International Journal of Natural and Engineering Sciences 8 (3): 01-06, 2014
ISSN: 1307-1149, E-ISSN: 2146-0086, www.nobel.gen.tr

Random-Valued Impulse Noise Reduction in Medical Images by Using Double-Checked Fast Adaptive Median Filter

Cafer BUDAK [1*] Mustafa TÜRK [2]
[1]Department of Electric-Electronic Engineering, University of Batman, Batman, Turkey
[2]Department of Electric-Electronic Engineering, University of Fırat, Elazığ, Turkey

*Corresponding author:
Email: cafer.budak@batman.edu.tr

Received: August 01, 2014
Accepted: September 09, 2014

Abstract

Median-filters have been used for a very long time as an influential non-linear technique to removal of impulse noise. There have been many suggestions regarding the filters that can get rid of this noise while keeping the necessary details. However, these filters have one thing in common: They are only effective at low noise rate and thus are practical only for low-noise in image. Another thing that is also obvious for these filters is that they produce a blur and blotch that is undesired in high-noise in image. This method is fast, simple, and additionally there is no need to adjust it for different applications. Furthermore, the method can remove the impulse noise effectively from the image, and at the same time can preserve the details in the image, even when the input image is very highly corrupted by the impulse noise. The presented method can be performed in noise removal in medical images and real time image processing.

Keyword: Impulse noise; Median-based filters, Digital images, Noise detector.

INTRODUCTION

Digital image domains such as GPS, satellite TVs, imaging on a magnetic resonance basis, diagnosis systems (computed axial tomography), ultra-sound imaging and astronomy are recently being used very widely [1]. We already know that images are often corrupted due to impulse noise caused by noisy sensors and communication channels [2]. Impulse noise does not resemble any other noise and there are various reasons for it to occur. As an example, lighting in an environment or atmospheric disorders can cause an image to become ruined when it is conveyed via a WLAN (Wireless Local Area Network) [3]. This noise can really damage the quality of image. It is necessary to reduction impulse noise noisy pixels in images, in order to facilitate the subsequent processing such as image analysis, segmentation, and pattern recognition etc. There may even be losses of data due to this reason [4]. Impulse noise reduction is among the most important problems in digital image processing [5]. Image processing purposes that to increase the quality of the image. During this process, the detail of the image must remain the same while the noise is removed. It is a widely held belief that noise is undesired and that it has to be removed and if not, it poses a serious threat for the quality of the image. Impulse noise is also named as "Salt & Pepper Noise". When an image is ruined by this noise, there are pixels which have two different values that exceed the normal expected values. These values are accepted as the "Minimum & Maximum Values" in the dynamic range (0 or 255). Therefore, impulse noise is obvious in the image as black & white spots [6]. During the processing of an image, these pixels have to be removed and replaced with neighboring values. The main purpose of this process is to suppress this noise and protect the details of the image. One of the best filter algorithms to restore the image is suppressing the noise and preserving the details. Nowadays the main approach for removing impulse noise is to use median- based filters since; well known that Linear filtering technique is not useful in restoring the corrupt images [7]. This issue, that is to say, the removal of the noise still worries the researchers, because this removal procedure can sometimes cause some blurring in the image that is being restored. Here, Standard Median (SM) should be mentioned which is very easy to apply with different variants such as the [8-17] Filter. The switching-based filters have been studied among these well-known filters. The traditional median works in space domains and works on windowing process and uses the ixj-size filter. Here, the "i" and "j" are the odd dimensions. If we consider an input image like "f", the filtered and restored image is "g" [6].

