Analysis of FCM Clustering on Pre and Post Iterative relaxed adaptive center weighted median filter in MRI & CT Brain Images

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Abstract

Image de-noising and clustering in medical images are quite complex because of narrow dynamic range and in-homogeneity. Pre processing steps like image de-noising do have influence over the subsequent image processing which misleads further image analysis. In this paper, a new method which incorporates the advantages of adaptive center weighted median filter and hybrid median filter, called Iterative relaxed adaptive center weighted median filter, has been proposed for image de-noising and the influence of such median filtering methods over Fuzzy C-Means Clustering is analyzed in MRI & CT images using Cluster Error Index and Average Cluster Error Index. This analysis leads to proper selection of de-noising algorithm for better clustering of image regions.

Keywords: *Image de-noising, Clustering, Median filtering, Cluster Error Index.*

1. Introduction

Medical images are normally characterized by narrow distribution of gray-levels, thus suffered from high spatial redundancy and low contrast and further degraded by noises particularly impulse noise which is introduced during image acquisition, transmission and storage [1]. Removing noises is highly complex because it requires the balance between the gained improvement and the introduced degradation by a particular filter. Among the non-linear statistical filters, the standard median filter and its modifications provide balancing performance in suppression of impulse noise [2,3,4]. These filtering methods adapt to the local properties and structures in the image. Despite its effectiveness in smoothing noise, it removes fine details of the image [5,6,7]. To preserve the fine details and to restore the image, other median filtering techniques such as adaptive median, hybrid median, relaxed median filtering methods have been used. The standard median filter (SMF) is an order statistics filter which provides a reasonable noise removal performance but removes thin lines and blurs fine details even at low noise densities [8]. At higher noise densities, SMF often blurs the image for larger window sizes and ineffective noise suppression for smaller window sizes [3, 9]. The impulse noise removing filters are designed to yield effective noise reduction without compromising high frequency content of images [3, 10]. However, most of the filters process both noise and noise free pixels. Adaptive median filter provides better performance at lower noise densities, due to the fact that there are few corrupted pixels replaced by median values. At higher noise densities, this replacement increases considerably by adaptive window size. However, the corrupted pixel values and replaced median values are less correlated [11]. Relaxed median filter (RMF) provides better noise removal and detail preservation but results in blurring at high noise densities. Hybrid median filter (HMF) uses diagonal neighborhood evaluation for de-noising, but does not perform well at low noise densities. Adaptive center weighted median filter (ACWMF) adaptively adjusts its threshold values to detect noisy pixels [8] and retains uncorrupted values.

Image segmentation plays an important role in the analysis and applications of medical image processing. The main purpose of medical image segmentation is to extract interesting regions which contain important diagnostic information for clinical diagnosis and pathology research. Fuzziness and in-homogeneity are common in medical images compared with ordinary images because of its imaging modalities and high complexity of human body tissues. Meanwhile, the rapid development of various complex and massive medical image data has put forward higher requirements for medical image segmentation. Segmentation of medical images is quiet complex due to the poor image contrast and artifacts which result in missing or diffused organ or tissue boundaries.

Many image processing techniques have been proposed for brain Magnetic resonance imaging (MRI) and Computed tomography (CT) images' segmentation, most popularly thresholding, region growing, edge detection and clustering. Among the statistical clustering algorithms, Fuzzy C-Means (FCM) clustering is most popular for medical image segmentation because of its robustness. A conventional FCM does not use spatial information in the image. Its advantages include a straightforward implementation, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data. A major disadvantage of its use in imaging applications [12], however, is that FCM does not incorporate information about spatial context, causing it to be sensitive to noise and other imaging artifacts. Since medical images include considerable uncertainty and unknown noise, this generally leads to further difficulties with clustering. Spatial operations performed on local neighbourhood of input pixels are used for image enhancement thus can contribute to the performance of FCM algorithm. The advantages [12] of spatial information into FCM are the following (i) Regions are more homogeneous (ii) It reduces the spurious blobs. (iii) It is less sensitive to noise than other techniques.

