Bilateral filtering is a simple, non-linear scheme for edge-preserving and smoothing [5].

In the input image, the intensity value of every pixel is restoring by a weighted average of intensity values from adjacent pixels. This weight can depend on a Gaussian distribution. The weights depend not only on the Euclidean distance of pixels, except that on the radiometric differences. It conserves pointed edges by logically looping through each pixel as well as regulates weights to the adjacent pixels accordingly [6]. The bilateral filter is defined as

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|)\, G_{\sigma_r}(I_{\mathbf{p}} - I_{\mathbf{q}})\, I_{\mathbf{q}} \qquad (2)$$

- '$BF[I]_p$' is the filtered image
- 'I' is the input image
- 'p, q' are the coordinates of the current pixel
- 's' is the window centered in q
- '$G_{\sigma s}$' is the range kernel for smoothing variations in intensities. It is a Gaussian function
- '$G_{\sigma r}$' is the spatial kernel for smoothing differences in coordinates. This function can be a Gaussian function that decreases the influence of pixels q with an intensity value different from I_p.

Where W_p is a normalization factor [6]:

$$W_{\mathbf{p}} = \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|)\, G_{\sigma_r}(I_{\mathbf{p}} - I_{\mathbf{q}}) \qquad (3)$$

This filtering technique improves the denoising effectiveness, conserves the excellent structures as well as decreases the bias due to rician noise. The visual and diagnostic quality of the image is well preserved.

b. Gaussian (fractional Brownian) Noise

This model also called as electronic noise because it arises in amplifiers or detectors. Gaussian noise generated through natural sources like thermal vibration of atoms also discrete nature of radiation of warm objects. The level of Gaussian noise is self-sufficient at every pixel and free of the signal intensity. By using small amount, every pixel in the image will be changed from its original value. Gaussian noise generally disturbs the gray values in digital images. So, Gaussian noise model essentially designed and characteristics by its Probability Density Function or normalizes histogram with respect to gray value [7]. The probability density function p of a Gaussian random variable z is given by

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \quad (4)$$

From the above equation, ‘z’ stands for the grey level, μ and σ represents the mean value as well as standard deviation respectively.

i. Linear (Mean) filter

Linear filters works finest with Gaussian noise. In this technique, the value of an output pixel is a linear permutation of the values of the pixels in the input pixel's zone. Mean filtering is a spatial filtering method, which consists of moving the filter mask from point to point in an image. It is usually thought of as a convolution filter. Similar to other convolutions, it is based around a kernel that corresponds to the shape as well as size of the region to be sampled when computing the mean [8].

It simply smoothes local variations in an image and noise is reduced as a result of blurring. This filter is a basic sliding-window spatial filter and substitutes the center value in the window with the mean value of all the pixel values in the window. The window is usually square but can be any shape. An example of mean filtering of a single 3x3 window of values is shown in Fig 2,

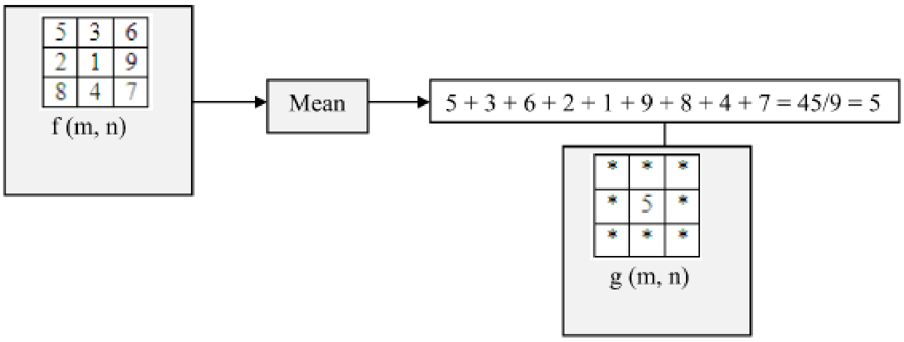

Fig.2. Mean filtering of a single 3x3 window

Center value (previously 1) is replaced by the mean of all nine values (5).The simplest mean filter is arithmetic mean filter. Let the source image is f (i, j). Let F represent the set of coordinates in a rectangular sub image window of size M×N, centered at point (i, j). The arithmetic mean filtering process computes the average value of the corrupted image f (i, j) in the area defined by F. The value of the restored image ‘g’ at any point (i, j) is simply the arithmetic mean computed using the pixels in the region defined by F.