$$g(x,y)=\underset{(s,t)\in s}{median}\{f(s,t)\} \qquad (1)$$

The ruined images which are affected by low-ratio impulse noise can be filtered by a small working window, and the images ruined by high-ratio impulse noise are filtered by a large working window. The Standard Median Filter replaces the median value of its neighbors in the center pixel of the image [5]. The most important drawback of the SMF is that it is effective just for low noise densities. Moreover, it demonstrates the blur when the size of the window is larger than the average size and when the window causes a noise reduction that is not enough or one that is lower than the expected values. If the level of the noise is over 50%, the original image details will not be protected by the MF (Median Filter). However, during the restore process the details must be protected without losing the high frequency components of the image. The DWM (Directional Weighted Median) that has been evaluated in has the duty of combining the functions of edge detection and reduction the noise. The Directional Weighted Median filter makes use of the differences that exist between the current pixel and the neighboring pixel on four-edge directions. The purpose of this is to find out whether the current pixel is the impulse noise or some other thing. If this is the impulse noise, the direction of the edge is determined by a Standard Deviation Based Method and in this condition the filter works properly [8]. The size of the MF (Median Filter) which is applied to the pixels is determined by the estimated value of the local noise level. A much bigger filter is applied to high-level areas; while a much smaller filter is being applied to low-level areas with low-level filtering (it is also possible by using AMF filter). When the density level is low, AMF gives better results. When the density is high, the edge is significantly blurred. Thanks to the noise pixels, the success in AMF Low-Noise density is best, because the noisy pixels are very rare. In Decision-based Median Filter (DBMF) or Switching Median Filter (SMF) the decision depends on a threshold value that has been defined prior to the process. The biggest disadvantage of this becomes obvious in determining a hard decision measure. Another type of the median-based method is the SM (Switching Method). This method is based on two different levels. In the first level, the noisy pixels are defined. In the second level, a new value is given for each noisy pixel. In the 2nd level just the noisy pixels are filtered by making use of [18]. The other pixels, which are also called "noise-free pixels", remain intact. These techniques are called "Switching Median Filters". This definition tells us that each pixel is either "noisy" or "noise-free". However, the performance of the above-mentioned techniques relies on noise detection algorithms. But the difficulty is finding an efficient noise detection algorithm. Other Noise Reduction methods are: Combination of Impulse Noise Detection and Impulse noise cancellation. It is important to know that the performance of these methods depends on Impulse Noise Detection. The traditional detector usually "misunderstands" the noise-free pixels as noise. This may cause important problems like the worsening of image quality. This usually happens during filtering in the latter part of the Switch Mode Fuzzy Adaptive Median Filter (SMFAMF) [17]. In general, these filters work in stereo-type style throughout the entire image. They tend to change the noise and the noise-free pixels. In this way, the degrading of the edges or the details is inevitable. For this reason, we need a noise-detection process to know the difference between "noisy" and "noise-free pixels" before the median filter is applied. The advanced techniques apply Noise-Detection and "Improved Median Filtering''. These are able to remove higher noise densities. The most common technique is applying the Filtering Technique only to "noisy pixels" thus leaving the other pixels intact. The principle of these filters is to detect the impulse-pixels and replace them with the estimated values, and leave leaving the remaining pixels unchanged. Here, we propose a new Median-Based Method: Switching Median Filter with a hybrid of adaptive median filter combination. Hereon, the proposed filter will be named as "Double Checked Fast Adaptive Median Filter (DCFAMF)".

DCFAMF gives faster, simpler and better results in comparison with the traditional Median-Based Filters. This method can get rid of impulse noise. Moreover, it can keep the necessary details of the image. No adjustments are needed for DCFAMF. Thus, it is much more suitable for automated systems. We do not need a pre-preparation for this technique.

Noise Models

A grayscale image is symbolized by a two-dimensional array where a location (i, j) is a position in image and named as a pixel or picture element. During this study, for images, standard matrix notation is used. For example, when U is an image, U (i, j) will represent the intensity value of U at the pixel location (i, j) in the image domain. Experiments were performed by varying the amount of noise. Generally; a noisy image can be modelled as:

$$U_{(i,j)} = \begin{cases} n_{i,j} \text{ with probability } p \\ O_{i,j} \text{ with probability } (1-p) \end{cases} \quad (2)$$

where p is the percentage of amount of noise and n (i, j) is the value of the impulse noise and O (i, j) is the original pixel value. Depending on the values which n (i, j) can take there are mainly two types of noise models used in this study. They are:

Fixed impulse noise model: n (i, j) can have only two values which can be (255 or 0) for an 8-bit image.

Random impulse noise model: n (i, j) can have any value which can be chosen uniformly from the range of [0, 255], for an 8-bit image.

Double-Checked Impulse Noise Detection Process

Detecting a noisy pixel in a random valued, noise corrupted image is much harder than detecting the fixed valued noise; because the value of a noisy pixel could be much higher or lower than the value of the neighbourhood. That is why conventional median filters do not perform well especially with random valued high noise rates. Many filters are used to determine whether a pixel is noisy or not. Main approach is the success and the simplicity of the algorithm.

	j-1	**j**	**j+1**
i-1	a_1	a_2	a_3
i	a_4	$\underline{A_{scan}}$	a_5
i+1	a_6	a_7	a_8

Figure 1. Pixels intensity and coordinates of a 3×3 window

The process of detecting the random valued noise consists of two phases.