The non-linear spatial median filtering methods listed above not only remove impulse noise but also provide neighbourhood information. Clustering performance of FCM algorithm changes according to the filtering methods applied to the images. Neighbourhood information given by the spatial filtering methods effectively reduces local minima problem in FCM clustering algorithm. In this paper, performance of FCM algorithm is analysed for MRI and CT images which are corrupted by impulse noise and restored by various median filtering methods. De-noising performance analysis is carried out for SMF, Adaptive center weighted median filter (ACWMF), HMF, RMF and the proposed method using peak signal to noise ratio (PSNR). Good denoising algorithm may result in poor segmentation and lead to wrong clinical analysis and pathology research. Selection of denoising algorithm to have proper clustering of homogeneous regions is possible by analysing PSNR, cluster error index (CEI) and average cluster error index (ACEI).

The remaining sections of this paper are organised as follows. Section 2 gives a brief on median filtering methods and the proposed method. Section 3 is about FCM algorithm and the steps involved for Simulation. Section 4 gives performance measures for both filtering and clustering. Performance analysis, simulation and results are given in Section 5. This is followed by conclusion.

2. Filtering methods

2.1 Relaxed median filter

Let $\{X_i\}$ be a m-dimensional sequence, where the index $i \in Z_m$. A sliding window is defined as a subset $W \subset Z_m$ of odd size 2N + 1. Given a sliding window W, define $W_i=\{X_{i+r}\}: r \in W$ to be the window located at position i.
Let X_i and Y_i be the input and the output at location i, respectively, then the standard median (SM) filter is given by

$$Y_i = \text{med}\{W_i\} = \text{med}\{X_{i+r}: r \in W\}; \quad (1)$$

where med{.} denotes the median operator.
Denoted by $[W_i](r)$, r = 1,...,2N+1, the r^{th} order statistic of the samples inside the window Wi.

$$[W_i]_{(1)} \leq [W_i]_{(2)} \leq [W_i]_{(3)} \leq \ldots \leq [W_i]_{(2N+1)}$$

The relaxed median filter works as follows [13]: Lower (l) and Upper (u) bounds, define a sublist inside the $[W_i](.)$, which contains the gray levels which are good enough not to be impulse noise. If the input belongs to the sub list, then it remains unfiltered, otherwise the standard median filter is output.
Let m = N + 1 and l, u such that $1 \leq l \leq m \leq u \leq 2N + 1$. The relaxed median filter with bounds l and u is defined as

$$Y_i = \text{Relaxed median}\{W_i\} = \begin{cases} X_i & \text{if } X_i \in [[W_i]_l, [W_i]_u]; \\ [W_i]_m & \text{otherwise}; \end{cases} \quad (2)$$

where $[W_i](m)$ is the median value of the samples inside the window W_i.

2.2 Adaptive Center Weighted Median filter [ACWMF] [8,11,19]

Let X_{ij} & Y_{ij} be the input and output of ACWMF at current pixel location (i,j). Consider a window symmetrically surrounding the current pixel
$W = \{(s,t) | -m \leq s \leq m, -m \leq t \leq m\}$. The output of ACWM filter can be described as [18]

$$Y_{ij}^w = \text{median}\left(X_{ij}^w\right) \quad (3)$$

where a weight adjustment is applied to the origin pixel and $X_{ij}^w = \left\{X_{i-s,j-t,} w \in X_{ij} | (s,t) \in W\right\}$, here the window size is 2L+1 with L>0. For current pixel X_{ij}, the differences are defined as

$$d_k = \left|Y_{ij}^w - X_{ij}\right| = \left|Y_{ij}^{2k+1} - X_{ij}\right| \quad (4)$$

where k=0,1,…,L-1 and $d_k \leq d_{k-1}$ where $k \geq 1$[19]. Information about the likely presence of impulse noise for the current pixel can be derived from the differences (d_k). If the absolute difference is large, the current pixel may be smallest or the largest among the samples within the window. Else the current pixel may be free of noise and left unaltered.

