International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 06, June 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

A NEW ALGORITHM FOR REMOVAL OF HIGH DENSITY SALT AND PEPPER NOISE IN MR IMAGES

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ABSTRACT

Magnetic Resonance Images (MRI) are corrupted by impulsive noise mainly due to sensor faults of image acquisition devices. This impulsive noise is most commonly referred to as "salt and pepper" noise. In this article, a new approach has been introduced for removal of "salt and pepper" noise while preserving the image details. This proposed method is basically a two-step method, wherein the first step; detect the corrupted pixel since the impulse noise affects only certain pixels in the corrupted image and the remaining pixel values are unchanged. In the second step, the corrupted pixel is replaced by the median value or by itsneighborhood uncorrupted pixelvalueof the considering window. This proposed algorithm (PA) has shown encouraging results, the Peak Signal to Noise Ratio (PSNR), Structured Similarity Index (SSIM) and Image Enhancement Factor (IEF) of the filtered image using the PA are much higher values than the Wiener Filter (WF), Mean Filter (MF), Standard Median Filter (SMF), Adaptive Median Filter (AMF)and other existing algorithms. ThePA is also effective for other types of highly corrupted gray-scale and color images to remove salt-and-pepper noise.

Keywords*- *De-noising, IEF, Impulse noise, Median filter, PSNR, Salt-and-Pepper noise, SSIM.

I. INTRODUCTION

Magnetic Resonance Images (MRI) are one of the most widely used medical imaging tools in both clinical and research applications [1]. The pixels in MR image, mainly gets corrupted due to the acquisition, bit errors in transmission and transformation process from analog to digital domain. In addition, images corrupted by these processes are mostly by the impulse noise. Also, impulse noise can be of two types namely, fixed valued impulse noise and random valued impulse noise [2]. Fixed valued impulse noise is also called as Salt and Pepper noise, which takes only two values either 0(Pepper) or 255(Salt), whereas random valued impulse noise can take any value between 0 and 255.

The process of removing noisy pixels is called as image de-noising [2]. Before performing any examination on corrupted MR image, it is necessary to eliminate the noisy pixels first. However, to remove Salt and Pepper noise from MR images many algorithms have been used, but one of the simplest and effective methods is the Standard Median filter (SMF). An SMF is basically a non-linear filter. In addition, linear filtering techniques are not effective in removing impulse noise, so non-linear filtering techniques are widely used in the restoration process [3]. The SMF is one of the most popular non-linear filters used to remove salt-and-pepper noise in a corrupted MR image. However, the major drawback of the SMF is that the filter is effective only for low noise densities. Also it exhibits blurring if the window size is large and leads to insufficient noise suppression if the Window size is small [3]. In the case of the highly corrupted image, the edge details of the original image will not be preserved and blurring effect in the filtered image is one of the major drawbacks of SMF. During the filtering process of the corrupted image, it is importantthat the edge details have to be preserved. The perfect approach is to apply the filtering technique only to noisy pixels.

To remove SMF problems, Median filters such as Adaptive Median Filter (AMF), Decision–based median filters can be used for selecting the corrupted pixels first, and then apply the filtering technique on the corrupted pixel. As a result, only noisy pixels will be replaced by the median value and uncorrupted pixels will be left unchanged. AMF gives satisfactory performance at low noise densities since the corrupted pixels which are replaced by the median values are very few. Also, at higher noise densities, window size has to be increased to get better noise removal which will lead to less correlation between corrupted pixel values and replaced median pixel values. In the decision-based median filters, the decision is based on a pre-defined threshold value. However, the major drawback of Decision–based median filters is that defining a robust decision measure is difficult [3].

To overcome existing filtering problems, we proposed a new algorithm in this paper.This is consists of two stages. In the first stage, each pixel values are checked if a windows center pixel is corrupted and classify the corrupted and uncorrupted pixels. In the second stage, corrupted pixels are replaced by either the median pixel or neighborhood uncorrupted pixel. This proposed algorithm (PA) has used a fixed window size of 3×3 resulting in lower processing time compared with AMF and a smooth transition between the image pixels. Edge preservation, remove all noisy pixels and better visual quality have been observed from the results. Also, it gives better PSNR, SSIM and IEF values compared to the other filtering techniques like Mean Filter, Wiener Filter, Standard Median Filter [1], Adaptive Median Filter [4], [5], Decision Based Algorithm (DBA) [3], Modify Standard Median Filter (MMF) [1],and other existing algorithms[7], [8], [9], [10].

II.LITERATURE REVIEW

Chan et al., [6] proposed an algorithm to overcome AMF problem, which consists of two stages. The first stage is to classify the corrupted and uncorrupted pixels by using AMF and in the second stage, regularization method is applied to the corrupted pixels to preserve edges and correct noisy pixels. Also, the drawback of this method is that for high impulse noise, it requires large window size of 39×39, so processing time is very high. Additionally, it requirescomplex circuitry for the implementation.

There are several approaches for identification and replacement of corrupted pixels butthe simplest approach is HanafyM.Ali [1] proposed algorithm. This algorithm consists of two stages. The first stage is to classify the corrupted and uncorrupted pixels and in the second stage, corrupted pixel is replaced by the median of its neighbors. However, the drawback of this method is that for high noise density, some noisy pixel values are left unchanged.

Madhu S. Nair et al.[3] proposed a New Decision-Based Algorithm (DBA) can be applied for high noise density. At the start, it makes a difference between the corrupted and the uncorrupted pixels. Then the filter is applied only to the corrupted pixels. The advantage of the DBA lies in removing only the noisy pixel either by the median value or by the mean of the previously processed neighboring pixel values.

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ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Esakkirajanet al. [7] proposed a Modified Decision Based Unsymmetrical Trimmed Median Filter (MDBUTMF) for the restoration of highly corrupted salt and pepper noise. In this algorithm, the noisy pixels is replaced by trimmed median value when other pixel values are 0's and 255's. When all pixel values are 0's and 255's, then the corrupted pixel is replaced by the mean value of all the elements present in the selected window.