First phase; at the beginning of iteration, the difference between the central pixel A_{scan} which is windowed in Figure 1 and a_4 and a_5 pixels whose values are closest to it from left and right should be calculated. The result should be lower than the values of $|A_{scan} - a_4|$ or $|A_{scan} - a_5|$. Same process is applied to a_2 and a_7 pixels which are the closest ones to the central pixel from bottom and top. The result should be lower than the values of $|A_{scan} - a_2|$ or $|A_{scan} - a_7|$.

$$F1 = |a4 - a5| \qquad F11 = |a2 - a7|$$
$$F2 = |Ascan - a4| \qquad F22 = |Ascan - a2|$$
$$F3 = |Ascan - a5| \qquad F33 = |Ascan - a7|$$

$$Ascan = \begin{cases} \text{Noisy pixel,} & \text{if (F2 or F3} > \text{F1) or} \\ & \text{(F22 or F33} > \text{F11)} \\ \text{Noise free pixel,} & \text{otherwise} \end{cases}$$

Second phase; sometimes, the values of noisy pixels in image whose noise intensity are high cannot be d etected in the first phase. In that situation the difference between the transversal values of central pixel should be compared. That process occurs in the second phase.

$$Fa = |a3 - a6| \qquad Faa = |a1 - a8|$$
$$Fb = |Ascan - a3| \qquad Fbb = |Ascan - a1|$$
$$Fc = |Ascan - a6| \qquad Fcc = |Ascan - a8|$$

$$Ascan = \begin{cases} \text{Noisy pixel,} & \text{if (Fb or Fc > Fa) or} \\ & \text{(Fbb or Fcc > Faa)} \\ \text{Noise free pixel,} & \text{otherwise} \end{cases}$$

Pixels which are found to be noisy should be marked. They will not be used in the restoration phase. If the pixels are found to be noisy after two phases, A_{scan} should be windowed then restoration phase begins [16].

Double-Checked Adaptive Filtering Scheme

Main success random valued noise removing detector depends on the success of the noise detector. The pixel that is marked by the detector as noise is passed through the following steps thus the most appropriate value is assigned. This filter becomes active for only those pixels which have been marked as noisy. The ruined images which are affected by low-ratio impulse noise can be filtered by a small working window, and the images ruined by high-ratio impulse noise are filtered by a large working window. Here the DCFAMF is as follows.

Section -1

$$\begin{array}{cc} & \begin{matrix} & & & j & & & \end{matrix} \\ i & \begin{pmatrix} 156 & 165 & 167 & 165 & 170 & 171 & 171 \\ 163 & 164 & 180 & 182 & 175 & 172 & 170 \\ * & 175 & 188 & 205 & 0 & 178 & * \\ 255 & 255 & * & * & 165 & * & * \\ 167 & 0 & 182 & * & * & * & * \\ 172 & 180 & 0 & * & * & * & * \\ 175 & 0 & 255 & 200 & * & * & * \end{pmatrix} \end{array}$$

If the central pixel is not marked as noise, (Noisy pixels are indicated by "*") as presented in section 1, there will be nothing that has to be done. The reason for this is that it was thought to be an inherent part of the image pixels. Here, they are not changed and the following is passed. By doing so, we avoid the pixel change that is not necessary thereby speeding up the algorithm.

Section -2

$$\begin{array}{cc} & \begin{matrix} & & & j & & & \end{matrix} \\ i & \begin{pmatrix} 156 & 165 & 167 & 165 & 170 & 171 & 171 \\ 163 & 164 & 180 & 182 & 175 & 172 & 170 \\ * & 175 & 185 & * & 0 & 178 & * \\ 255 & * & * & * & 165 & * & * \\ 167 & * & 160 & * & * & * & * \\ 172 & 180 & 0 & 205 & 150 & * & * \\ 175 & 0 & 255 & 200 & * & * & 0 \end{pmatrix} \end{array}$$

If the central pixel is marked as noise, as presented in section 2, it will be U (i, j) = Flag that undergoes the windowing process.