Impulse detection procedure in the filter is implemented using predefined thresholds T_k where k=0,1,…,L-1 and $T_{k-1} > T_k$. Impulse detector can be realized as follows:

$$\hat{X}_{ij} = \begin{cases} Y_{ij}^1, & \text{if } k, d_k > T_k \\ X_{ij}, & \text{otherwise} \end{cases} \quad (5)$$

where $\hat{X}_{ij}$ denotes the final estimate of current pixel X_{ij}. Threshold values T_k are evaluated based on median of absolute deviation from the median and given as MD

$$MD = \text{median}\{|X_{i-s,j-t} - Y_{ij}^1| \,|(s,t)\epsilon W\} \quad (6)$$

This gives a robust estimate of dispersion. The thresholds are described as $T_k = s.MD + \delta_k$. Where δ_k, (k = 0,1,2,3) are the threshold values taken between [0 & 255].

2.3 Hybrid Median Filter [20]

In this filter, three median values are calculated in the N x N window: MRI is the median of horizontal and vertical R pixels, and MD is the median of diagonal D pixels. The hybrid median value is the median of the two median values and the central pixel C. For N=5;

$$\begin{vmatrix} D & * & R & * & D \\ * & D & R & D & * \\ R & R & C & R & R \\ * & D & R & D & * \\ D & * & R & * & D \end{vmatrix} \quad (7)$$

MD = median{D pixels & C};
MR = median{ R pixels & C };
Let X_{ij} and Y_{ij} be the input and the output at location (i,j) respectively, then the hybrid median filter is given by

$$Y_{ij} = \text{median}_{ij}\{MR, MD, C\}; \quad (8)$$

2.4 Proposed method

Iterative Relaxed Adaptive Center Weighted Median Filter (IRACWMF)

This method exhibits the advantage of ACWMF and HMF to detect noisy pixels. ACWMF adaptively adjusts window size to decide threshold values and HMF uses directional neighborhood evaluation for noise detection.

Let X_i^k and Y_i^k be the noisy input and the restored image of IRACWMF at pixel location i where k is the iteration steps. Let Z_i^k be the image restored by ACWMF and W_i^k be the output of HMF respectively. Z_i^k and W_i^k are used to form the subset to detect noisy pixels. Corrupted pixels are replaced by ACWMF value if the X_i belongs to the subset otherwise original value is retained.

$$Y_i^k = \text{Relaxed adaptive center weighted median}\{X_i^k\} = \begin{cases} Z_i^k, & \text{if } X_i \epsilon [Z_i^k \;\&\; W_i^k] \\ X_i, & \text{otherwise} \end{cases} \quad (9)$$

PSNR is evaluated between noisy image and the restored image Y_i^k. Y_i is fed back as noisy input in the next iteration step till PSNR value is maximized or k reaches maximum number of iterations.

Simulation Steps

1. ACWMF and HMF is applied to noisy MRI and CT image with various noise probability densities
2. Form a sublist with the median values of ACWMF and HMF
3. Apply IRACWMF and calculate PSNR and MAE
4. Feed the restored image as input and repeat steps 1-4 till the following conditions are satisfied
   If $[PSNR(k) - PSNR(k-1)] \leq 0$, where k is iteration step
   Restored image at the (k-1)th iteration step is the output image with optimized PSNR and MAE
   or
   If Number of iterations = Maximum number of iterations
   Restored image at the kth iteration step is the output image with optimized PSNR and MAE

3. FCM Clustering Algorithm

FCM is an unsupervised clustering algorithm [14,15,16] which allows one piece input vector to two or more clusters. It is based on minimization of the given objective function

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^m \|x_i - c_j\|^2 \quad (10)$$

where m is any real value greater than one and set to two by Bezdek [14]. u_{ij} is the degree of membership of x_i in the cluster j. x_i is the ith of d-dimensional data. C_j is the centre of the cluster j and $\|*\|$ is any norm showing the similarity between any measured data and the centre.

