

## A NOVEL APPROACH NOISE FILTRATION FOR MRI IMAGE SAMPLE IN MEDICAL IMAGE PROCESSING

Lalitha Y. S.<sup>1\*</sup> and Mrityunjaya V. Latte<sup>2</sup>

<sup>1</sup>Appa Institute of Engineering & Technology Gulbarga, Karnataka, India.

<sup>2</sup>JSS Academy of Technical Education, Bangalore, India.

### ABSTRACT

In this paper a modified spatial filtration approach is suggested for image denoising applications. The existing spatial filtration techniques were improved for the ability to reconstruct noise-affected medical images. The developed modified approach is developed to adaptively decide the masking center for a given MRI image. The conventional filtration techniques using mean, median and spatial median filters were analyzed for the improvement in modified approach. The developed approach is compared with current image smoothing techniques. The proposed approach is observed to be more accurate in reconstruction over other conventional techniques.

**Keywords:** Spatial Filter, Image Denoising, Modified Spatial Filter, RMSE.

### 1. INTRODUCTION

Digital image processing algorithms are generally sensitive to noise. The final result of an automatic vision system may change according whether the input MRI image is corrupted by noise or not. Noise filters are then very important in the family of preprocessing tools. Inappropriate and coarse results may strongly deteriorate the relevance and the robustness of a computer vision application. The main challenge in noise removal consists in suppressing the corrupted information while preserving the integrity of fine medical image structures. Several and well-established techniques, such as median filtering are successfully used in gray scale imaging.

Median filtering approach is particularly adapted for impulsive noise suppression. It has been shown that median filters present the advantage to remove noise without blurring edges since they are nonlinear operators of the class of rank filters and since their output is one of the original gray values [1]-[2]. The extension of the concept of median filtering to color images is not trivial. The main difficulty in defining a rank filter in color image is that there is no "natural" and unambiguous order in the data [3]-[4]. During the last years, different methods were proposed to use median filters in color medical image processing [5]-[6]. Whatever the vector filtering method, the challenge is to detect and replace noisy pixels whereas the relevant information is preserved. But it is recognized that in some MRI image areas most of vector filters blur thin details and image edges [7]-[8]. Even if many works such as Khriji and Gabbouj [9]. Generally impulse noise contaminates medical images during data acquisition

by camera sensors and transmission in the communication channel. In [10] Chan and Nikolova proposed a two-phase algorithm. In the first phase of this algorithm, an adaptive median filter (AMF) is used to classify corrupted and uncorrupted pixels; in the second phase, specialized regularization method is applied to the noisy pixels to preserve the edges and noise suppression. The main drawback of this method is that the processing time is very high because it uses a very large window size of 39X39 in both phases to obtain the optimum output; in addition, more Complex circuitry is needed for their implementation. In [11] Srinivasan and Ebenezer proposed a sorting based algorithm in which the corrupted pixels are replaced by either the median pixel or neighborhood pixel in contrast to AMF and other existing algorithms that use only median values for replacement of corrupted pixels. At higher noise densities this algorithm does not preserve edge and fine details satisfactorily. In this paper a novel robust estimation based filter is proposed to remove fixed value impulse noise effectively. The proposed filter removes low to high density fixed value impulse noise with edge and detail preservation upto a noise density of 90%. Recently, nonlinear estimation techniques are gaining popularity for the problem of image denoising. The well-known Wiener filter for minimum mean-square error (MMSE) estimation is designed under the assumption of wide-sense stationary signal and noise (a random process is said to be stationary when its statistical characteristics are spatially invariant) [12]. For most of the natural MRI images, the stationary condition is not satisfied. In the past, many of the noise removing filters were designed with the stationary assumption. These filters remove noise but tend to blur edges and fine details. This algorithm fails to remove impulse noise in high frequency

\* Corresponding Author: patil\_lalitha12@yahoo.com

regions such as edges in the MRI image. To overcome the above mentioned difficulties a nonlinear estimation technique for the problem of medical image denoising has been developed based on robust statistics. Robust statistics addresses the problem of estimation when the idealized assumptions about a system are occasionally violated. The contaminating noise in an image is considered as a violation of the assumption of spatial coherence of the medical image intensities and is treated as an outlier random variable [12]. In [13] Kashyap and Eom developed a robust parameter estimation algorithm for the medical image model that contains a mixture of Gaussian and impulsive noise. In [12] a robust estimation based filter is proposed to remove low to medium density Gaussian noise with detail preservation. Though these techniques were developed for filtration of Gaussian or impulsive noise they are been developed for gray level images and are not suitable for color images. In this paper a modified approach to spatial median filter is proposed for the noise removal in digital medical images. The paper is further presented in six sections. Where conventional spatial filtration methods and their limitations were presented in Section 2. Section 3 outlines the proposed modified median filtration approach for MRI images. The simulation observations were presented in section 4.

