

# Impulse Noise Reduction in Brain Magnetic Resonance Imaging Using Fuzzy Filters

Benjamin Y. M. Kwan and Hon Keung Kwan

**Abstract**—Noise contamination in a magnetic resonance (MR) image could occur during acquisition, storage, and transmission in which effective filtering is required to avoid repeating the MR procedure. In this paper, an iterative asymmetrical triangle fuzzy filter with moving average center (ATMAVi filter) is used to reduce different levels of salt and pepper noise in a brain MR image. Besides visual inspection on filtered images, the mean squared error (MSE) is used as an objective measurement. When compared with the median filter, simulation results indicate that the ATMAVi filter is effective especially for filtering a higher level noise (such as noise density = 0.45) using a smaller window size (such as  $3 \times 3$ ) when operated iteratively or using a larger window size (such as  $5 \times 5$ ) when operated non-iteratively.

**Keywords**—Brain images, Fuzzy filters, Magnetic resonance imaging, Salt and pepper noise reduction.

## I. INTRODUCTION

A noisy image can be caused by a transient during image acquisition, a faulty sensor in a camera, a faulty memory, and noise in a channel during transmission. As a result, the values of some pixels are changed. The amount of noise (or noise density) of a noisy image depends on a number of factors including image acquisition environments, quality of equipment, and channel conditions. Noise in a medical image affects clinical visualization for making diagnostic interpretations. In general, there are two approaches to reduce noise in a medical image. The first approach is to acquire a second image which results in a longer acquisition time and an increased cost. The second approach is to apply some image processing technique to reduce the noise in an acquired image which usually requires less time and can reduce cost.

A typical form of impulse noise in a medical image is salt and pepper noise which represents itself as randomly occurring white (salt) and black (pepper) pixels. The noise density is a term used to quantify the amount of salt and pepper noise in an image. A total noise density of  $d$  in an  $M \times N$  image means that  $d \times M \times N$  pixels contain noise. In general, if the total noise density of a salt and pepper noise is  $d$ , then it implies that each of the salt noise and the pepper noise has a noise density of  $d/2$ . It is possible that the salt noise and the pepper noise have different noise densities as  $d_1$  and  $d_2$ , and consequently the total noise density is  $d = d_1 + d_2$ .

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Impulse noise reduction can be achieved through the use of denoising filters. The median filter is a nonlinear digital filter which is often used in digital image processing to reduce noise in an image. In practice, besides reducing noise, it is important to preserve the edges of an image as edges provide critical information on the visual appearance of an image. Median filtering is a smoothing technique which is effective in reducing noise in the smooth regions of an image, but can adversely affect the sharpness in edges. For small to moderate levels of salt and pepper noise, the median filter has been shown [1] to be useful in reducing noise whilst preserving edges, with deteriorating performances at a high level of noise.

A filtering method based on the linear minimum mean square error (LMMSE) noise and signal estimator in magnitude MRI and Rician distributed images was introduced in [2]. Experiments using synthetic and real images indicated [2] that it can preserve the original image structure while suppressing much of the noise. In [3], an enhanced nonlocal means (NLM) filter with pre-processing for 3D MR images was introduced. The NLM filter removes noise by calculating the weighted average of the pixels in the global region. As reported in [3], using the proposed filter, the noise bias can be removed and the original information can be successfully restored which outperforms three other methods both visually and in peak signal-to-noise ratio (PSNR). An image filtering method based on rough set theory was proposed in [4] to denoise speckle noise in medical images. The filter is realized by applying different denoising methods to different subsets. Experimental results obtained in [4] showed that the method can reduce noise while keeping edges and details. In [5], an improved spatial filtering approach was introduced for image denoising applications. The conventional filtering techniques using mean, median and spatial median filters were analyzed to attain the improvement. The approach adaptively decides the masking center for a given MRI image. When compared with conventional image smoothing techniques, the proposed approach was observed to be more accurate in reconstructing an image [5]. A rule based fuzzy filter for reducing high impulse noise called Rule Based Fuzzy Adaptive Median (RBFAM) Filter was introduced in [6]. The RBFAM filter is an improved version of the Adaptive Median Filter (AMF) which can preserve image details better than the AMF while suppressing additive salt and pepper or impulse type noise. In [7], a Fuzzy Adaptive Median Filter with Adaptive Membership Parameters (FAMFAMP) was proposed for the noise reduction of magnetic resonance images corrupted with heavy impulse (salt and pepper) noise, while preserving image

edges and details.

