Impulse Noise Removal From Highly Corrupted Astronomical Images using Modified Progressive Switching Median Filter Guided by Neural Networks

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Abstract

In this paper, a novel and effective method for impulse noise removal in corrupted color images is discussed. The new method consists of three phases. The first phase is a noise detection phase where a modified self-organizing neural network is used to detect impulse noise pixels. The second is a noise filtering phase process is performed in recursive manner. Third phase is Histogram Equalizer the processed (output) image is obtained by mapping each pixel with level r_k in the input image into a corresponding pixel with levels s_k in the output image is presented. we propose a technique based on impulse noise detection by means of a self-organizing neural network and a class of the Modified Progressive Switching Median Filter(MPSM) that can remove impulse noise effectively while preserving details. Also, we add a histogram equalizer filter at the output of our proposed system in order to enhance the final output images. Experimental results demonstrate that the performance of the proposed technique is superior to that of the traditional median filter family for impulse noise removal in image applications.

Keywords: Image enhancement, Impulse noise removal, Self-organizing neural network, Noise-exclusive filtering, Switching approach, Modified Progressive Switching Median Filter.

1. Introduction

Digital images could be contaminated by impulse noise during image acquisition or transmission. The intensity of impulse noise has the tendency of being either relatively high or relatively low. Two types of impulse noise can be modeled:

1) Fixed valued impulse noise (salt& pepper) and
2) Random valued impulse noise.

Various filters have been proposed for denoising in the past and it is well known that linear filters could produce serious image blurring. As a result, nonlinear filters have been widely exploited due to their much improved filtering performance, in terms of noise removal and edges/details preservation. Median filter is one of the order-statistic filters, which falls in the group of non-linear filter; very much suitable for impulse noise filtering because of their simplicity and capability of preserving image edges/details. Nevertheless, because the typical median filters are implemented uniformly across the images, they tend to modify both 'noise' and ‘noise free’ pixels[12]. Different remedies of the median filter have been proposed, e.g. the Standard Median Filter (SMF), Weighted Median Filter (WMF) and Adaptive Median Filter. These filters first identify possible noisy pixels and then replace them by using the median filter or its variants, while leaving all other pixels unchanged. In these filters more weight is given to some pixels in the processing window. At higher noise densities the median may also be a noisy pixel and this produces streaking at higher noise densities. The major disadvantage of this method is, the quality of the restored image degrades as the noise level increases above 50 percentage [3,10].

Hence details and edges are not recovered satisfactorily, especially when the noise level is high. Decision Based Median Filtering Algorithm(DBA), Robust Estimation Algorithm(REA) [10] was proposed to remove high density impulse noise. Decision Based Algorithm removes high density salt and pepper noise. The corrupted pixels are replaced by median

or the immediate neighborhood pixel. At higher noise densities the median may also be a noisy pixel and this produces streaking at higher noise densities. The major disadvantage of this method is, the quality of the restored image degrades as the noise level increases above 50 percentage[10].

An impulse detector is required to determine the noise corrupted pixels. A median filter based switching scheme is used to design the impulse detector. The basic idea is to calculate the absolute difference between the median filtered value and the original input value for each pixel. If the difference is larger than a given threshold, the output is the median filtered value; otherwise, the output is the original input value. It must be noted that it’s important to replace the corrupted value with one from a local window or some linear combination of local samples. In other words, only ranking the statistical information concerning neighboring pixel values is employed insufficiently to represent the real structure, such as direction and curvature, of the local region. Substantially different from previous algorithms, one approach is developed by modeling the local region using some function approximation algorithms.

In this paper, present impulse noise removal systems that use the neural networks to detect impulse and use the PSM (Progressive Switching Median) filter to restore images corrupted by salt-pepper impulse noise[5]. The algorithm is developed by the following two main points: (1) switching scheme - an impulse detection neural network is used before filtering, thus only a proportion of all the pixels will be filtered and (2) progressive methods both the impulse detection and the noise filtering procedures are progressively applied through several iterations. In addition to a histogram equalizer to enhance the resultant quality, which yields, better restoration results, especially for the cases where the images are highly corrupted. The rest of the paper is organized as follows; 2.Modified progressive switching median Filter is presented in Section 2. Section 3 introduces the proposed for Self-organizing neural network work. Section 4 reports the experimental results to demonstrate the performance of the proposed system. Finally, conclusions are drawn in section 4.