Fuzzy portioning is done through an iterative optimization of the objective function with the updating of membership of uij and the C_j cluster centres

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \quad (11)$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (12)$$

Termination of iteration is given by

$$\max_{ij}\{|u_{ij}^{k+1} - u_{ij}^k|\} < \varepsilon \quad (13)$$

where ε is a termination criterion between 0 and 1and k is the iteration steps.

3.1 Simulation Steps

1. For MRI & CT brain images corrupted by impulse noise of 30% probability densities, apply median filtering methods
2. Replace each pixel value by its spatially modified and filtered value and apply FCM algorithm.

FCM Algorithm [16]

3. Initialize U=[u_j] matrix, U(0)
4. At k-step, determine the centres vectors C(k)=[c_j] with U(k)
$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m}.x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{14}$$
5. Update U(k), U(k+1)
$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \tag{15}$$
6. If $\|U(k+1) - U(k)\| < \varepsilon$, then stop the iterations otherwise go to step 2.

4. Performance Metrics

4.1 Peak Signal to Noise Ratio

The median filtering methods are evaluated in terms of Peak signal-to-noise ratio and defined [17] as

$$PSNR = \frac{255^2}{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(I(i,j) - I_0(i,j))^2} \tag{16}$$

4.2 Cluster Error Index & Average Cluster Error Index

Quality of a partition provided by clustering algorithms is evaluated by a function called cluster error index and average cluster error index which are calculated by the following steps [18]
Let x(i) be the original image and y(i) be the noise filtered output of image, where i=1,2,...,N. N is number of pixels in the input image.
Let $x_r(i)$ and $y_r(i)$ be the clustered regions of x(i) and y(i) respectively, where r=1,...,C. C is number of clusters which is taken as 3 here.
Find out number of pixels in $x_r(i)$ and $y_r(i)$ denoted as N_r and M_r respectively.
CEI is given by

$$CEI = \frac{|N_r - M_r|}{N}; r = 1, \ldots, C \tag{17}$$

Average CEI of all the clusters is given by

$$ACEI = \frac{\sum_{r=1}^{C}\frac{|N_r - M_r|}{N}}{C} \tag{18}$$

5. Simulation and Results

5.1 Configuration

Among the commonly tested MRI Brain gray images, results have been tabulated for a MR image with a size of 260 X 260 and dynamic range of [0, 255]. MR images are subjected to salt and pepper noise with the probability densities ranging from 10% to 70%. For clustering analysis, MR image with 30% noise probability density has been taken. Various median filtering methods like standard median filter, Hybrid median filter , Relaxed median filter , Adaptive center weighted median filter and proposed method are tested over the input images. For restoration performance analysis, PSNR is calculated as given in equation.16 and tabulated in Table 1.

Among the commonly tested CT brain images, results have been tabulated in Table 2 for a CT brain gray image of size 256 x 256. Noise with probability densities ranging from 10% to 70% is introduced to the CT image and restoration is carried out using above mentioned filtering methods. CT brain image with 30% noise density is taken for clustering analysis.

For different median filtering algorithms, window size of 3 X 3 and 5 X 5 are variably used. Various window sizes have been experimented for different filters and the window sizes given here result in improved noise removal. SMF uses a window of size 3 X 3. 5 X 5 window often leads to blurring of edges in SMF. ACWMF starts with a window size of 3 X 3 and adaptively adjusts window size based on noise density. For the threshold values of $[\delta_0, \delta_1, \delta_2, \delta_3] = [55,40,25,15]$, ACWMF consistently performs well in removing fixed-valued impulses for all noise densities [11, 19]. Values of $[\delta_0, \delta_1, \delta_2, \delta_3] = [40,25,10,5]$ give better noise removal at very low noise densities. Parameter $s(\geq 0)$ varies for different images degraded with different noise densities, and performs well using $0 \leq s \leq 0.6$. For simulation s value is taken as 0.1. HMF uses 5 X 5 window by default. Window size of 3 X 3 leads to poor PSNR and MAE in HMF. RMF uses median filtering of window size 3 X 3 & 5 X 5. Since the proposed method uses ACWMF and HMF for sublist formation, variable window sizes are adopted.
Noise modeling, Image restoration and parameter calculations are carried out in MATLAB 7.7 (R2008b) environment.