## 2. SPATIAL FILTRATION

The simplest of smoothing algorithms is the Mean Filter. Mean filtering is a simple, intuitive and easy to implement method of *smoothing* medical images, *i.e.* reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in MRI images. The idea of mean filtering is simply to replace each pixel value in an image with the mean ('average') value of its neighbors, including itself. This has the effect of eliminating pixel values, which are unrepresentative of their surroundings. The mean value is defined by,

$$MnF(x_i) = \frac{1}{N} \sum_{i=1}^N x_i \quad (1)$$

Where,  $N$  : number of pixels

$x_i$  : corresponding pixel value,

$I$  : 1.....  $N$ .

The mean filtration technique is observed to be lower in maintaining edges within the images. To improve this limitation a median filtration technique is developed. The median filter is a non-linear digital filtering technique, often used to remove noise from medical images or other signals. Median filtering is a common step in image processing. It is particularly useful to reduce speckle noise and salt and pepper noise. Its edge-preserving nature makes it useful in cases where edge

blurring is undesirable. The idea is to calculate the median of neighbouring pixels' values. This can be done by repeating these steps for each pixel in the medical image.

- a) Store the neighbouring pixels in an array. The neighbouring pixels can be chosen by any kind of shape, for example a box or a cross. The array is called the window, and it should be odd sized.
- b) Sort the window in numerical order
- c) Pick the median from the window as the pixels value.

The median is defined by,

$$MdF(x_i) = Median(\|x_i\|^2) \quad (2)$$

where,  $i = 1 \dots N$ . These filtration techniques were found to be effective in gray scale images. When processed over color images these filtration techniques give lesser performance. To achieve accurate reconstruction of medical image the median filtration technique is modified to spatial median filtration. The Spatial Median Filter is a uniform smoothing algorithm with the purpose of removing noise and fine points of medical image data while maintaining edges around larger shapes. The basic algorithm for spatial median filter is as outlined below, the algorithm determines the Spatial Median of a set of points,  $x_1, \dots, x_N$ :

1. For each vector  $x$ , compute  $S$ , which is a set of the sum of the spatial depths from  $x$  to every other vector.
2. Find the maximum spatial depth of this set,  $S_{max}$
3.  $S_{max}$  is the Spatial Median of the set of points.

The spatial depth between a point and set of points is defined by,

$$S_{depth}(X, x_i) = 1 - \frac{1}{(N-1)} \left\| \sum_{i=1}^N (X - x_i) \right\| \quad (3)$$

The Spatial Median Filter is an unbiased smoothing algorithm and will replace every point that is not the maximum spatial depth among its set of mask neighbors. To eliminate this limitation in this paper a Modified Spatial Median Filter for MRI image denoising is proposed.

## 3. MODIFIED SPATIAL FILTER

In a Spatial Median Filter the vectors are ranked by some criteria and the top ranking point is used to replace the center point. No consideration is made to determine if that center point is original data or not. The unfortunate drawback to using these filters is the smoothing that occurs uniformly across the image. Across areas where there is no noise, original medical image data is removed unnecessarily. In the Modified Spatial Median Filter,

after the spatial depths between each point within the mask are computed, an attempt is made to use this information to first decide if the mask's center point is an uncorrupted point. If the determination is made that a point is not corrupted, then the point will not be changed. The proposed modified filtration works as explained below:

- 1) Calculate the spatial depth of every point within the mask selected.
- 2) Sort these spatial depths in descending order.
- 3) The point with the largest spatial depth represents the Spatial Median of the set. In cases where noise is determined to exist, this representative point is used to replace the point currently located under the center of the mask.
- 4) The point with the smallest spatial depth will be considered the least similar point of the set.
- 5) By ranking these spatial depths in the set in descending order, a spatial order statistic of depth levels is created.
- 6) The largest depth measures, which represent the collection of uncorrupted points, are pushed to the front of the ordered set.
- 7) The smallest depth measures, representing points with the largest spatial difference among others in the mask and possibly the most corrupted points, and they are pushed to the end of the list.