2.Modified Progressive Switching Median Filter

An algorithm (MPSM) is based on the known progressive switching median filter (PSM) [5] and adaptive central weighted median filter. It uses switching schema which

includes two stages of noisy image processing[13]:

1. Preliminarily detection of noise corrupted pixels of digital image.

can also be properly filtered. Figure (1) shows the system block diagram

2. Filtering of noise impulses which have been detected in first stage of processing using gathered information about image properties.

At first stage Adaptive Central Weighted Median filter (ACWM)-based impulse detector is used for detect noise corrupted pixels and at the second stage PSM filtering procedure is used to replace such pixels with approximately correct values. At the next section some results of image enhancement are depicted.

Digital image enhancement techniques are concerned with the improvement of the quality of the digital image. The principal reason of enhancement techniques is to process an image so that the result is more suitable than the original image for a specific application. The objective of all noise-reducing processes is to suppress noise without blurring or degrading the digital image quality. Table (1) show Comparison of filters values on Astronomy Images by different percentages of impulse noise.

We name D(Ki,j) as a direction index. Each direction index is sensitive to the edge aligned with a given direction. Then, the minimum of these four direction indexes is used for impulse detection, which can be denoted as:

$$R_{i,j}=\min D(K_{i,j}) \qquad (1)$$

Where $1 \leq K \leq 4$. Now, we will discuss the value of Ri,j in three cases:

1) When the current pixel is a noise-free flat-region pixel, Ri,j is small, because of the four small direction indexes.

2) When the current pixel is an edge pixel, Ri,j is also small, because at least one of direction indexes is small.

3) When the current pixel is an impulse, Ri,j is large, because of the four large direction indexes.

In definition of Ri,j , we make full use of the information aligned with four directions. So from the above analysis, we can find that by employing a threshold T we can identify the impulse from the noise-free pixels, no matter which are in a flat region, edge, or thin line. Then, we define the im pulse detector as:

$$y_{i,j}= \begin{cases} \text{noisy pixel if } r_{i,j} > T, \\ \text{noise-free pixel if } r_{i,j} \leq T \end{cases} \qquad (2)$$

Application to the Color Images ,the DWM filter also can be extended to remove random-valued impulse noise for color images. In impulse detector, we will treat each color component as an independent entity. After calculating the direction indexes corresponding to the three color channels, we add up them, and find the minimum value as ri;j , like in (1). Then, impulse detector can be defined in the same way asin (2). In the noise filtering, the vector median filter with the 3 * 3 window will be used to restore the noisy pixels identified. Figuer (2)show Original image , Gray image, Binary image and Enhancement Image which Appling in our system.

The performance of imaging sensors is affected by a variety of factors, such as environmental conditions during image acquisition, and by the quality of the sensing elements themselves. For instance, in acquiring images with a charged coupled device (CCD) camera, light levels and sensors temperature are major factors affecting the amount of noise in the resulting image.

3. Proposed Technique

A hybrid technique is presented to restore images corrupted by impulse noise. As a preprocessing procedure of the noise cancellation filter, neural network impulse detector is used to generate a binary flag image, which gives each pixel a flag indicating whether it is an impulse. This flag image has two uses: (1) a pixel is modified only when it is considered as an impulse; otherwise, it is left unchanged, and (2) only the values of the good pixels are employed as useful information by the noise cancellation filter. To remove noses from the corrupted image, we use the filtering operation by iteratively applying the median where the noisy pixels in the current iteration are used to help the process of filtering other pixels in the subsequent iterations. An important distinction between the two parts is that in the first part the processing depend on the whole corrupted pixels, but in the second part the processing depend on the clean pixels only. A main advantage of the recursive manner of the second part is that some impulse pixels located in the middle of large noise blotches .The Histogram equalization Filter is dedicated to enhance the visual quality of the filtered image .