5.2 De-noising Performance Analysis

De-noising performance for MRI images is analyzed by PSNR and Intensity values of single row as given in Tab 1 and Fig 1. From Tab 1, it is very clear that the proposed method outperforms other methods with considerable improvement. At noise densities upto 70%, proposed method proves superiority interms of PSNR over other methods. Fig.1 shows the similarity between intensity values of noise free MRI image and top two median filtering methods and is evident that the proposed method preserves most of the details of the original image.

Because of narrow distribution of gray levels in CT images, it is evident from Tab.2 that the proposed method shows slight improvement over other methods. Fig.2 also proves that the proposed method is superior to other methods in preserving fine details. For noise densities upto 60%, proposed method shows slightly improved results than other methods.

5.3 Clustering Performance analysis

Influence of above mentioned median filtering methods on subsequent Fuzzy C-Means Clustering of MRI images are given by CEI and ACEI in Fig. 3(a) - (b). In low intensity values, proposed method leads to more clustering error than other methods, but performs very well in mid and high intensity values. With respect to clustering, proposed method retains most of the original gray values in mid and high intensity range. Because of poor performance at low intensity values, ACEI of proposed method is also higher than other methods. Subjective analysis of Fig.5 also reveals that the proposed has very moderate influence over clustering of gray values using FCM clustering.

Clustering performance analysis of CT images are given in Fig. 4(a)- (b). Because of low contrast of CT images, proposed method results in good performance in low and mid intensity values. For high intensity values, HMF results in minimum error and proposed method ends in moderate error. ACEI, given in Fig. (b), also proves that the influence of proposed method over FCM Clustering is very less as compared to other methods. IRACWMF is able to restore most of the actual pixel values from the noise affected image inturn results in very small clustering error with respect to clustering of original image. Subjective analysis of Fig.6 also reveals that the proposed has very small influence over clustering of gray values using FCM clustering.

For MRI images, proposed method leads to better de-noising but results in high cluster error at low gray values. SMF leads to very small ACEI but ends in poor PSNR. HMF performs moderately in both clustering and de-noising. For CT images, proposed method proves good for de-noising as well as clustering. RMF and ACWMF give competitive de-noising performance but lead to poor clustering.

6. Conclusion

IRACWMF takes the advantages of ACWMF and HMF for noise removal. Based on simulation and analysis, it is evident that the proposed method performs well for image de-noising over other methods and influence of this method on FCM clustering is very less for CT images. For mid and high intensities of MRI image, influence of proposed method over clustering is very less. On the whole, it is concluded that the proposed de-noising algorithm provides better noise removal and has very less impact on clustering of gray values into different regions.

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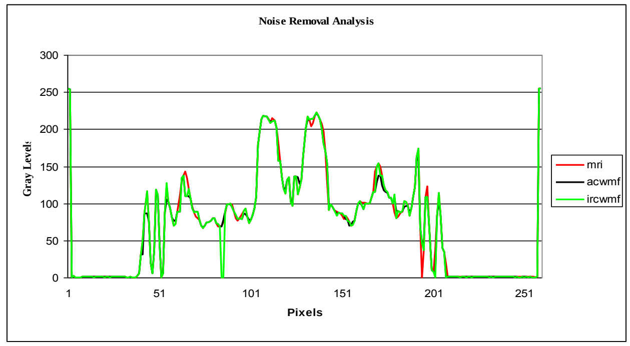