A.K. Samantarayet al. [8] proposed First Order Neighborhood DecisionBased Median Filter (FONDBMF) motivated by MDBUTMF filter. In this algorithm, the noisy pixels is replaced by the first order neighborhood pixels trimmed median value when other first order neighborhood pixel values are 0's and 255's. When all first order neighborhood pixel values are 0's and 255's, then the corrupted pixel is replaced by the mean value of the first order neighborhood pixels in the selected window.

Biswal, Satyabrata, and NilamaniBhoi[9]proposed a new method (NMF) for removal of high density salt and pepper noise. In this technique when the processing pixel is corrupted then its neighbors are checked. When all theneighbors are corruptedthen the processing pixel isreplaced with the mean value of the window. When some of the neighbors arecorrupted then processing pixel is replaced by the unsymmetric trimmed mean value.

Aswini K Samantarayet al. [10] proposed a Decision Based Adaptive Neighborhood Median Filter (DBANMF).That is consists of three stages. In the first stage, it considers only the first order neighborhood (FON) pixels. In that if it finds one un-corrupted pixel, then that un-corrupted pixel replaces the corrupted center pixel. If it finds more than one un-corrupted pixel among the FON pixels, then the median value of those un-corrupted pixels replaces the corrupted center pixel. The second stage is followed by the first phase if and only if it does not find at least one un-corrupted pixel in the FON pixels. In the second stage, it considers only the diagonal neighborhood (DN) pixels. In DN if it finds only one un-corrupted pixel, then that un-corrupted pixel replaces the corrupted center pixel.And if it finds more than one un-corrupted pixel, then the median value of those un-corrupted pixels replaces the corrupted center pixel. If the method fails in above two phases i.e. if it does not find at least one un-corrupted pixel in its neighborhood, then it goes to the third phase. In this stage it calculates the mean of all the neighborhood pixels and replaces the corrupted center pixel by the calculated mean value.

III. SALT-AND-PEPPER NOISE

An image containing salt-and-pepper noise will have dark pixels in bright areas and bright pixels in dark areas. Also, the negative impulse appears as black point (pepper noise) and the positive impulse appears as white point (salt noise) [1]. This type of noise can be caused by dead pixels, analog-to-digital converter errors, bit errors in transmission, fault memory locations in hardware or transmission in a noisy channel etc. This noise can be dark/bright pixels [11]. However, all pixels are not corrupted by salt and pepper noise in an image instead of some pixel values are changed and remaining pixels are unchanged. It is also known as fixed valued impulse noise and it is restricted to the minimum (0) or the maximum (255) intensity value [1]. The minimum intensity 0 appears as black pixels on the MR images. On the other hand, the maximum intensity 255 appears as white pixels on the MR images.

The Salt and Pepper noise model, the distribution P (N) of noise intensity N is defined in the equation as follows:

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 06, June 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

$$P(N) = \begin{cases} 0.5P & \text{Pepper Noise, } N = \\ 1 - P & \text{Noise Free Pixels}, 0 < N < 2 \\ 0.5P & \text{Salt Noise, } N = 2 \end{cases} \quad (1)$$

IV. PRELIMINARY STUDY

Image de-noising is avery important task in image processing for the analysis of images. MR image de-noising methods can be linear as well as non-linear. Linear methods do not preserved the details of the images, whereas the non-linear methods preserved the details of the images. The non-linear filters like Median filter, provides good restoration from the noisy image [12]. It move filtering window over the noisy image and replace each center pixel by the median of the filtering window. The Median filter arecommonly used for removing impulse noise in MRI due to its good de-noisy property.

The standard median filter (SMF) is derived from the median filter.It attempts to remove noise by changing the center pixel value of the filtering window with the median of the neighbor's pixel values. The median value is calculated by arranging all the neighbor's pixel values in ascending order and select the middle pixel. SMF is very useful in salt -and-pepper noise filtering because they do not depend on values which are significantly different from the typical values in the neighborhood. The basic principal behind SMF is that the original pixel value, which is replaced by a newer one, that is closer to or the same as the median value eliminates isolated noise points [1]. However, the drawback of SMF is that itremoves thin lines and blurs image details even at medium noise densities. Also, the major drawback of SMF method is that it changed middle pixels value of selected 3x3 window without checking whether, it is corrupted or not.

There are several MRI image de-noising methods based on median filter like SMF, MMF [1] DBA [3], MDBUTMF [7], FONBDMF [8], NMF [9] and DBANMF [10], but they have the disadvantage of blurring edges. So, the aim of the new algorithm is to remove all corrupted pixel and maintaining reasonably edge of the MRI images even at the high noise density.

V. THE PROPOSED ALGORITHM

Median filters have chosen for removing salt-and-pepper noise because of their simplicity and less computational complexity. This paper describesa new decision based non-linear filteringtechnique for tackling the problem of median filters with minimal increase in computational load.Also, it preserved edges and restored all the noisy pixels. In most of the existing algorithms including SMF and AMF, only median values are used for the replacement of the corrupted pixels. The proposed de-noising algorithm (PA) is based on non-linear filtering technique. The PA first detects the salt and pepper noise in the image. The corrupted pixels in the image are detected by checking the pixel element value against the 0 and 255 values in the selected 3x3 window. Afterwards, inthe case of impulse noise corrupted pixel value is 0 or 255 and other values remain unchanged. In addition, this proposed algorithm (PA) consists of two stages. In the first stage, each pixel values are checked if a windows center pixel is corrupted and classify the corrupted and uncorrupted pixels. In the second stage, corrupted pixels are replaced by either the median pixel or neighborhood uncorrupted pixel. If the pixel have a value between 0 and 255 values in the 3x3 window of processing, then it is an uncorrupted pixel and any kind of changes are not required.

The steps of the proposed algorithm as follows:

Step 1. Select a 2-D Window W of size 3x3. Assume that the center pixel is $A_{2,2}$.

Step 2. If 0< $A_{2,2}$ <255, then $A_{2,2}$ is an uncorrupted pixel.Its value is left unchanged and go to Step 7.

Otherwise, $A_{2,2}$ is a noisy pixel.

Step 3. Find Wmin, Wmed and Wmax - the minimum, median and maximum pixel values respectively of W by arranging the pixel values in ascending order.

Step 4. If $A_{2,2}$ is a noisy pixel, it will be replaced by Wmed, the median value of the W.

Step 5. If Wmin=0 or Wmax =255, then read each pixel values of the W row wise.