$$\begin{array}{cc} & \begin{matrix} & & & j & & & & & \end{matrix} \\ i & \begin{pmatrix} * & * & \boxed{160 \;\; 175 \;\; 185} & * & * & * & * \end{pmatrix} \end{array}$$

While the pixels that are windowed in all traditional median-based filters are aligned with the noise; in our algorithm, the noisy pixels are never aligned. Even in high noise levels there is no wrong selection. As shown in the example, the 3 pixels that do not have noise are aligned and the selection becomes, U (i, j) =175

Section -2.1

$$\begin{array}{cc} & \begin{matrix} & & & j & & & \end{matrix} \\ i & \begin{pmatrix} 156 & 165 & 167 & 165 & 170 & 171 & 171 \\ 163 & 164 & * & 182 & 175 & 172 & 170 \\ * & 175 & 188 & 205 & 0 & 178 & * \\ 255 & 255 & * & * & * & * & * \\ 167 & 0 & 182 & * & * & * & * \\ 172 & 180 & 0 & * & * & * & * \\ 175 & 0 & * & 200 & * & 204 & * \end{pmatrix} \end{array}$$

$$\begin{array}{cc} & \begin{matrix} & & j & & & & \end{matrix} \\ i & \begin{pmatrix} * & \boxed{* \;\; * \;\; *} & * & * & * & * & * \end{pmatrix} \end{array}$$

If the pixels that are windowed in high level are all noise, the size of the windowing is increased one level. 5X5 windowing is preferred.

Section -2.2

$$\begin{array}{cc} & \begin{matrix} & & & j & & & \end{matrix} \\ i & \begin{pmatrix} 156 & 165 & 167 & 165 & 170 & 171 & 171 \\ 163 & 164 & * & 182 & 175 & 172 & 170 \\ * & 175 & 188 & 205 & 0 & 178 & * \\ 255 & 255 & * & * & * & * & * \\ 167 & 0 & 182 & * & * & * & * \\ 172 & 180 & 0 & * & * & * & * \\ 175 & 0 & * & 200 & * & 204 & * \end{pmatrix} \end{array}$$

Section -3

If the windowed pixels are still noisy in spite of the window size being 5X5, the window size is increased to 7x7. If the pixels are still noisy even after doing so, then the window size is no longer increased, because as the window size is increased the details are lost, and hence clarity decreases.

Section -4

Last stage: Instead of increasing the window size further, the neighboring pixel value is assigned which was estimated during the previous operation. Iteration is carried out in this manner until the last pixel. Especially this stage has high effect on the Picture quality and the speed of the algorithm because it does not increase the window size further.

Experimental Results aand Simulation Analysis

MATLAB is used to implement and make an analysis of the results. For example we can use it on Brain MR images [19]. The algorithm is tested with gray-scale images as Brain.jpg, because these kinds of images have [0, 255] DRV (Dynamic Range of Values)." The noise levels are varied from 50% to 95% with increments of 10%, The restoration performances results are quantitatively measured by the "Peak Signal-Noise Ratio" (PSNR) and the MSE "Mean Square error" [20].

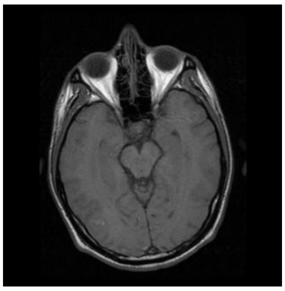
$$MSE = \frac{\sum_{ij} \left(r_{ij} - x_{ij} \right)^2}{MXN} \quad (3)$$

$$PSNR = 10 Log10 \left(\frac{255^2}{MSE} \right) \quad (4)$$

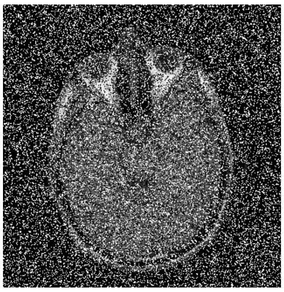
The abbreviations above stand for the following

MxN= Size of image, n=corrupted image, r=Original image, x=Restored image.

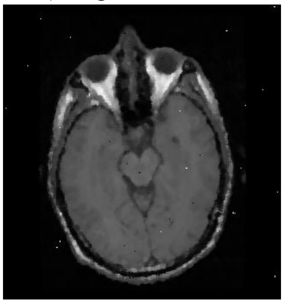
In the following image, in order to prove the visual performance of DCFAMF, 40% noise is added to a Brain MRI, and DCFAMF and some other filters are compared by calculating the P.S.N.R and MSE value.