At any point (i, j), the value of the filtered image g (i, j) is the arithmetic mean computed using the neighbor pixels of the center pixel. That is

$$g(i,j) = \frac{1}{M\times N}\sum_{(m,n)\epsilon s} f(m,n) \quad (5)$$

m = 1, 2…M, n = 1, 2…N (usually m = n)

In the Equation (5), S is the neighborhood defined by the filter mask of the point f (i, j), centered at point f (i, j). Equation (5) is the expression of the traditional mean filtering algorithm. For the pixel f (i, j), this algorithm computes the all pixels in the filtering region. For the next pixel, the same computation is repeated. It takes a lot of time to calculate the neighborhood pixels [8]. This operation can be implemented using a convolution mask in which all coefficients have value 1/mn. The size of the filter controls the amount of filtering (and blurring).

c. *Impulse Noise*

Images are regularly degraded by impulse noise occurred by transmission errors, defective memory locations and timing errors in analog-to-digital switch. Salt and pepper noise is one type of impulse noise that can corrupt the image, where the noisy pixels can take only the maximum and minimum values in the dynamic range. The Probability Density Function of Impulse (salt and pepper) noise is given by

$$p(z) = \begin{cases} P_a & for\ z = a \\ P_b & for\ z = b \\ 0 & otherwise \end{cases} \quad (6)$$

From equation (6), If b>a, gray-level b appears as a light dot in the image. Conversely, level an appears like a dark dot. If either P_a or else P_b is zero, the impulse noise is called unipolar. If the probability is zero otherwise if they are roughly equal means impulse noise arbitrarily scattered over the image. The median filter is one of the most popular non-linear filters used to remove salt and pepper noise due to its high-quality denoising power as well as computational efficiency.

i. Median Filter

Median filtering is a classical nonlinear image processing technology based on order-statistics theory. In image median filtering, the value of the target pixel in an image is replaced with the median value of its neighborhood, and then the isolated noise points will be eliminated. This algorithm can preserve the high frequency part of image to large scope, thus ensures the visual effect of the image. Their fundamental advantage is that they can suppress the impulsive noise (also known as the salt and pepper noise) without edge blurring.

The standard median filter is replaced each point's value in the digital image or the digital sequence with median value of its neighborhoods. The definition of median value is listed as follows, A group of numbers: x_1, x2... x_n, arranged in order of size: $x_{i1} \leq x_{i2} \leq \leq x_{in}$.

$$Y = \text{Median}\{x_1, x_{2 \ldots} x_n\}$$

$$= \begin{cases} x_{i(n+1)/2} & , n\ is\ odd \\ [x_{i(n/2)} + x_{i(n/2+1)}]/2 & , n\ is\ even \end{cases} \quad (7)$$

Where Median {…} expressed the process of computing the median from the sequence $\{x_n\}$, Y indicates this median. We called a neighborhood of a pixel's specific length in a sequence or shape in an image as filtering window [9].

The noisy value of a digital image or a sequence is replaced by the median of the filter mask. The pixels in the mask are ranked in the order of their gray levels, and the median of the mask is stored to replace the noisy value in the mask. The median filter output is

$$g(x,y) = med\{f(x-i, y-j), i, j \in W\} \quad (8)$$

In Equation (8), where $f(x, y)$ and $g(x, y)$ are the original image and output image, respectively. W is a two-dimensional mask, the mask size is n× n (where n is commonly odd) such as 3× 3, 5× 5, and etc [10]. The median filter effects depend on two things, the size of the mask and the distribution of the noise. The median filter performance of random impulse noise is better than the average filter performance [10]. . Fig 3 shows the median filtering of a single 3x3 window of values.From this example center value is previously 97 and it is replaced by the median of the entire nine values of 4.