A number of non-fuzzy and fuzzy denoising methods have been described in the last paragraph. The challenge remains is to develop a filter that can reduce different levels of impulse noise, while preserving image details, and be computationally efficient. This forms the motivations of the present work. In this paper, a simple and effective iterative filtering is introduced based on a fuzzy filter described in [1] and its performance is compared to that of the median filter for reducing salt and pepper type of impulse noise on brain MR images.

## II. FUZZY FILTER

Let  $x(i, j)$  be the input of a 2-dimensional fuzzy filter, the output of the fuzzy filter is defined as

$$y(i, j) = \frac{\sum_{(r, s) \in A} F[x(i+r, j+s)] \times x(i+r, j+s)}{\sum_{(r, s) \in A} F[x(i+r, j+s)]} \quad (1)$$

$F[x(i, j)]$  is the general window function and  $A$  is the area of the window. For a square window of dimensions  $L \times L$ , the range of  $r$  and  $s$  are:  $-R \leq r \leq R$  and  $-S \leq s \leq S$ , where  $L = 2R+1 = 2S+1$ .

In the case of a standard median filter (MED filter), the window function is defined as

$$F[x(i+r, j+s)] = \begin{cases} 1 & \text{for } x(i+r, j+s) = x_{med}(i, j) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

such that the output value  $y(i, j)$  at the center of a window  $A$  is replaced by the median value  $x_{med}(i, j)$  among all the input values  $x(i+r, j+s)$  for  $r, s \in A$  at discrete indexes  $(i, j)$ . The iterative version of the MED filter (denoted by MEDi filter) in which the filtering is applied iteratively until noise is reduced to a satisfactory level

The asymmetrical triangular fuzzy filter with the moving average value within a window chosen as its center value (ATMAV filter) is defined [1] as

$$F[x(i+r, j+s)] = \begin{cases} 1 - [x_{mav}(i, j) - x(i+r, j+s)] / [x_{mav}(i, j) - x_{min}(i, j)] & \text{for } x_{min}(i, j) \leq x(i+r, j+s) \leq x_{mav}(i, j) \\ 1 - [x(i+r, j+s) - x_{mav}(i, j)] / [x_{max}(i, j) - x_{mav}(i, j)] & \text{for } x_{mav}(i, j) < x(i+r, j+s) \leq x_{max}(i, j) \\ 1 & \text{for } x_{mav}(i, j) - x_{min}(i, j) = 0 \text{ or } x_{max}(i, j) - x_{mav}(i, j) = 0 \end{cases} \quad (3)$$

The degree of asymmetry depends on the difference between  $x_{mav}(i, j) - x_{min}(i, j)$  and  $x_{max}(i, j) - x_{mav}(i, j)$ .  $x_{max}(i, j)$ ,  $x_{min}(i, j)$  and  $x_{mav}(i, j)$  represent, respectively, the maximum value, the minimum value, and the moving average value of  $x(i+r, j+s)$  within the window  $A$  at discrete indexes  $(i, j)$ . The iterative version of the ATMAV filter (denoted by ATMAVi filter) is a filter in which filtering is applied iteratively until noise has been reduced to a satisfactory level.

## III. SIMULATIONS AND RESULTS

In the simulations, the MR brain images of healthy volunteers collected and made available by the CASILab at The University of North Carolina at Chapel Hill were downloaded from [8]. An example of how this kind of image database can be used is given in [9]. In the simulations, the brain image "Normal001-T2" was chosen and the central region of its "axial\_slice\_0064" image of dimensions  $M \times N$  ( $=403 \times 303$ ) pixels was used. The pixels  $x(i, j)$  for  $1 \leq i \leq M$  and  $1 \leq j \leq N$ , of the image is corrupted by salt and pepper noise,  $n(i, j)$ . Low, medium, and high levels of salt and pepper noise, each with a noise density value of 0.15, 0.30, and 0.45, respectively, is added to the original image (Fig. 1) to form three noisy images (Fig. 2 for noise density = 0.30, Fig. 4 for noise density = 0.45). Each of these three noisy images is to be filtered by the four types of filters (MED, MEDi, ATMAV, ATMAVi) using three different square windows of dimensions  $L \times L$  pixels and with values of  $L = 3, 5, 7$ . For objective measurement, the mean squared error (MSE) is used to compare the relative filtering performances of various filters. The MSE between the filtered output image  $y(i, j)$  and the original image  $x(i, j)$  of dimensions  $M \times N$  pixels is defined as

$$MSE = \frac{\sum_{i=1}^M \sum_{j=1}^N [y(i, j) - x(i, j)]^2}{M \times N} \quad (4)$$