Else go to Step 7.

Step 6. For each pixel Ax, yin the W do

If 0< Ax, y <255, then Ax, y is an uncorrupted pixel and its value is left unchanged.

Otherwise Ax, y is a noisy pixel.

Case (i) If Ax, y is a noisy pixel and x=y=1 then Ax, y will be replaced by the right neighbor ($A_{1,2}$) pixel value, if the right neighbor pixel value is also noisy pixel then Ax, y will be replaced by the down neighbor ($A_{2,1}$) pixel value, if the down neighbor pixel value is also noisy then Ax, y will be replaced by $A_{2,2.}$

Case (ii) If Ax, y is a noisy pixel, where x ≠ y and y=2, then Ax, y will be replaced by the right neighbor pixel value, if the right neighbor pixel value is also noisy pixel then Ax, y will be replaced by the left neighbor pixel value.

Case (iii) If Ax, y is a noisy pixel, x ≠ y and x=2 then Ax, y will be replaced by the down neighbor pixel value, if the down neighbor pixel value is also noisy pixel then Ax, y will be replaced by the right/left neighbor ($A_{2,2}$) pixel value.

Case (iv) If Ax, y is a noisy pixel, where x =1 and y= 3 then Ax, y will be replaced by the down neighbor ($A_{2,3}$) pixel value, if the down neighbor pixel value is also noisy then Ax, y will be replaced by the left neighbor ($A_{1,2}$) pixel value.

Case (v) If Ax, y is a noisy pixel, where x =3 and y= 1 then Ax,y will be replaced by the right neighbor ($A_{3,2}$) pixel value, if the right neighbor pixel value is also noisy pixel then Ax, y will be replaced by the upper neighbor ($A_{2,1}$) pixel value.

Step 7. Repeat Steps 1 to 6 until all the pixels in the entire image are processed.

In the PA, the nature of the pixel being processed first, that is, it is corrupted or not, is checked. The value of the pixel being processed is then replaced with the corresponding value as in Step 4 and cases (i), (ii), (iii), (iv), (v) of Step 6. The window is then subsequently moved to form a new set of values. This process is repeated until the last image pixel is processed.

VI. METHODOLOGY OF THE PROPOSED ALGORITHM

Consider a 3x3 window:

$$\begin{pmatrix} \mathbf{P1} & \mathbf{P2} & \mathbf{P3} \\ \mathbf{P4} & \mathbf{P5} & \mathbf{P6} \\ \mathbf{P7} & \mathbf{P8} & \mathbf{P9} \end{pmatrix}$$

For each selected 3x3 window first checked pixel value **P5** is corrupted or not.

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ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Case1: If **P5** is corrupted pixel then **P5** is replaced by the median pixel value of the selected 3x3 window and checked its neighbor**P1, P2, P3, P4, P6, P7** and **P8** pixels are corrupted or not respectively. Else select the next window and repeat case1.

Case2: If **P1**is a corrupted pixel then itis replaced by **P2**if **P2** is also corrupted pixel then **P1** is replaced by **P4** if **P2** and **P4** both are corrupted pixelsthen **P1** is replaced by **P5**. Here, **P5** is already processed pixel, so no need to check.

Case3: If**P2** pixel is corrupted then it is replaced by **P3**if **P3** is also corrupted pixel then **P2** is replaced by **P1**. Here, **P1** is already processed pixel values so no need to check.

Case4: If **P3** pixel is corrupted then it is replaced by **P6** if **P6** is also corrupted pixel then **P3** is replaced by **P2**. Here, **P2** is already processed pixel values so no need to check.

Case5: If **P4** pixel is corrupted then it is replaced by **P7** if **P7** is also corrupted pixel then **P4** is replaced by **P5**. Here, **P5** is already processed pixel values so no need to check.

Case6: If **P6** pixel is corrupted then it is replaced by **P9** if **P9** is also corrupted pixel then **P6** is replaced by **P5**. Here, **P5** is already processed pixel values so no need to check.

Case7: If **P7** pixel is corrupted then it is replaced by **P8** if **P8** is also corrupted pixel then **P7** is replaced by **P4**. Here, **P4** is already processed pixel values so no need to check.

Case8: If **P8** pixel is corrupted then it is replaced by **P9** if **P9** is also corrupted pixel then **P8** is replaced by **P7**. Here, **P7** is already processed pixel values so no need to check.

(Note: **P9** pixel value is not checked, if **P9** is corrupted then **P9** is correct at subsequent window moves on the image.)

Consider a corrupted 8x5 windows pixel values of an image. Modification of corruptedpixels using the PA is shown inFig.1.

255	220	252	254	255	254	253	253
237	0	115	253	255	252	252	254
150	154	255	253	254	252	254	254
254	254	255	225	252	253	255	255
253	254	252	254	253	255	254	254

(A)

220	220	252	254	255	254	253	253
237	220	115	253	255	252	252	254
150	154	255	253	254	252	254	254
254	254	255	225	252	253	255	255
253	254	252	254	253	255	254	254

(B)

220	220	252	254	254	254	253	253
237	220	115	253	254	252	252	254
150	154	255	253	254	252	254	254
254	254	255	225	252	253	255	255
253	254	252	254	253	255	254	254

(C)

220	220	252	254	254	254	253	253
237	220	115	253	254	252	252	254
150	154	253	253	254	252	254	254
254	254	254	225	252	253	255	255
253	254	252	254	253	255	254	254

(D)

220	220	252	254	254	254	253	253
237	220	115	253	254	252	252	254
150	154	253	253	254	252	254	254
254	254	254	225	252	253	254	254
253	254	252	254	253	254	254	254

(E)

Fig. 1.(A) 22% corrupted imagespixel values and 1st selected window (B) 1st window modification and 2nd selected window (C) 2nd window modification and 3rd selected window (D) 3rd window modification and 4th selected window (E) 4th window modification and final restored image pixels.

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ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

VII. IMAGE QUALITY ASSESSMENT

The performance of the de-noising process is measured by the Peak Signal-to-Noise Ratio (PSNR), Structured Similarity Index (SSIM) and Image Enhancement Factor (IEF). The PSNR, SSIM and IEF can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. Larger PSNR, SSIM and IEF indicate a minor difference between the original image and the filtered image.