This prevents the smoothing by looking for the position of the center point in the spatial order statistic list. For a given parameter  $\zeta$  (where  $1 \leq \zeta \leq \text{mask size}$ ), which represents the estimated number of original points under a mask of points. As stated earlier, points with high spatial depths are at the beginning of the list. Pixels with low spatial depths appear at the end.

If center point ' $c$ '  $\leq \zeta$  then current pixel MSF ( $\zeta, x_i$ ) =  $r_c$

elseif center point ' $c$ '  $> \zeta$  then current pixel MSF ( $\zeta, x_i$ ) =  $r_1$

else if  $c = 1$  then, pixel cannot be modified.

If the position of the center mask point appears within the first  $\zeta$  bins of the spatial order statistic list, then the center point is not the best representative point of the mask, and it is still original data and should not be replaced.

Two things should be noted about the use of  $\zeta$  in this approach. When  $\zeta$  is 1, this is the equivalent to the unmodified Spatial Median Filter. When  $\zeta$  is equal to the size of the mask, the center point will always fall within the first  $\zeta$  bins of the spatial order statistic and every point is determined to be original. This is the equivalent of performing no filtering at all, since all of the points are left unchanged. The algorithm to detect the least noisy point depends on a number of conditions.

First, the uncorrupted points should outnumber, or be more similar, to the corrupted points. If two or more similar corrupted points happen in close proximity, then the algorithm will interpret the occurrence as original data and maintain the corrupted portions. While  $\zeta$  is an estimation of the average number of uncorrupted points under a mask of points, the experimental testing made no attempt to measure the impulse noise composition of a medical image prior to executing the filter.

#### 4. RESULTS AND DISCUSSION

Different stages of filtered MRI images are shown in Fig.1. To test the accuracy of the modified spatial median filter, a medical image with corruption applied by some means is applied. To estimate the quality of a reconstructed MRI image, first calculate the Root-Mean-Squared Error between the original and the reconstructed image. The Root-Mean-Squared Error (RMSE) for an original image  $I$  and reconstructed MRI image  $R$  is defined by,

$$RMSE(I, R) = \sqrt{\frac{1}{I_w \times I_h} \sum_{i=0}^{I_w} \sum_{j=0}^{I_h} \|I(i, j) - R(i, j)\|^2} \quad (4)$$

The algorithm for the Modified Spatial Median Filter (MSMF) requires two parameters. The first parameter considered is the size of the mask to use for each filtering operation. The second parameter, threshold  $\zeta$ , represents the estimated number of original points for any given sample under a mask. A collection of ten MRI images of various sizes was used in these tests. These images are a variety of textures and subject matter. The texture of these MRI images impact on the threshold chosen than the window mask size. The tests to determine the best mask size were conducted in this manner: 1. Each of the ten MRI images in the collection was artificially distorted with  $\rho=0.0$ ,  $\rho=0.05$ ,  $\rho=0.10$ , and  $\rho=0.20$  noise composition, resulting in 40 images 2. Each of the forty medical noisy images was then reconstructed using the SMF with mask sizes of  $N=3$ ,  $N=5$ , and  $N=7$  (the second argument, threshold  $\zeta$ , is set to 1), resulting in 120 reconstructed medical images. 3. The Root-Mean-Squared Error was computed between all 120 reconstructed MRI images and the originals. The RMSE is a simple estimation score of the difference between two MRI images. An ideal RMSE would be zero, which means that the algorithm correctly identified each noisy point and also correctly derived the original data at that location in the signal. For the evaluation of the work a performance evaluation is carried out for various samples and the results obtained were as shown below. As seen in the figure 2, a mask size of 3 clearly outperformed the other tested sizes of 5 and 7. Neither the amount of noise, the size of the MRI image, nor the subject matter of the image effects on which mask size performed the best. Less thorough tests were run on higher mask sizes such as 9 and 11. With

each increase in mask size, the RMSE of each test increased. Most of the medical images are images of various scenes, such as portrait shots, nature shots, animal shots, scenic shots of snow-capped mountains