Fig. 1 Detail preservation of different methods given by gray values of horizontal scan line (row 150) of noise filtered MRI image

Noise Probability Densities	10%	20%	30%	40%	50%	60%	70%
SMF	26.23676	21.99232	18.79891	15.17316	12.52275	10.10219	7.908269
HMF	25.35421	22.91017	20.3812	17.44455	14.25005	11.45329	8.716423
RMF	25.63921	21.78556	18.83202	15.5197	12.90797	10.4317	8.028857
ACWMF	28.42438	23.95687	20.01271	15.89291	12.99196	10.39117	8.104661
IRACWMF	30.14414	26.46362	23.72209	20.73653	18.77777	16.50418	13.0217

Tab.1. PSNR of various median filtering methods for MRI Brain image with 30% noise probability density.

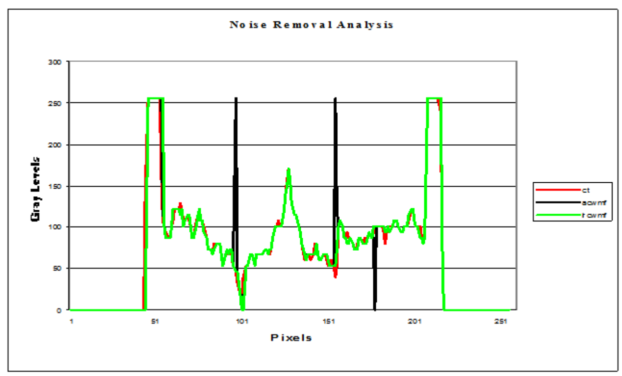
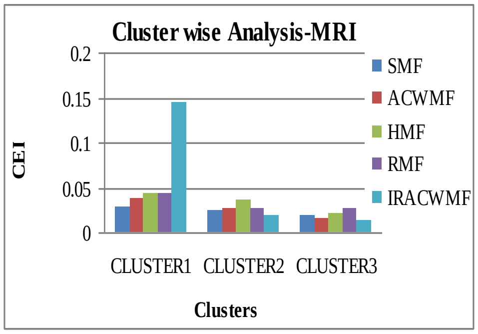


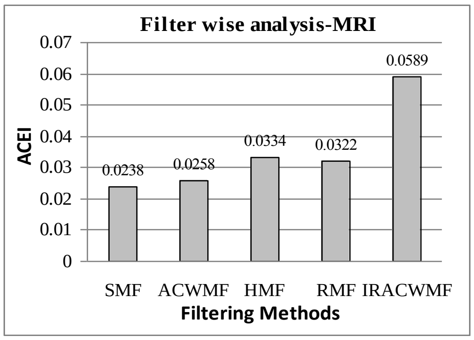
Fig. 2 Detail preservation of different methods given by gray values of horizontal scan line (row 150) of noise filtered CT image

Noise Probability Densities	10%	20%	30%	40%	50%	60%	70%
SMF	27.9343	23.71571	20.35378	16.48503	13.25434	10.62586	8.397197
HMF	25.01634	23.07113	21.07057	17.88876	14.68546	11.61596	9.072984
RMF	28.46101	24.34488	21.40063	17.81896	14.5354	11.78209	9.262981
ACWMF	28.17547	23.85203	20.2933	16.33103	13.14218	10.51931	8.304432
IRACWMF	28.99472	24.50788	23.54695	21.7155	19.8891	18.34733	8.026187

Tab.2. PSNR of various median filtering methods for CT Brain image with 30% noise probability density