The mean squared error (MSE) is defined for an image as [13] :

$$\mathrm{MSI} \qquad (2)$$

Where, A is the original image, I is the restored image and size of the image is m×n.

PSNR is the most widely used objective image quality/distortion measure [14]. The following equation describes the PSNR [2],[15] :

(3)

Where, MAX is the maximum possible pixel value of an image that is 255.

The Structural Similarity (SSIM) index is a novel technique for measuring the similarity between two images. It is an improved version of the Universal Image Quality Index (UIQI).Structural similarity provides an alternative and complementary approach to the problem of image quality assessment. The following equation describes the SSIM [3]:

(4)

$$L(O,R) = (2\mu_O\mu_R + C_1) / (\mu_O^2 + \mu_R^2 + C_1)$$

$$C(O,R) = (2\,\sigma_O\sigma_R + C_2) / (\sigma_O^2 + \sigma_R^2 + C_2)$$

$$S(O,R) = (\sigma_{OR} + C_3) / (\sigma_O\sigma_R + C_3)$$

, ,

G=255; K_1, K_2<<1, (K_1=0.001, K_2=0.002)

The following equation describes the IEF [3] :

$$\mathrm{IEF} = (\textstyle\sum_{m,n}[P(m,n) - O(m,n)]^2)/(\sum_{m,r} \qquad (5)$$

where, Ois the original Image, R is the restored image, P is the corrupted image, m×nis the size of the image, L is the luminance comparison, C is the contrast comparison, S is the structure comparison, μ is the mean and σ is the standard deviation.

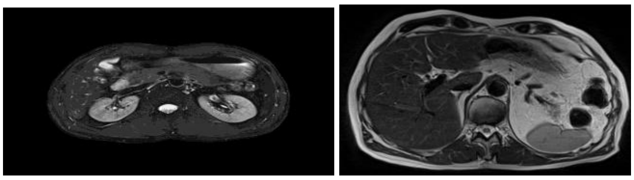
The PSNR, SSIM and IEF are computed for purposes of comparison.To validate the proposed scheme, simulation has been carried out in MATLAB (r2009a) on standard MR images.

VIII. RESULTS OF THE PROPOSED ALGORITHM

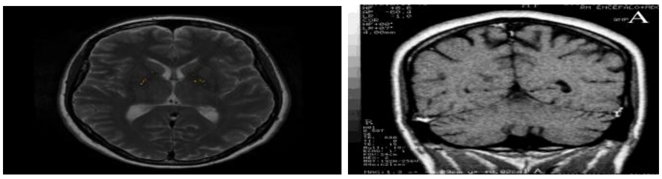
Four MR images have been used to test the performance of the proposed algorithm (PA) with different noise densities using MATLAB (r2009a). Images will be corrupted by salt-and-pepper noise at different noise

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

densities. Then PA is applied to the corrupted image to remove the noise. The sample MRI images considered during the experimental process is shown in Fig. 2(A) – Fig. 2(D). The de-noising of MR images corrupted by salt-and-pepper noise at different noise density are shown in Fig. 3(A) – Fig. 3(F).

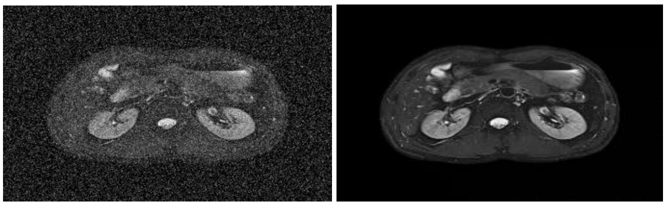


(A) **(B)**

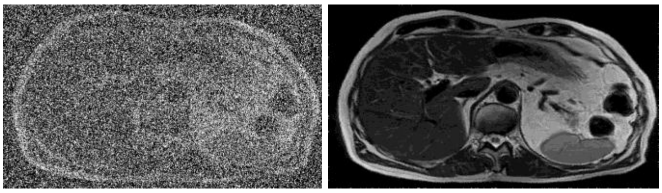


(C) **(D)**

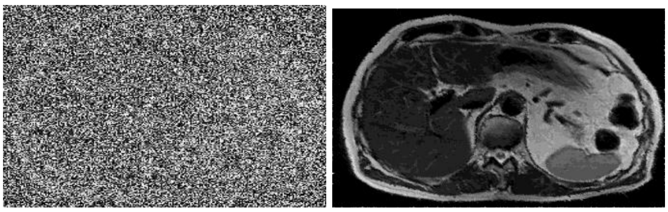
Fig. 2. The Original MRI images (A) Kidney, (B) Liver, (C)Sectional View of the Brain, (D) Back view of the Brain.



(A)



(B)



(C)

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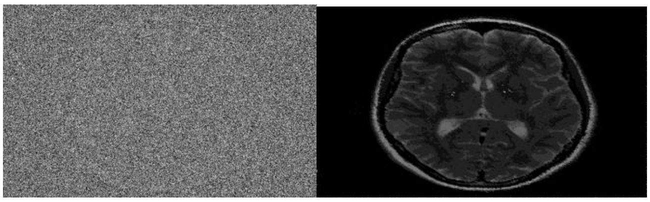
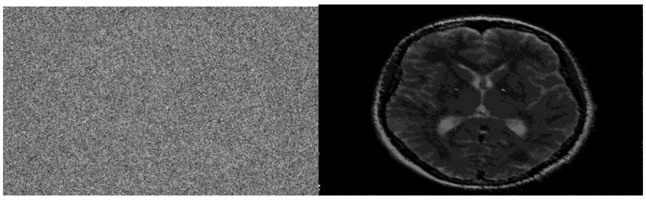
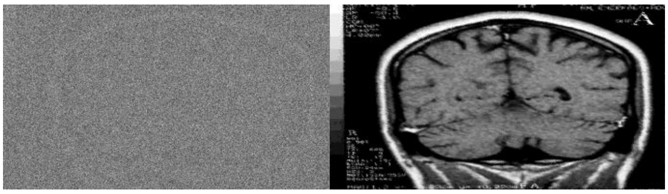
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346



(D)



(E)



(F)