3.1 Neural Network Impulse Noise Detection

The noise considered by our algorithm is only salt-pepper impulsive noise which means:
only a proportion of all the image pixels are corrupted while other pixels are noise-free a noise pixel takes either a very large value as a positive impulse or a very small value as a negative impulse.
In this paper, we use noise ratio R($0\leq R\leq 1$) to represent how much an image is corrupted. For example, if an image is corrupted by R = 50 % impulse noise, then 25 % of the pixels in the image are corrupted by positive impulses and 25 % of the pixels by negative impulses.
Noisy pixels can be characterized by their local statistical properties. To extract features from local statistics, a window is used to pass through the entire corrupted image. In this paper two local features are chosen to form the input vector Z. one is the pixel value and the other is the median deviation that is calculated from the difference between the median of the pixels in the window and the pixel value [6]. If we use Ωi^{WD} to represent the set of the pixels within a WxW window centered about i

$$\Omega i^{WD} = \{j=(j_1,j_2) | i_1 - (W-1)/2 \leq j_1 \leq i_1 + (W-1)/2,\ i_2 - (W-1)/2 \leq j_2 \leq i_2 + (W-1)/2\} \quad (3)$$

Where W is the window size

Thus:

$$Z = (P_1 , P_2) \quad (4)$$

Where :

$P_1=V_i$; V_i is the value of the pixel in the center of the window; $V_i \in \Omega i^{WD}$

$$P_2=\mathrm{Median}\{V_j | j \in \Omega_i^{WD}\} - V_i \quad (5)$$

The essential point of the neural network used in this paper is to build up the clusters using the Euclidean distance measure between the input Z and the weights W i assuming:

$$W_i=(W_{i1},W_{i2}) \quad (6)$$

3.2 Impulse Noise Filtering

The filtering process is performed in recursive manner. Let $G_i^{(n)}$ a binary flag image, where $G_i^{(n)} = 0$ means that the pixel i is a good and $G_i^{(n)} = 1$ means that it is an impulse that should be filtered. Figuer(3)show Original Images with Appling filters to find Median Images and MPSM Images.

In the nth iteration (n=1 , 2 , . . .) , for each pixel $Vi^{(n-1)}$, we compute its median value $mi^{(n-1)}$ of $W_F * W_F$ (W_F is an odd integer and not smaller than 3) window centered about it. But the median value here is selected from only good pixels. Let M denote the number of all the pixels with $Gi^{(n)} = 0$ in the $W_F * W_F$ window. If M is odd, then:

$$\mathbf{mi^{(n-1)} = Median \{Vj^{(n-1)} | Gj^{(n-1)} = 0, j \in \Omega i^{WF}\}} \quad \textbf{(7)}$$

if M is even but not 0, then :

$$\mathbf{mi^{(n-1)} = (Med_L \{ Vj^{(n-1)} | Gj^{(n-1)} = 0, j \in \Omega i^{WF} \} + Med_R \{ Vj^{(n-1)} | Gj^{(n-1)} = 0, j \in \Omega i^{WF} \}) / 2} \quad \textbf{(^)}$$

where Med_L and Med_R denote the left and the right median values, respectively [11]. That is, Med_L which is $(M/2)^{th}$ largest value and Med_R which is (M/2+1)th largest value of the sorted data. The value of $Vi^{(n)}$ is modified only when the pixel i is an impulse and M>0 :

$$\mathbf{V_i^{(n)} = \begin{cases} m_i^{(n-1)} & \text{if } G_i^{(n-1)} = 1 , M > 0 \\ V_i^{(n-1)} & \text{else} \end{cases}} \quad \textbf{(9)}$$

Once an impulse pixel is modified, it is considered as a good pixel in the subsequent iterations:

$$\boldsymbol{G_i^{(n)}} = \begin{cases} \mathbf{G_i^{(n-1)}} & \textbf{if } \mathbf{V_i^{(n)} = V_i^{(n-1)}} \\ \mathbf{0} & \textbf{if } \mathbf{V_i^{(n)} = m_i^{(n-1)}} \end{cases} \quad \textbf{(10)}$$

The procedure stops after the NF^{th} iteration when all the impulse pixels have been good pixels, i.e., $\Sigma i \, Gi^{(NF)} = 0$ Then obtain the image $\{Vi^{(NF)}\}$ that is the filtered image.