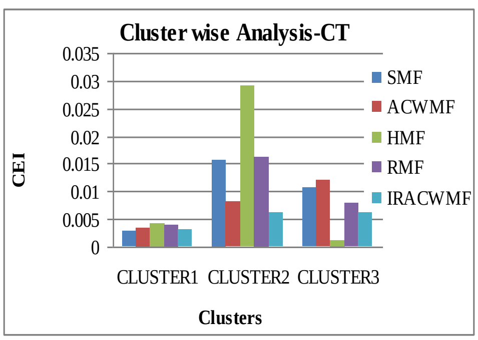


(a)

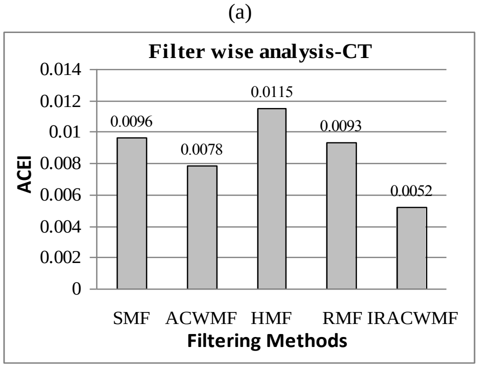


(b)

Fig. 3.(a) - (b) CEI and ACEI of FCM clustering of noise filtered MRI image



(a)



(b)