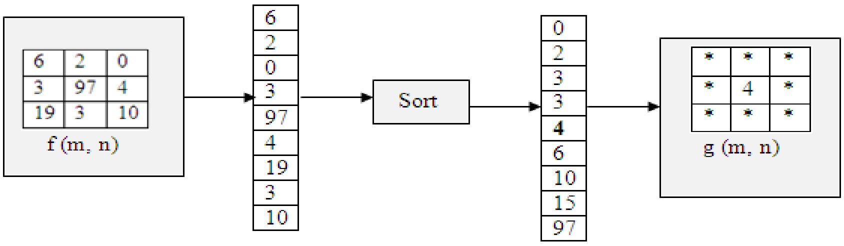

Fig.3 Median filtering of a single 3x3 window

d. Poisson noise

Medical images are frequently noisy due to the physical mechanisms of the acquisition process. Poisson noise is a kind of electronic noise whichcauses when the finite number of particles that carry energy, like electrons in an electronic circuit or photons in an optical device, is small enough to give rise to detectable statistical fluctuations in a measurement The majority of the denoising algorithms assume additive white Gaussian noise. However, some of the most popular medical image modalities are degraded by some type of non-Gaussian noise. Among these types, we refer the Poisson noise. Poisson noise is signal-dependent, that is often seen in photon images. The variance of the noise is proportional to the original image values [11].

$$d(m,n) \sim \frac{1}{\lambda}\text{Poisson}\{\lambda o(m,n)\} \quad (9)$$

The noise model is described as where o (m, n) and d(m, n) mean the pixel values in the original and degraded images, respectively. The degraded image is generated by multiplying the original pixel values by λ and by using these as the input to a random number generator which returns Poisson-distributed values. The amount of noise depends on λ.

i. Wiener Filter

Wiener filter is a linear filter. It provides linear estimation of a desired signal sequence from another related sequence [12]. Wiener filter provide solution for stationary signals in finding signal estimation problems. It provides successful results in removing noise from images .Wiener filter is based on statistical approach. The Wiener filter is:

$$G(u, v) = \frac{H^*(u, v)\, P_s(u, v)}{|H(u, v)|^2 P_s(u, v) + P_n(u, v)} \quad (10)$$

Dividing through by P_s makes its behavior easier to explain:

$$G(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + \frac{P_n(u, v)}{P_s(u, v)}} \quad (11)$$

From Equation (10) and (11),

H (u, v): Degradation function

H*(u, v):Composite conjugate of H (u, v)

P_n (u, v): Power Spectral Density of Noise

P_s (u, v): Power Spectral Density of un-degraded image

The term P_n /P_s can be interpreted as the reciprocal of the signal to-noise ratio [13].

3. Literature Survey

Noise filtering of MRI images is the most important phase in image analysis that executes noise reduction techniques which are utilized to improve the image superiority. Image is enhanced in the way that finer details are improved and noise is removed from the image. This paper discusses some filters which are utilized to reduce the noise from medical images. The overviews of all these filters were explained in this section.

Priyanka. Balwinder Singh utilizedstandard Median Filter algorithm for removing the salt and pepper noise from the medical images. In this proposedmethod, a window slides beside the image also the median intensity value of the pixels within the window becomes the output concentration value of the pixel being processed. Each pixel is set to median of the pixel values in the neighborhood of the corresponding input pixels. This filter is used to remove these noises and bounding box method is implemented to identify the location of the tumor [14].

M. N. Nobi et al. proposed the order statistics filters. It present a basic and resourceful technique to eliminate noise from the medical images that merges both median filtering and mean filtering to detect the pixel value in the noise less image. This method is used to remove the Rician noise that affects the MRI images [15].

C.Ramalakshmi et al. developed anisotropic filter to remove the background noise and thus preserving the edge points in the image. This technique applies a concurrent filtering and contrast stitching. A diffusion constant related to the noise gradient and smoothing the background noise by filtering a proper threshold value is chosen.[16].