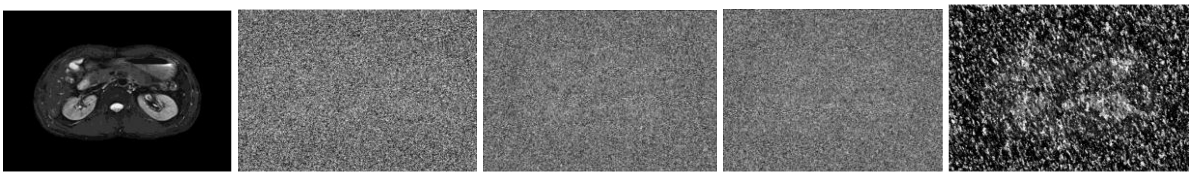
Fig. 3.(A) 25% Salt and pepper Noise density and Restored Image of Kidney; (B) 65% Salt and pepper Noise density and Restored Image of Liver; (C) 85% Salt and pepper Noise density and Restored Image of Liver; (D) 90% Salt and pepper Noise density and Restored Image of Sectional View of the Brain; (E) 93% Salt and pepper Noise density and Restored Image of Sectional View of the Brain; (F) 96% Salt and pepper Noise density and Restored Image of Back view of the Brain.

IX. COMPARISON

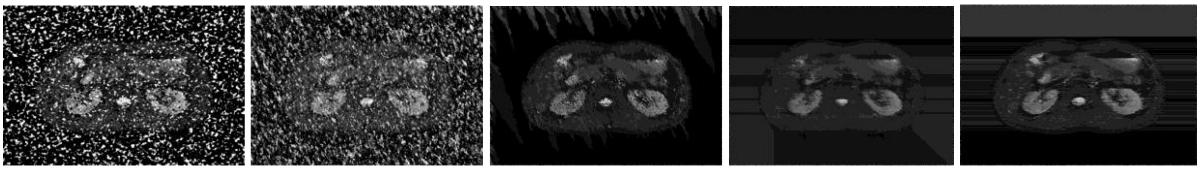
In this work, three MR images have been used to test the performance of the proposed algorithm compared to the other algorithms at different noise levels using MATLAB (r2009a). The standard MRI images have taken into consideration, namely Kidney, lateral view ofthe Brain, and Spine. Images will be corrupted by salt-and-pepper noise at different noise densities, such as low noise (20%), medium noise (60%) and high noise (90%). Then the PA is applied to the corrupted image to remove the noise. Afterwards, the de-noising performance of the restoration process is quantified using PSNR, SSIM and IEF as defined in (3), (4),and (5) respectively. Simultaneously, other experienced schemes are also simulated and their results have been compared. The PSNR, SSIM and IEF values of the proposed work are compared against the Wiener filter, Mean filter, Standard median filter (SMF), Adaptive median filter (AMF) [5],MMF [1], DBA [3], MDBUTMF [7], FONDBMF [8], NMF [9], and DBANMF [10] by varying noise density. The PSNR value (in dB) obtained for MR images using different filtering methods are shown in Table I, Table IV and Table VII. SSIM values are shown in Table II, Table Vand Table VIII.Also, IEF values are shown in Table III, Table VI and Table IX. It has been observed that the proposed filtering method outperforms as compared to the Wiener Filter, Mean Filter, Standard Median Filter, Adaptive Median Filter and other existing algorithmsat both low and high noise densities. The different

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 06, June 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

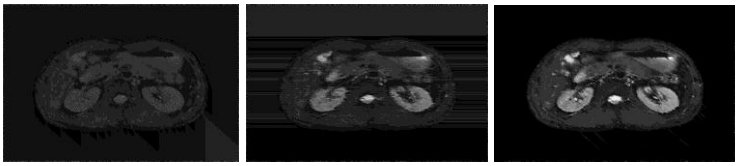
sample MR images considered during the experimental process is shown in Fig.4(A), Fig.6(A), and Fig.8(A).The comparative analysisof different de-noising algorithms of MR images corrupted by salt-and-pepper noise at 90%dB noise density is shown in Fig.4, Fig. 6, and Fig. 8.



(A) Original Image (B) 90% Noisy Image (C) Wiener Filter (D) Mean Filter (E) SMF



(F) AMF (G) MMF (H) DBA (I) MDBUTMF (J) FONDBMF



(K) NMF (L) DBANMF (M) PA

Fig. 4. Comparative analyses of Noise removal techniques for Kidney MRI in 90% Salt and pepper Noise density.

Table.I. PSNR Values for Kidney MRI with Different Noise Densities.

Table.II.

Noise Density	**PSNR(in dB)**										
	Wiener Filter	**Mean Filter**	**SMF**	**AMF**	**MMF**	**DBA**	**MDBUTMF**	**FONDBMF**	**NMF**	**DBANMF**	**Proposed Work**
20%	15.1957	17.8390	30.4242	30.8463	32.7474	31.9831	24.5818	20.4361	21.3606	23.6471	40.9367
40%	12.4776	13.3085	26.7528	33.1571	28.2958	28.7554	24.0284	20.3253	20.5749	23.2866	36.0589
60%	10.1919	10.4700	21.6923	19.6024	22.7682	26.4517	22.9961	19.9512	20.0642	22.6349	32.5678
80%	8.2577	8.3687	14.4877	12.9988	15.0826	23.4988	21.4280	19.2747	19.5535	21.5397	28.6285
90%	7.4097	7.4568	9.7477	8.5779	10.3158	19.5552	18.8884	18.5227	19.1617	20.4181	25.2627