The MSE values obtained for the first three iterative filtering are summarized in Table I. The filters with the top MSE performance are summarized in Table II under iterative filtering (two or more repeated filtering) and non-iterative filtering (only one filtering). For iterative filtering: (a) Top performance can be achieved using a window of  $3 \times 3$ . (b) For noise density equal to 0.15, the MEDi filter can achieve a MSE value of 3.31; and for noise density equal to 0.30 and 0.45, the ATMAVi filter can achieve MSE values of 9.62 (Fig. 3) and 13.46 (Fig. 5) respectively. For non-iterative filtering: (a) Top performance can be achieved using a window of  $5 \times 5$ . (b) For noise density equals to 0.15 and 0.30, the MED filter can achieve lowest MSE values equal to 4.81 and 12.41 respectively; and for noise density equal to 0.45, the ATMAV filter can achieve lowest MSE value equal to 27.65 (Fig. 6).

## IV. CONCLUSIONS

In this paper, iterative and non-iterative filtering of brain MR images contaminated with salt and pepper noise using the ATMAVi filter has been presented. Based on the performed simulations, results indicate that  $3 \times 3$  window size is appropriate for iterative filtering and  $5 \times 5$  window size is appropriate for non-iterative filtering. In general, iterative filtering using the ATMAVi filter can offer an improved MSE performance especially for images contaminated with a high noise density. The ATMAVi filter is a fuzzy filter, a data-dependent filter, and a fast filter, which offers a simple and effective way to reduce different levels of salt and pepper noise while preserving details in MR images.

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TABLE II

MSE COMPARISON (I: NUMBER OF ITERATIONS; L: LxL GIVES WINDOW SIZE)

		Noise density		
		0.15	0.30	0.45
Iterative filtering	Filter	MEDi	ATMAVi	ATMAVi
	I	2	2	3
	L	3	3	3
	MSE	3.308274	9.617098	13.458889
Non-iterative filtering	Filter	MED	MED	ATMAV
	I	1	1	1
	L	5	5	5
	MSE	4.806607	12.407996	27.645194

Original image

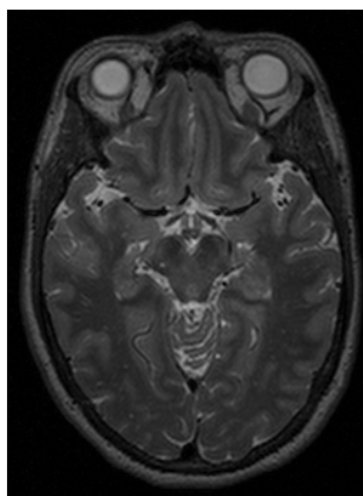


Fig. 1 Original image

Noisy image

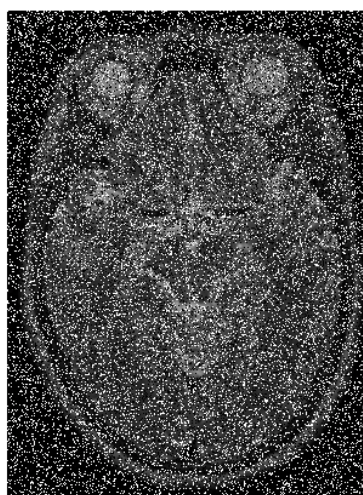


Fig. 2 Noisy image (Salt and pepper noise, noise density=0.3)

TABLE I

MSE OF NOISY IMAGE AND FILTERED IMAGES (I: NUMBER OF ITERATIONS; L: LxL GIVES WINDOW SIZE)