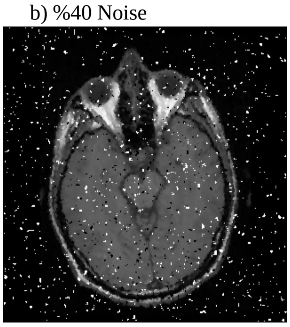
a) Original



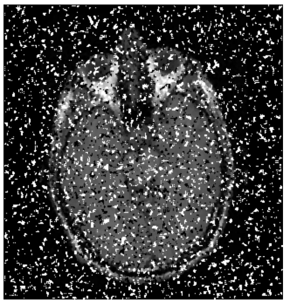
b) %40 Noise



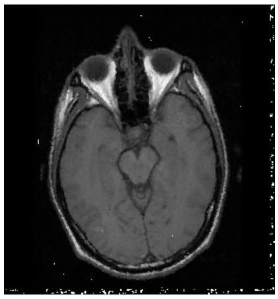
c) IDBA [15]



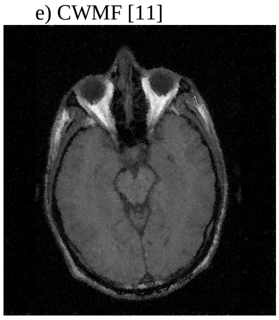
d) BDND [10]



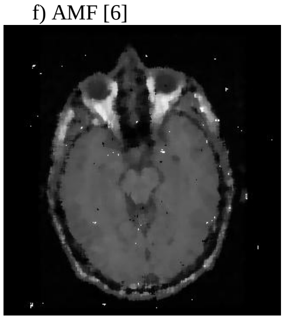
e) CWMF [11]



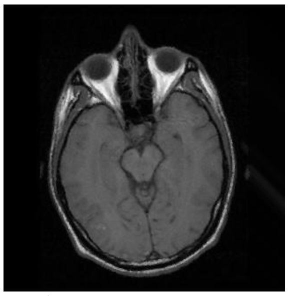
f) AMF [6]



g) S.M.F.A.M.F [17]



h) S.N.F.F [16]

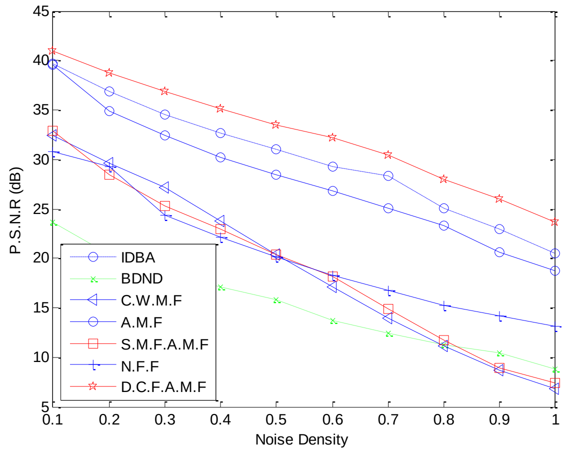


i) D.C.F.A.M.F

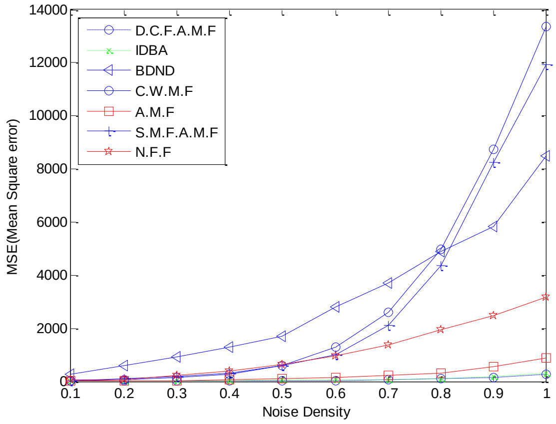
Figure 2. Restore results of some filters. a) Original Image b) Noisy Image c) IDBA of output d) BDND of output e) CWMF of output f) AMF of output g) SMFAMF of output h) Simple Neuro-Fuzzy Filter of output i) DCFAMF of output.