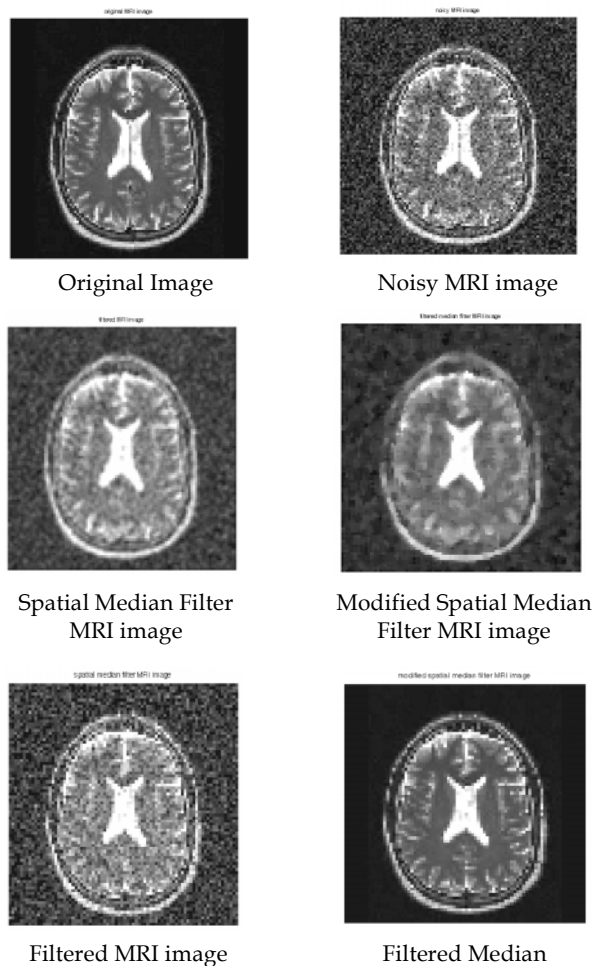


Figure 1: MRI Image

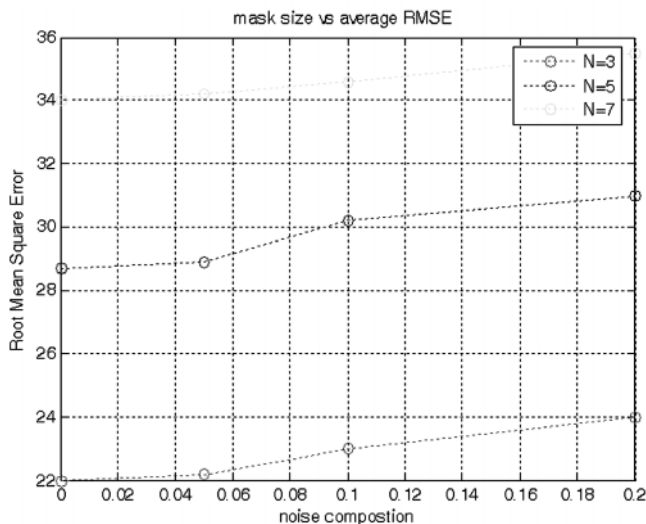


Figure 2: Comparisons of Mask Sizes and Average RMSE with Various Noise Compositions

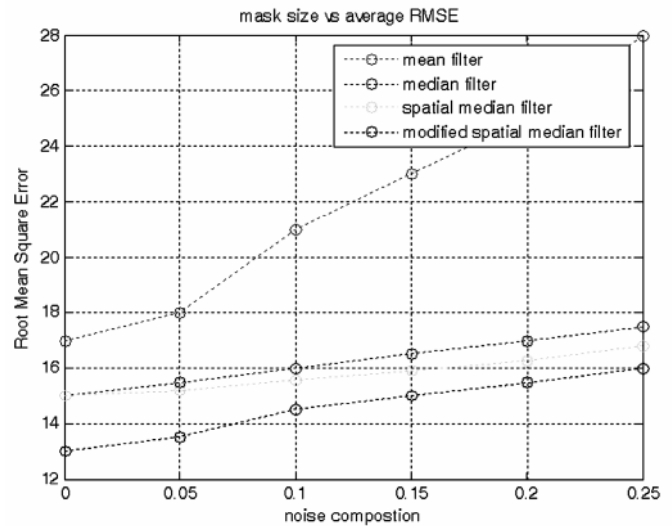


Figure 3: Effectiveness of Noise Filters for Various Noise Compositions

and sandy beaches. When comparing the Modified Spatial Median Filter, the Spatial Median Filter, the Median Filter, and the Mean Filter, a 2000 image subset of the 59,895 images were used.