J.Jaya et al. applied weighted median filter to remove high frequency components as well as remove salt and pepper noise from MRI without troubling of the edges. It is applied for each pixel of a 3*3,5*5,7*7,9*9.11*11 window of adjacent pixels are extracted [17].

4. Conclusion

This paper attempts to describe various noise models and different image filtering techniques. It have focused on only most frequently affected noises such as impulse noise, Poisson noise and Gaussian noise with various noise intensity range from low to high and also analyzed the noise removal algorithms for these noises. The constraints for this analysis were minimum cost, less time, high level of noise detection, preserving features and edges etc,. There is lack of equality in how methods are evaluated so it is careless to declare which methods indeed have lowest error rate with highest noise ratio. Therefore, our analysis has produced relative performance of methods. From this analysis, noise removal is still a challenging task in order to obtain better recognition rate. So, observance in view, a powerful system should fulfill all the above parameters with multiple noises removal in a single image and in multiple images.

References

1. Huang H, Zhang J, van Zijl PC, Mori S. Analysis of noise effects on DTI-based tractography using the brute-force and multi-ROI approach. Magn Reson Med 2004;52(3):559–65.
2. http://www.sprawls.org/mripmt/MRI10/index.html
3. Dougherty G. (2010) “Digital Image Processing for Medical Applications,” second ed., Cambridge University presses.
4. M. N. Nobi and M. A. Yousuf "A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images" J. Sci. Res. 3 (1), 81-89 (2011),www.banglajol.info/index.php/JSR.
5. C. Tomasi, R. Manduchi "Bilateral Filtering for Gray and Color Images" Proceedings of the 1998 IEEE International Conference on Computer Vision, Bombay, India
6. PARIS, S. AND DURAND, F. 2006. A Fast Approximation of the Bilateral Filter using a Signal Processing Approach. ECCV 2006.
7. Ajay Kumar Boyat and Brijendra Kumar Joshi, „A Review Paper: Noise Models In Digital Image Processing‟, SIPIJ, Vol.6, No.2, April 2015

8. Jian-Jia Pan, Yuan-Yan Tang, Bao-Chang PAN, “The Algorithm of Fast Mean Filtering” Proceedings of the 2007 International Conference on Wavelet Analysis and Pattern Recognition, Beijing, China, 2-4 Nov. 2007.
9. Ping Kuang, Lei Sun, “An Improved Two-Dimensional Multi-Level Median Filtering Algorithm” IEEE, 2010.
10. Zhu Youlian, Huang Cheng, “An Improved Median Filtering Algorithm Combined with Average Filtering” Third International Conference on Measuring Technology and Mechatronics Automation, IEEE, 2011.
11. R. Vio, J. Bardsley, and W. Wamsteker, "Least-squares methods with poissonian noise: an analysis and a comparison with the richardson-lucy algorithm," Astronomy and Astrophysics, vol. 436, pp. 741-755, 2005.
12. Shi Zhong, Vladimir Cherkassky, “ Image De-noisingusing Wavelet Thresholding and Model Selection ”, IEEE,Proceedings 2000.

13. Wavelet domain image de-noising by thresholding and Wiener filtering.Kazubek, M. Signal Processing Letters, IEEE, Volume: 10, Issue: 11, Nov. 2003 265 Vol.3.
14. Priyanka, and Balwinder Singh, “AN IMPROVEMENT IN BRAIN TUMOR DETECTION USING SEGMENTATION ANDBOUNDING BOX” IJCSMC, Vol. 2, pp.239 – 246, 2013.
15. Nobi, M. N., and Yousuf, M. A., “A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images”,JOURNAL OFSCIENTIFIC RESEARCH, Vol. 3, pp. 81-89, 2011.
16. Ramalakshmi, C., andJayaChandran, A.,“Automatic Brain Tumor Detection in MR Images Using Neural Network BasedClassification”,International Journal of Computer Science and Network security,Vol. 14, pp.5,2014.
17. Jaya, J., Thanushkodi, K., and Karnan, M., “Tracking Algorithm for De-Noising of MR Brain Images”, IJCSNS International Journal ofComputer Science and Network Security, Vol. 9, pp. 11, 2009.