Table 1. Comparative MSE and PSNR of Various Filters for Brain MR Image

Filters		**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**95%**
DCFAMF	PSNR	**41,71**	**38,77**	**36,92**	**35,14**	**33,52**	**32,25**	**30,45**	**28,48**	**26,82**	**23,68**
(Proposed)	MSE	**4,39**	**8,63**	**13,22**	**19,91**	**28,91**	**38,73**	**58,62**	**92,27**	**135,23**	**278,66**
IDBA [15]	PSNR	39,66	36,85	34,53	32,65	31,05	29,32	**28,01**	**25,09**	**22,06**	20.48
	MSE	7,03	13,43	22,91	35,32	51,06	76,05	74,83	102,82	166,76	291,8
BDND[10]	PSNR	23,64	20,41	18,55	17,06	15,78	13,68	12,45	11,25	10,48	8,85
	MSE	281,24	591,67	907,99	1279,62	1718,23	2786,64	3698,97	4876,19	5822,1	8473,8
CWMF [11]	PSNR	32,42	29,61	27,18	23,81	20,43	17,07	13,96	11,15	8,72	6,87
	MSE	37,25	71,1	124	270	588	1276	2612	4989	8731	13368
AMF [6]	PSNR	39,52	34,86	32,38	30,24	28,46	26,83	25,02	23,29	20,62	18,75
	MSE	7,26	21,24	37,59	61,53	92,7	134,92	204,68	304,85	563,74	867,12
SMFAMF [17]	PSNR	32,86	28,41	25,35	23,01	20,42	18,1	14,86	11,72	8,96	7,36
	MSE	33,66	93,77	189,71	325,15	590,31	1007,12	2123,64	4376,03	8261,9	11942
SNFF [16]	PSNR	30,89	29,3	24,45	22,12	20,1	18,36	16,81	15,23	14,22	13,12
	MSE	52,98	76,4	233,39	399,1	635,45	948,59	1355,44	1950,21	2460,8	3170,1
Average	PSNR	**34,39**	**31,17**	**28,48**	**26,29**	**24,25**	**22,23**	**20,42**	**18,45**	**16,53**	**14,59**
	MSE	**60,54**	**125,18**	**218,47**	**341,58**	**529,37**	**895,53**	**1446,98**	**2384,59**	**3734,56**	**5484,5**



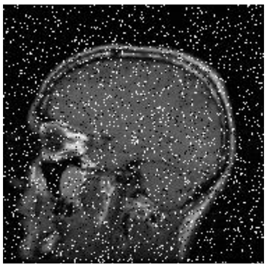
a)



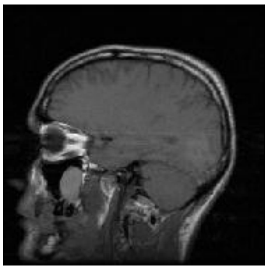
b)

Figure 3. Graphic view of the performances of different filters
a) PSNR (dB) b) MSE

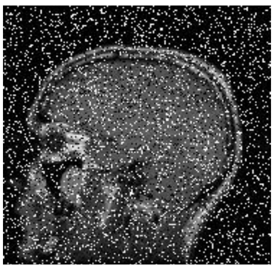
As we can see in Figure 3 success at higher level noise rates is increased. Furthermore, the performance of DCFAMF is tested with different medical images at different noise rates ranging from 10% to 90%.