	I	L	Noise density		
			0.15	0.30	0.45
Noisy image			3542.675675	7070.735859	10593.602961
MED	1	3	12.965154	194.578778	1188.583290
		5	4.806607	12.407996	69.117149
		7	8.276229	18.387498	32.947522
MEDi	2	3	3.308274	13.082615	212.170020
		5	4.813666	12.380578	25.916190
		7	8.280553	18.386794	32.942306
MEDi	3	3	3.313499	9.873842	56.219533
		5	4.816082	12.382363	25.916312
		7	8.281224	18.386810	32.941994
ATMAV	1	3	10.692142	39.373706	142.563907
		5	8.800879	17.579499	27.645194
		7	15.080712	31.604501	47.693115
ATMAVi	2	3	4.852941	9.617098	15.414857
		5	8.819145	17.618988	26.648350
		7	15.115282	31.641042	47.746178
ATMAVi	3	3	4.853000	9.617399	13.458889
		5	8.819137	17.618988	26.648372
		7	15.115282	31.641042	47.746178

Filtered image

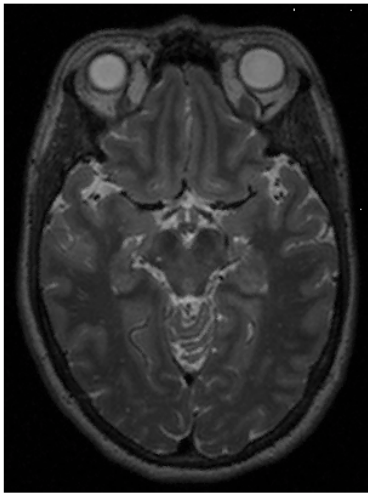


Fig. 3 Filtered image obtained by ATMAVi filter (Salt and pepper noise, noise density=0.3;  $I=2$ ;  $L=3$ ;  $MSE=9.617098$ )

Filtered image

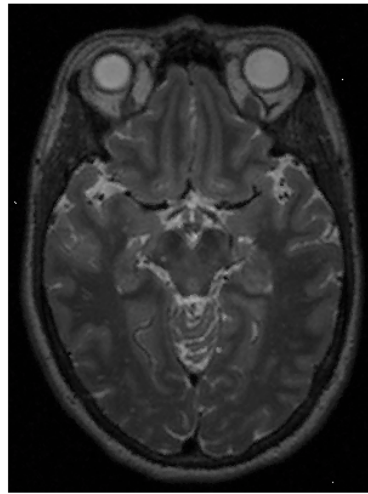


Fig. 5 Filtered image obtained by ATMAVi filter (Salt and pepper noise, noise density=0.45;  $I=3$ ;  $L=3$ ;  $MSE=13.458889$ )

Noisy image

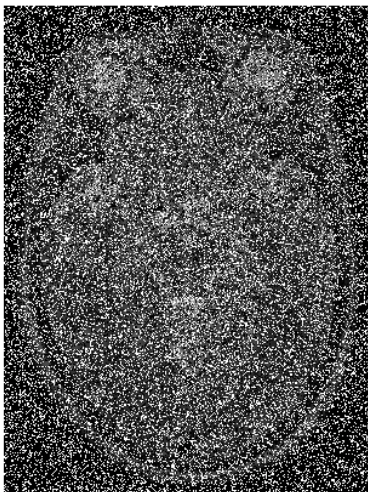


Fig. 4 Noisy image (Salt and pepper noise, noise density=0.45)

Filtered image

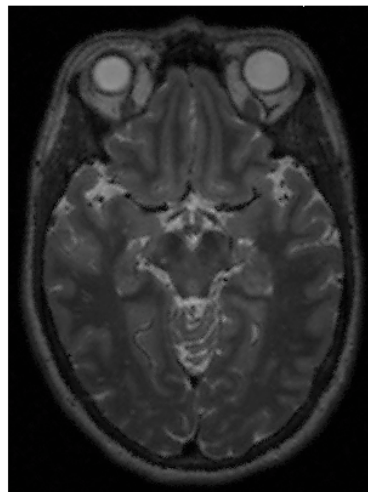


Fig. 6 Filtered image obtained by ATMAV filter (Salt and pepper noise, noise density=0.45;  $I=1$ ;  $L=5$ ;  $MSE=27.645194$ )