3.3 Histogram Equalizer

The histogram of a digital image with gray levels in the range [0,L-1] is a discrete function $h(r_k) = n_k$, where rk is the kth gray level and nk is the number of pixels in the image having gray level rk . we assume that rk has been normalized to the interval [0,1], with r0 representing black and r1 representing white. It is common practice to normalize a histogram by dividing each of its values by total number of pixels in the image, denoted by n. Thus, the normalized histogram is given by [4]:

$$\mathbf{Pr(r_k) = n_k / n, \quad for\ k=0,1,2, \ldots,L-1.} \quad \textbf{(11)}$$

Histograms are the basis for numerous spatial domain processing techniques. Histogram manipulate can be used effectively for image enhancement. For any rk satisfying the aforementioned conditions, we focus attention on transformation of the form:

$$s_k = T(r_k) = \sum_{j=0}^{k} p_r(r_j)$$

$$= \sum_{j=0}^{k} \frac{n_j}{n}, \qquad k = 0,1,2,\ldots\ \ldots\ldots, \quad L - 1 \qquad (12)$$

that produces a level sk for every pixel value rk in the original image. For reasons that we assume that the transformation function $T(r_k)$ satisfies the following conditions:
$T(r_k)$ is single –values and monotonically increasing in the interval $0 \le r_k \le 1$; and $0 \le T(r_k) \le 1$ for $0 \le r_k \le 1$.
Thus, the processed (output) image is obtained by mapping each pixel with level rk in the input image into a corresponding pixel with levels s_k in the output image. As known, a plot of $Pr(r_k)$ versus rk is called a histogram.
The above discussed method works for gray scale images. In order to extend it to color images, we apply this method to each channel independently. If a pixel is classified as noisy in any of the three R, G or B channels, then it is classified as a corrupted pixel in the color image.
Each pixel value in the difference image is the vectorial difference between the original and the recovered image in RGB color space.
Since most of the difference values lie in the range [0–64], the pixel values in the difference images presented represent only those values which lie in the range [0 − 64] but scaled by a factor of 4 to observe the difference more keenly.

4. Simulation Results

In general, a corrupted image can be modeled as:

$$\mathbf{X(i, j)} = \begin{cases} \mathbf{O(i, j)\ with\ a\ probability\ of\ 1 - p} \\ \mathbf{N(i, j)\ with\ a\ probability\ of\ p} \end{cases}$$

(1٣)

where (i, j) is the pixel location, 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. There are mainly three types of noise Models used in this paper depending on the values which N(i, j) can take.
In our experiments, the original test images are corrupted with fixed valued salt and pepper impulses for Highly Corrupted Astronomy Images.

N(i, j) = O(i, j) + X **(1٤)**

where X is a random value chosen uniformly from the range [0,maximam values for pixel].
The qualitative assessment of the recovered image is done by forming a difference (between the original and the recovered) image. For quantitative assessment of the restoration quality, the commonly used Peak Signal to Noise Ratio (PSNR) was used[9]where Signal-to-noise ratio expressed in dB is:

$$\mathrm{SNR} = 10 \cdot \log_{10} \left[\frac{\sum_{0}^{n_x-1} \sum_{0}^{n_y-1} [r(x,y)]^2}{\sum_{0}^{n_x-1} \sum_{0}^{n_y-1} [r(x,y) - t(x,y)]^2} \right]$$

. **(15)**

And Peak Signal to Noise Ratio (PSNR) is:

PSNR=10log10 (2552/MSE) (16)

where m is the total number of color components, N the total number of image pixels and xik and oik the kth component of the noisy image pixel channel and its original value at pixel position “i” respectively .

For the evaluation of the detail-preservation capabilities of the proposed filter, the Mean Absolute Error has been used.

$$\textbf{MAE}=\sum_{i=1}^{n}\sum_{k=1}^{m}(xik-oik)/nm \qquad \textbf{(17)}$$

Superior performance of the technique is indicated by high PSNR values and low MAE values.

Normalized Mean Square Error (NMSE), which is used to evaluate the restoration performance.

Table (1): Comparison of filters on “Astronomy Image” image by different percentages of impulse noise using NMSE.

$$\text{NMSE} = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(F_{ij}-Y_{ij})^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(F_{ij})^2} \qquad \textbf{(18)}$$

Where Fij is the original image, Yij is the filtered image and NxN is the size of the image.