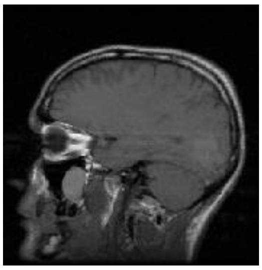
%10 Noise



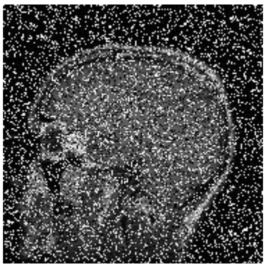
Rénovation Image



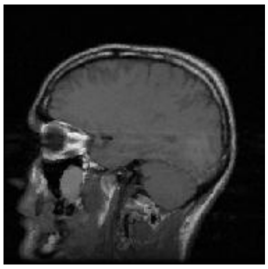
%20 Noise



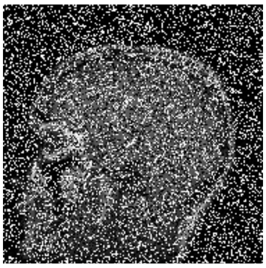
Rénovation Image



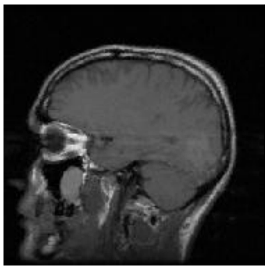
%30 Noise



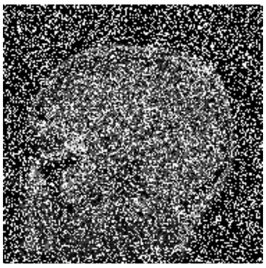
Rénovation Image



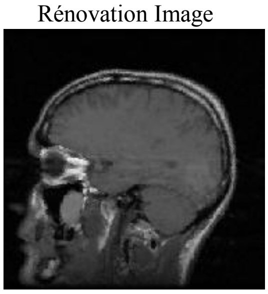
%40 Noise



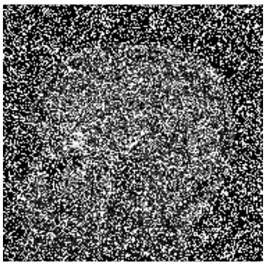
Rénovation Image



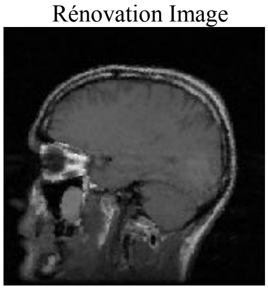
%50 Noise



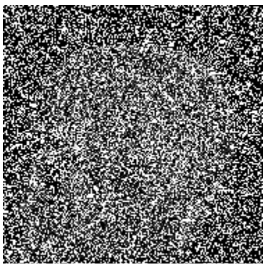
Rénovation Image



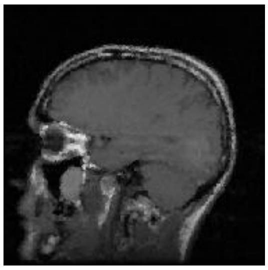
%60 Noise



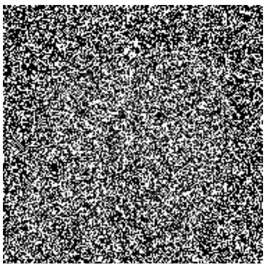
Rénovation Image



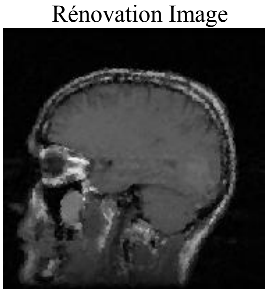
%70 Noise



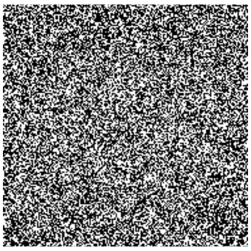
Rénovation Image

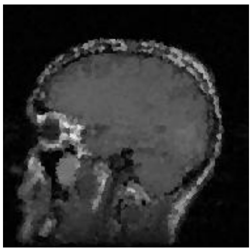


%80 Noise



Rénovation Image





%90 Noise Rénovation Image

Figure 4. The visual performance of a Brain MR image in 10% - 90% noise values.

CONCLUDING COMMENTS

In this study, a new algorithm about efficient impulse noise removal is presented. This algorithm is simple and easy-to-adapt to local noise level as well as being fast. This method can get rid of the impulse noise from the image and protect the necessary details.

The effectiveness of the proposed approach relies on the filter capability to detect the true noise configurations even under high noise density. It needs no calibration, and is therefore suited to automated systems. Another perfect aspect of this method is that, it does not require any training. Experiments results demonstrate that the new algorithm can suppress ımpulse noise and may be less computationally expensive and better quality than many other well-known algorithms. As a result, it was seen that the presented algorithm can be performed in noise removal in medical images and it can be adapted to real time images as well.

REFERENCES

[1] S. Deivalakshmi, P. Palanisamy, “Improved tolerance based selective arithmetic mean filter for detection and removal of impulse noise”, Industrial and Information Systems (ICIIS), *2010* International Conference on, pp. 309 - 313, 2010.

[2] Wenxue Zhang, Yongzhen Cao, Rongxin Zhang, and Yuanquan Wang, “Image Denoising Using Total Variation Model Guided by Steerable Filter,” *Mathematical Problems in Engineering*, vol. 2014, Article ID 423761, 2014. doi:10.1155/2014/423761

[3] A.Toprak, İ. Güler, “Angiograph image restoration with the use of rule base fuzzy 2D Kalman filter”, *Expert Systems with Applications*, 35(4), (2008)1752-1761.