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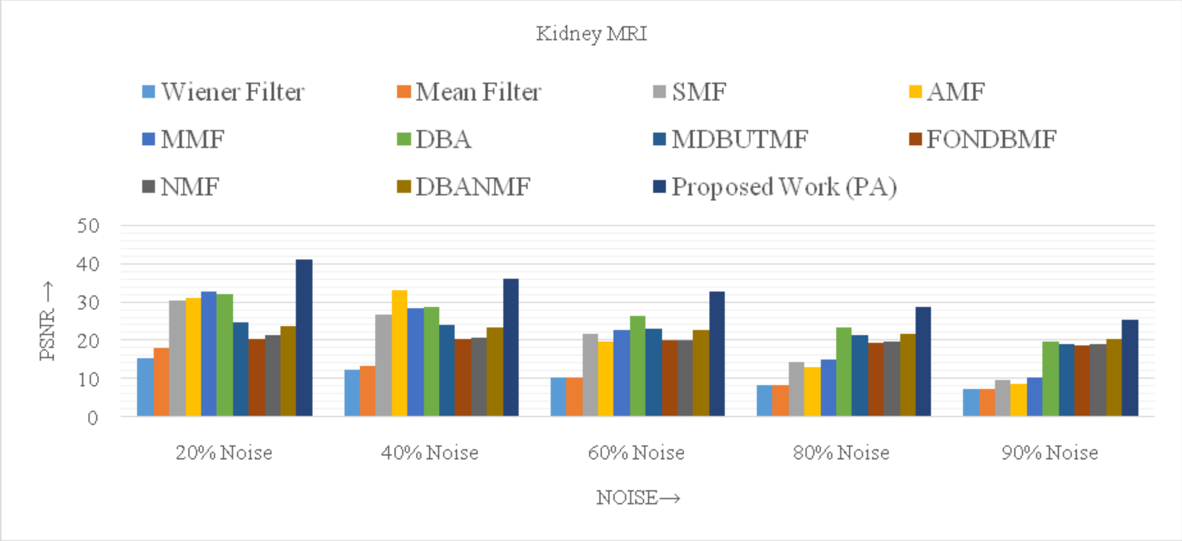

Fig. 5.PSNR Performance of various algorithms over Kidney MRI corrupted by salt and pepper noise.

Table.III. SSIM for Kidney MRI with Different Noise Densities.

Noise Density	SSIM										
	Wiener Filter	**Mean Filter**	**SMF**	**AMF**	**MMF**	**DBA**	**MDBUTMF**	**FONDBMF**	**NMF**	**DBANMF**	**Proposed Work**
20%	0.1010	0.1202	0.8994	0.9540	0. 9703	0.8852	0.5924	0.5924	0.3637	0.5262	0.9699
40%	0.0555	0.0615	0.8166	0.9593	0. 9188	0.8680	0.5694	0.5784	0.3322	0.5463	0.9470
60%	0.0354	0.0374	0.5728	0.6899	0. 6858	0.8205	0.4506	0.4912	0.3054	0.5054	0.9194
80%	0.0217	0.0210	0.1589	0.4001	0. 2164	0.6648	0.3292	0.4582	0.2718	0.4336	0.8489
90%	0.0157	0.0168	0.0405	0.2329	0. 0647	0.3916	0.2359	0.3555	0.2440	0.2801	0.7387

Table.IV. IEF for Kidney MRI with Different Noise Densities.

Noise Density	IEF										
	Wiener Filter	**Mean Filter**	**SMF**	**AMF**	**MMF**	**DBA**	**MDBUTMF**	**FONDBMF**	**NMF**	**DBANMF**	**Proposed Work**
20%	0.9597	1.7607	21.042	32.2438	56.1639	28.0905	5.4808	2.1100	2.6105	4.4196	356.6682
40%	0.5140	0.6260	9.1071	58.3219	19.9338	14.3100	4.8188	2.0542	2.1757	4.0623	118.1964
60%	0.3073	0.3275	2.8104	2.0549	5.5389	8.4080	3.7945	1.8821	1.9317	3.4915	54.9869
80%	0.1967	0.2000	0.5342	0.4825	0.9168	4.2545	2.6410	1.6085	1.7152	2.7097	21.5740
90%	0.1622	0.1634	0.1792	0.2178	0.3071	1.7188	1.4707	1.3520	1.5661	2.0917	8.9016

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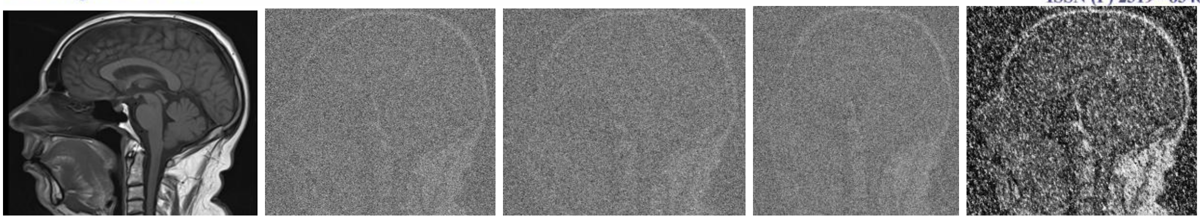
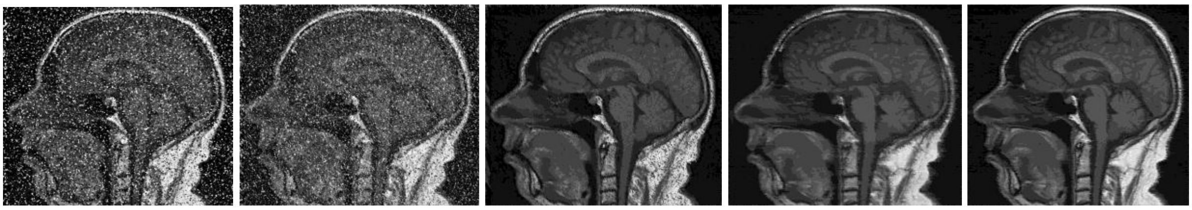
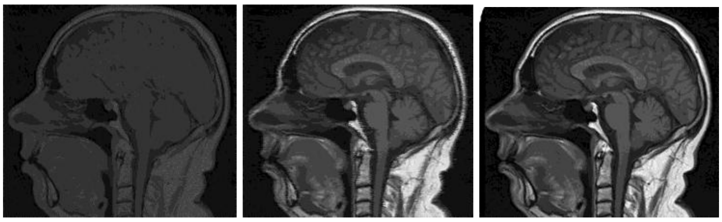
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346



(A) Original Image (B) 90% Noisy Image (C) Wiener Filter (D) Mean Filter (E) SMF



(F) AMF (G) MMF (H) DBA (I) MDBUTMF (J) FONDBMF



(K) NMF (L) DBANMF (M) PA

Fig. 6. Comparative analyses of Noise removal techniques forlateral view of the Brain MRI in 90% Salt and pepper Noise density.