Fig. 4.(a) - (b) CEI and ACEI of FCM clustering of noise filtered CT image

INPUT AND OUTPUT IMAGES

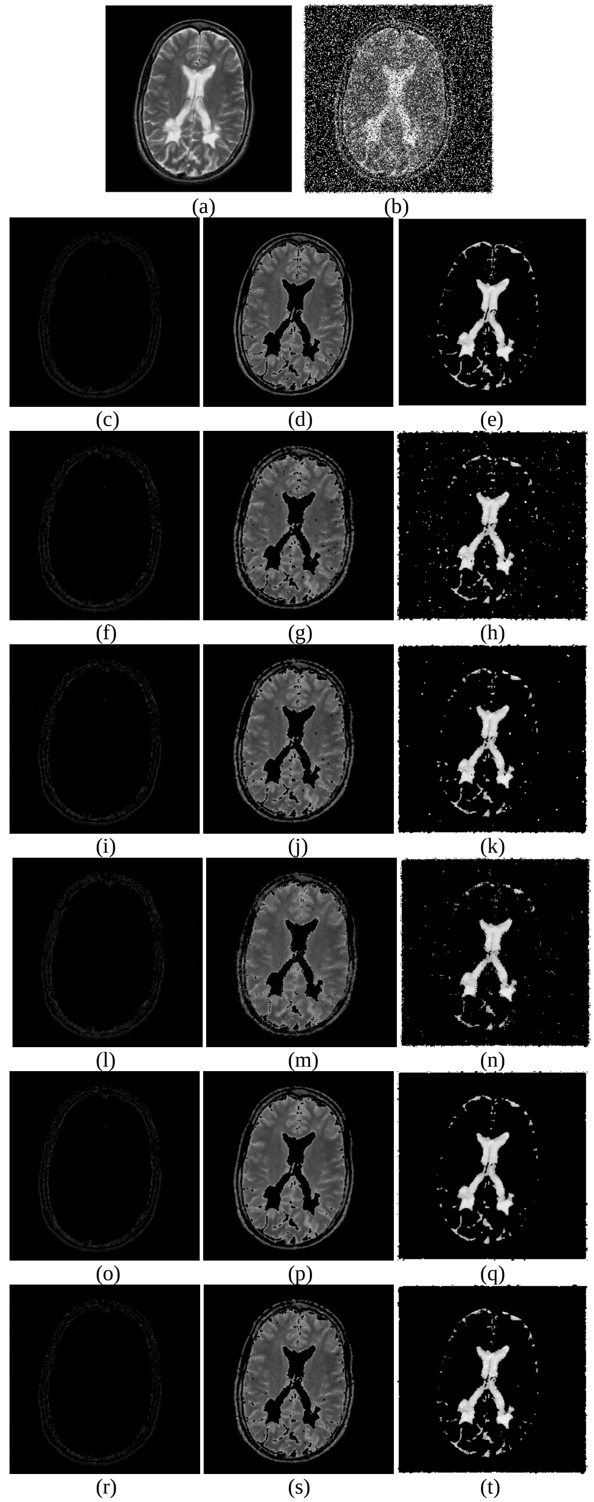
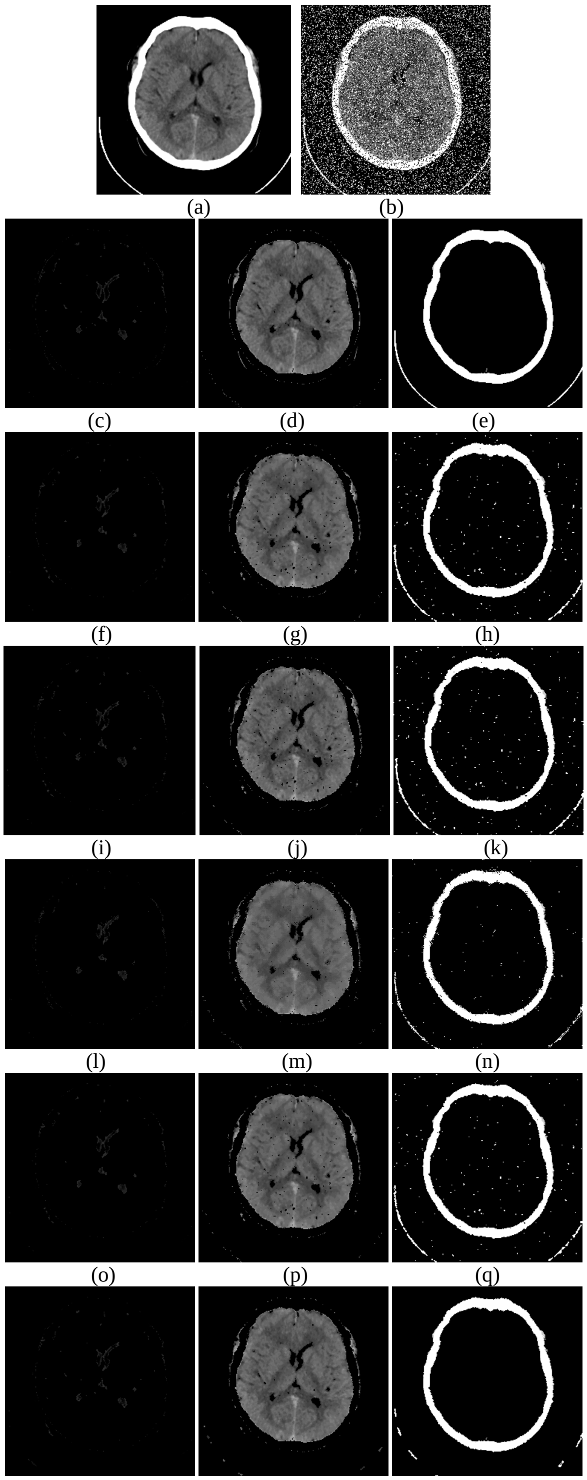


Figure 5 (a) MRI Brain Image (b) Image with 30% Impulse noise (c)-(t) Clustered regions of (c)-(e) Original Image (f)-(h) SMF (i)-(k) ACWMF (l)-(n) HMF (o)-(q)RMF (r)-(t) IRACWMF

INPUT AND OUTPUT IMAGES



(a) (b)

(c) (d) (e)

(f) (g) (h)

(i) (j) (k)

(l) (m) (n)

(o) (p) (q)

(r) (s) (t)

Figure 6 (a) CT Brain Image (b) Image with 30% Impulse noise (c)-(t) Clustered regions of (c)-(e) Original Image (f)-(h) SMF (i)-(k) ACWMF (l)-(n) HMF (o)-(q)RMF (r)-(t) IRACWMF