[4] Di Guo, Xiaobo Qu, Xiaofeng Du, Keshou Wu, and Xuhui Chen, “Salt and Pepper Noise Removal with Noise Detection and a Patch-Based Sparse Representation,” Advances in Multimedia, vol. 2014, Article ID 682747, 2014. doi:10.1155/2014/682747

[5] Shuhan Chen, Weiren Shi, and Wenjie Zhang, “An Efficient Universal Noise Removal Algorithm Combining Spatial Gradient and Impulse Statistic,” *Mathematical Problems in Engineering*, vol. 2013, Article ID 480274, 2013. doi:10.1155/2013/480274

[6] H. Ibrahim, N. S. P. Kong, and T. F. Ng, “Simple adaptive median filter for the removal of impulse noise from highly corrupted images,” *IEEE Transactions on Consumer Electronics*, vol. 54, no. 4, pp. 1920-1927, November 2008.

[7] Latifoğlu F., “A Novel Approach To Speckle Noise Filtering Based On Artificial Bee Colony Algorithm: An Ultrasound Image Application”, *Computer Methods And Programs in Biomedicine* (111) (2013) 561-569.

[8] Y. Dong and S. Xu, "A New Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise," *Signal Processing Letters, IEEE* , vol.14, no.3, pp.193,196, March 2007

[9] T.R. Kishore, K.D. Rao, "A fast and reliable median filter for extremely corrupted images," TENCON 2008 - 2008 IEEE Region 10 Conference , vol. 1, no. 5, pp. 19-21, Nov. 2008.

[10] P. E. Ng and K. K. Ma, “A switching median filter with boundary discriminative noise detection for extremely corrupted images,” *IEEE Trans. Image Process*., vol. 15, no. 6, pp. 1506-1516, June 2006.

[11] T. Song, M. Gabbouj, and Y. Neuvo, “Center weighted median filters: some properties and applications in image processing,” *Signal Processing*, vol. 35, no. 3, pp. 213–229, 1994.

[12] A. Toprak, “Quantum noise suppression in X-ray images using fuzzy 2-D Wiener filter”, *Journal of Medical Systems,vol.*31, no.5, pp. 351-355, 2007.

[13] Jafar, I.F.; AlNa'mneh, R.A.; Darabkh, K.A., “Efficient Improvements on the BDND Filtering Algorithm for the Removal of High-Density Impulse Noise”, *Image Processing, IEEE Transactions on*, 22(3), (2013) 1223, 1232**.**

[14] C Budak, M Türk, A Toprak, “Reduction in impulse noise in digital images through a new adaptive artificial neural network model” *Neural Computing and Applications*,2014,
doi: http://dx.doi.org/10.1007/s00521-014-1767-x

[15] N.S.Madhu, K. Revathy, R. Tatavarti, “Removal of salt-and- pepper noise in images: A new decision-based algorithm”, IAENG International Multiconference of Engineers and Computer Scientists,IMECS 2008 (2008) 611-616.

[16] M.E.Yüksel, A. Bastürk, “Efficient removal of impulse noise from highly corrupted digital images by a simple neuro-fuzzy operator”, *AEUInternat. J. Electron. Comm*. Vol. 57, no. 3, pp. 214–219, 2003.

[17] A. Toprak, and I. Guler, “Impulse noise reduction in medical images with the use of switch mode fuzzy adaptive median filter,” *Digital Signal Processing*, vol. 17, no. 4, pp. 711-723, 2007

[18] S. Thota, M.V.G. Rao, P.R. Kumar, “FPGA Implementation of Adaptive Median Filter for the Removal of Impulse Noise”, *International Journal of Electronics & Communication Technology*, IJECT 2, pp. 20-24, 2011.

[19] Brain MRI images database, [Online]. Available: http://overcode.yak.net/15?size=M. Oct 2012.

[20] C Budak, M Türk, A Toprak, “Biyomedikal Resimlerdeki Rastgele Değerli Darbe Gürültüsünün Çift Gürültü Kontrollü Hızlı Adaptif Medyan Filtre ile Azaltılması”, *URSI-TÜRKİYE’2014 VII. Bilimsel Kongresi,* 28-30 Ağustos 2014, ELAZIĞ