Table.V. PSNR Values for Lateral View of the Brain MRI with Different Noise Densities.

Noise Density	PSNR(in dB)										
	Wiener Filter	Mean Filter	SMF	AMF	MMF	DBA	MDBUTMF	FONDBMF	NMF	DBANMF	Proposed Work
20%	16.5501	19.4576	34.6163	31.8374	35.9835	33.0613	34.3421	34.4109	19.6237	33.8876	39.2702
40%	14.1732	15.8965	29.2198	31.0974	31.5799	31.2902	31.7591	31.3298	17.2184	31.4223	36.7606
60%	12.7853	12.8954	22.9422	20.9010	25.6205	28.5272	29.3492	29.2988	16.0623	29.1921	34.0662
80%	10.5657	10.3688	15.4284	15.2577	17.7879	23.7167	25.1120	25.8649	15.4775	25.8476	28.8815
90%	9.6787	9.4578	10.9893	11.6341	13.1338	20.0359	20.6904	22.6137	15.3067	22.5945	23.8479

International Journal of Advance Research in Science and Engineering
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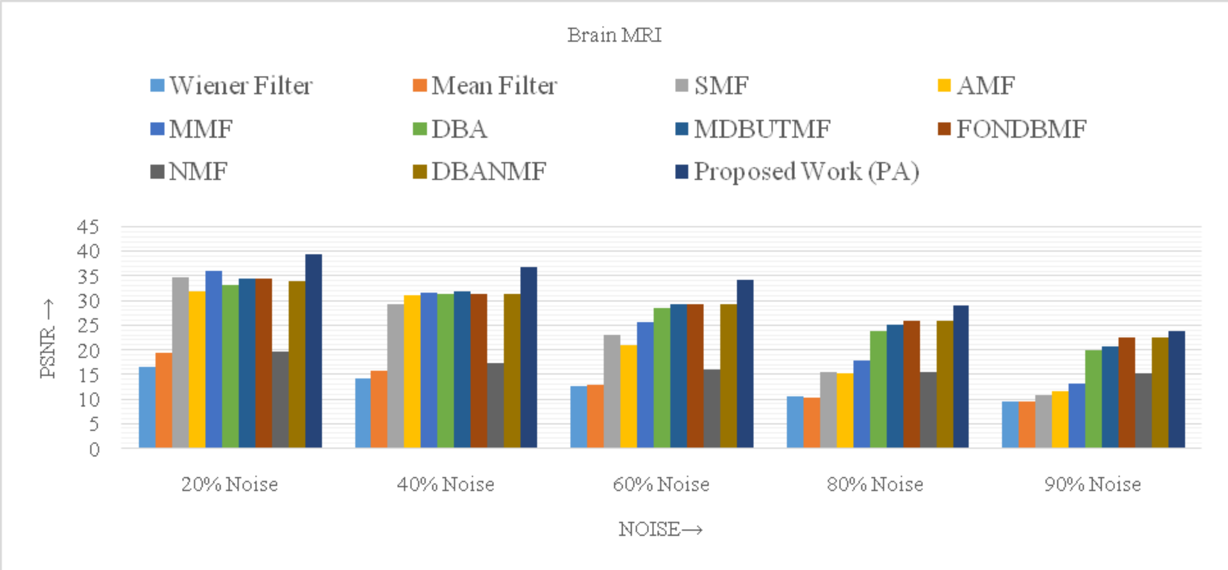

Fig. 7.PSNR Performance of various algorithms over lateral view of the Brain MRI corrupted by salt and pepper noise.

Table.VI. SSIM for Lateral View of the Brain MRI with Different Noise Densities.

Noise Density	SSIM										
	Wiener Filter	Mean Filter	SMF	AMF	MMF	DBA	MDBUTMF	FONDBMF	NMF	DBANMF	Proposed Work
20%	0.1466	0.2153	0.9831	0.9538	0.9970	0.9897	0.9779	0.9750	0.5341	0.9751	0.9975
40%	0.0879	0.1114	0.9064	0.4870	0.9755	0.9801	0.9689	0.9627	0.5045	0.9629	0.9825
60%	0.0590	0.0687	0.6464	0.7160	0.7848	0.9385	0.9422	0.9367	0.5261	0.9367	0.9595
80%	0.0410	0.0452	0.2273	0.4518	0.3533	0.8147	0.8682	0.8713	0.5871	0.8709	0.8863
90%	0.0338	0.0369	0.0795	0.2393	0.1335	0.6953	0.7794	0.7882	0.6410	0.7879	0.7932

Table.VII. IEF for Lateral View of the Brain MRI with Different Noise Densities.

Noise Density	IEF										
	Wiener Filter	Mean Filter	SMF	AMF	MMF	DBA	MDBUTMF	FONDBMF	NMF	DBANMF	Proposed Work
20%	4.6008	8.9613	294.3830	153.4624	396.8069	205.786	276.3710	280.7859	9.3251	248.9122	876.8195
40%	2.6430	3.4256	84.9393	7.9875	140.2624	136.819	152.4166	138.0722	5.3576	141.0450	522.7693
60%	1.6800	1.8476	20.0072	12.2499	36.6455	72.3919	87.4782	86.4659	4.1039	84.3693	113.7744
80%	1.1260	1.1606	3.5453	3.4610	6.2984	23.9047	32.9621	39.2021	3.5856	39.0459	49.5144
90%	0.9358	0.9549	1.2755	1.4497	2.0749	10.2405	11.9062	18.5398	3.4468	18.4583	25.9005