The above figure 3. gives the comparison of all the four-filtration techniques used in this approach. The worst performing filter of the four tests was the Mean filter. For all noise models containing at least  $\rho = 0.10$  noise, it produced the least accurate results. The unmodified Median Filter was only marginally better than the Mean filter. The most stable of the filters was the Median Filter, which is the best accuracy across all eleven tested noise models. For noise models containing  $\rho = 0.15$ , we see from Fig. 3 that Modified Spatial Median Filter produced the most accurate images.

### 5. CONCLUSIONS

This paper introduces two new filters for removing impulse noise from images and shown how they compare to other well-known techniques for noise removal. First, common noise filtering algorithms were discussed. Next, a Spatial Median Filter was proposed based on a combination of work on the Median Filter and the Spatial Median quantile order statistic. Seeing that the order statistic could be utilized in order to make a judgment as to whether a point in the signal is considered noise or not, a Modified Spatial Median Statistic is proposed. The Modified Spatial Median Filter requires two parameters: A window size and a threshold T of the estimated non-noisy pixels under a mask. In the results, the best threshold T to use in the Modified Spatial Median Filter and determined that the best threshold is 4 when using a 3x3 window mask size. Using these as parameters, this filter was included in a comparison of the Mean, Median, and Spatial Median Noise Filters. In the broad comparison of noise removal filters, it was

concluded that for images containing  $p = 0.15$  noise composition, the Modified Spatial Median Filter performed the best and that the Component Median Filter performed the best over all noise models tested.

## REFERENCE

- [1] R. Hodgson, D. Bailey, M. Naylor, A. Ng, and S. McCNeil, "Properties, Implementations and Applications of Rank filters", *Image Vision Comput.*, **3**, pp. 3-14, 1985.
- [2] M. Cree, "Observations on Adaptive Vector Filters for Noise Reduction in Color Images", *IEEE Signal Processing Letters*, **11**, No. 2, pp. 140-143, 2004.
- [3] P. Lambert and L. Macaire, "Filtering and Segmentation: The Specificity of Color Images", *Proc. Conference on Color in Graphics and Image Processing*, Saint-Etienne.
- [4] I. Pitas and P. Tsakalides, "Multivariate Ordering in Color Image Filtering", *IEEE Transactions on Circuits and Systems for Video Technology*, **1**, pp. 247-259, 1991.
- [5] R. Lukac, B. Smolka, K. Plataniotis, and A. Venetsanopoulos, "Selection Weighted Vector Directional Filters", *Computer Vision and Image Understanding*, **94**, pp. 140-167, 2004.
- [6] M. Vardavoulia, I. Andreadis, and P. Tsalides, "A New Median Filter for Colour Image Processing", *Pattern Recognition Letters*, **22**, pp. 675-689, 2001.
- [7] A. Koschan and M. Abidi, "A Comparison of Median Filter Techniques for Noise Removal in Color Images", *Proc. 7th German Workshop on Color Image Processing*, **34**, No. 15, pp. 69-79, 2001.
- [8] R. Lukac, "Adaptive Vector Median Filtering", *Pattern Recognition Letters*, **24**, pp. 1889-1899, 2002.
- [9] L. Khriji and M. Gabbouj, "Vector Medianrational Hybrid Filters for Multichannel Image Processing", *IEEE Signal Processing Letters*, **6**, No. 7, pp. 186-190, 1999.
- [10] Raymond H. Chan, Chung-Wa Ho, and Mila Nikolova, "Salt-and-Pepper Noise Removal by Median-Type Noise Detectors and Detail-Preserving Regularization", *IEEE Trans. Image Processing*, **14**, No. 10, 2005.
- [11] K. S. Srinivasan and D. Ebenezer, "New Fast and Efficient Decision-Based Algorithm for Removal of High-Density Impulse Noises", *IEEE Signal Processing Letters*, **14**, No. 3, 2007.
- [12] Rabie, "Robust Estimation Approach for Blind Denoising", *IEEE Trans. Image Processing*, **14**, No.11, pp. 1755-1765, 2005.
- [13] R. Kashyap and K. Eom, "Robust Image Modeling Techniques with an Image Restoration Application", *IEEE Trans. Acoust. Speech Signal Process*, **36**, No. 8, pp.1313-325, 1988.