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 06, June 2017
www.ijarse.com
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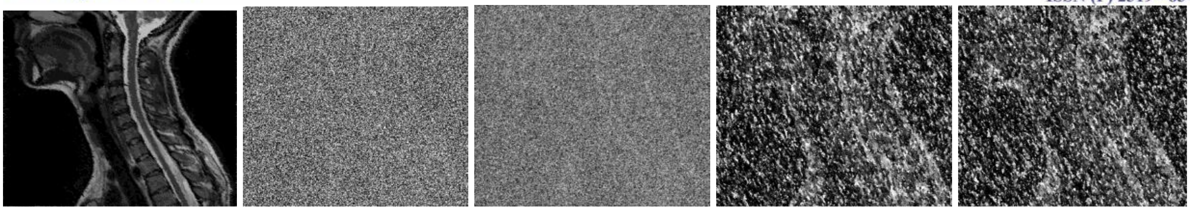
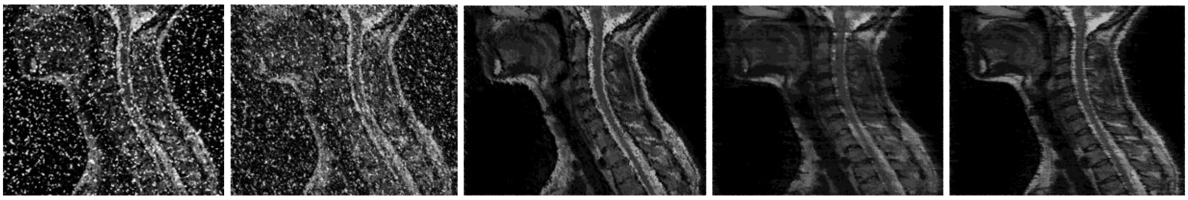
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346



(A) Original Image (B) 90% Noisy Image (C) Wiener Filter (D) Mean Filter (E) SMF



(F) AMF (G) MMF (H) DBA (I) MDBUTMF (J) FONDBMF

(K) NMF (L) DBANMF (M) PA

Fig. 8.Comparative analyses of Noise removal techniques for Spine MRI in 90% Salt and pepper Noise density.

Fig. 9.

Table.VIII. PSNR Values for Spine MRI with Different Noise Densities.

Noise Density	PSNR(in dB)										
	Wiener Filter	Mean Filter	SMF	AMF	MMF	DBA	MDBUTMF	FONDBMF	NMF	DBANMF	Proposed Work
20%	15.7868	18.7966	31.2038	31.7787	33.7678	33.4819	34.0545	32.8670	23.3264	33.2116	36.0860
40%	13.2789	14.9665	27.0891	32.9764	30.7686	29.9418	29.9038	29.1834	20.7021	29.3794	33.2285
60%	11.1679	11.9765	21.7707	20.1435	24.4694	27.1076	26.9666	26.5197	19.6197	26.5764	30.6918
80%	9.2905	9.8906	14.7292	14.8227	17.9675	23.5782	22.9508	23.1175	19.0168	23.0791	26.6784
90%	8.7864	8.9064	10.4517	11.6789	12.3146	20.8385	19.7741	20.6477	18.7891	20.4619	22.7890

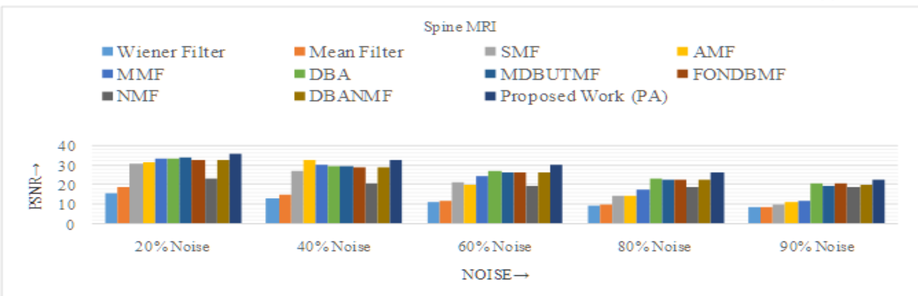


Fig. 10. PSNR Performance of various algorithms over Spine MRI corrupted by salt and pepper noise.

International Journal of Advance Research in Science and Engineering
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Table.IX. SSIM for Spine MRI with Different Noise Densities.

Noise Density	SSIM										
	Wiener Filter	Mean Filter	SMF	AMF	MMF	DBA	MDBUTMF	FONDBMF	NMF	DBANMF	Proposed Work
20%	0.1807	0.2445	0.9520	0.9574	0. 9920	0.9924	0.9936	0.9914	0.8059	0.9913	0.9897
40%	0.1078	0.1261	0.8723	0.5398	0. 9574	0.9727	0.9738	0.9656	0.7705	0.9661	0.9695
60%	0.0680	0.0763	0.6361	0.7348	0. 7922	0.9226	0.9248	0.9127	0.7623	0.9141	0.9429
80%	0.0393	0.0419	0.2381	0.4716	0. 3807	0.8042	0.8119	0.8051	0.7555	0.8030	0.8478
90%	0.0287	0.0314	0.0872	0.2814	0. 1540	0.6958	0.7017	0.6996	0.7357	0.6927	0.7215

IEF for Spine MRI with Different Noise Densities.

Noise Density	IEF										
	Wiener Filter	Mean Filter	SMF	AMF	MMF	DBA	MDBUTMF	FONDBMF	NMF	DBANMF	Proposed Work
20%	1.9883	3.7994	67.6807	69.7236	113.5984	114.366	130.4805	99.2672	11.034	107.4602	138.5915
40%	1.1008	1.3749	26.2189	3.2919	45.1715	50.5706	50.1283	42.4656	6.0245	44.4259	83.9790
60%	0.6793	0.7317	7.6981	5.5893	14.0765	26.3072	25.4667	22.9762	4.6912	23.2791	51.8682
80%	0.4433	0.4561	1.5200	1.5231	2.6178	11.6619	10.0926	10.4875	4.0793	10.3943	20.2124
90%	0.3679	0.3725	0.5674	0.6982	0.9246	6.2025	4.8547	5.9361	3.8694	5.6873	8.5629

X. CONCLUSION

In this paper, we have introduced a new and effective filtering method for Salt and Pepper noise which is strong to various noise levels. The PA detect the corrupted pixel first, since the impulse noise only affect certain pixels in the image and remaining pixels are unchanged. The proposed filter compared with the traditional filtering techniques (mean filter, wiener filter, and standard median filter) and other existingfiltering (AMF, MMF, DBA, MDBUTMF, FONDBMF, NMF, and DBANMF) techniques.Experimental results indicate that this proposed filtering algorithm(PA) can reduce salt and pepper noise effectively and maintain details of the MR images in comparison with other noise removal algorithms in terms of PSNR, SSIM and IEF.

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