5. Self-organizing feature maps

The Self-Organizing Feature Map is an unsupervised, competitive learning technique, which works on a regular neuron grid of given lattice topology. The algorithm requires a given set of data points in form of vectors:

$$\mathbf{x}=[\xi_1,\xi_2,\ldots,\xi_n]\in\mathbb{R} \qquad (19)$$

The neurons are stored similarly in vector form:

$$\mathbf{m}=[\mu_1,\mu_2,\ldots,\mu_n]\in\mathbb{R} \qquad \textbf{(20)}$$

supposed we have n-dimensional data space. The algorithm consists of two steps[14]:

1. ordering, which is a phase delivering only rough weights
2. tuning, which refines the neurons weight vectors.

Each step has the same sub steps, namely

1. the selection of the winner neuron
2. the weight update for the winner and its neighbors.

The winner is selected by the evaluation of a distance measure between the data points and the neuron weights:

$$\|\mathbf{x}-\mathbf{m}_c\|=\min_i\{\|\mathbf{x}-\mathbf{m}_i\|\} \qquad \textbf{(21)}$$

Where **c** is the identifier of the winner neuron. The reformulated condition gives directly the identifier **c** :

$$c=\arg\min_i\{\|\mathbf{x}-\mathbf{m}_i\|\} \qquad \textbf{(22)}$$

The distance measure can be any distance norm, in the practice mostly the Euclidean one is used. In the weight update phase the weights of the winner and its neighboring neurons are modified as follows:

$$\mathbf{m}_i(t+1)=\mathbf{m}_i(t)+h_{ci}(t)[\mathbf{x}-\mathbf{m}_i(t)] \qquad \textbf{(23)}$$

Where
$\mathbf{m}_i(t)$ is the current weight vector to be modified
$\mathbf{m}_i(t+1)$ is the weight vector of neuron *i* in the next iteration (called epoch)
$h_{ci}(t)$ a weight factor.

Equation (23) is the *Kohonen learning rule*; it means, that the weights after the modifications are calculated from the difference (distance) between the neuron and the data point multiplied by a factor.
The factor is a monotonically decreasing function in time, and it consists of a second distance norm to consider the neuron neighborhood[14]:

$$h_{ci}(t) = \begin{cases} \alpha(t) & \text{if } i \in N_c(t) \\ 0 & \text{if } i \notin N_c(t) \end{cases} \tag{24}$$

where
$N_c(t)$ is the neighborhood function – it decreases in function of t
$\alpha(t)$ is the learning rate (also a monotonically) decreasing function of t .

Figure(4) show the regular neuron grid is the base of the SOFM algorithm. After the winner has been found, its neighborhood $N_c(t)$ must be defined, as marked by concentric gray squares.
Figures (5)show the behavior of the SOM with a different learning rate initialized during the training epoch. With a high learning rate, unit seasily overwrite their prototype vector with each newkind of input vector. As per the empirical study the results say with a smaller learning rate it does not do preserve their prototype vectors, and provides less accuracy. Similar data clusters in a particular region of the environment populated with sensor units. Figure (6) show Comparison between the proposed one and its modification for Images while Figure (7) show Comparison between different techniques and the proposed one at different signal to noise ratios.

6. Conclusions

The pixel values and the median deviations are then used to identify the noise classes. Sorting is first performed in terms of median deviation. Ten pixel values corresponding to the maximum and the minimum median deviations are selected. The histogram of these values is calculated, and the peak value of each group is selected as the noise class. Since the cluster centers, which represent the impulse noise, have been detected the binary image which is generated from this part becomes the output of matching pixels with the cluster centers.
A neural network guided progressive switching median (PSM) Filter is introduced to remove impulse noise in images. Detecting the positions of the noisy pixels and then applying a progressive switching filter do this. By utilizing the uncorrupted image pixels only, the scheme is capable of effectively eliminating the impulses while retaining image integrity. The visual examples and associated statistics show that the proposed methods is better than the traditional median-type filters in the aspects of the noise removal, edge and fine details preservation, as well as minimal signal distortion. However, the traditional median-type filters have smaller time calculations than the proposed method. Therefore, the proposed system is used for better noise removal and minimal signal distortion especially at high percentages of impulse noise regardless of the processing time. On the other hand, the traditional median-type filters with a small processing time can be used especially at low percentage of the impulse noise at the expense of minimum noise removal and signal distortion occurrence.

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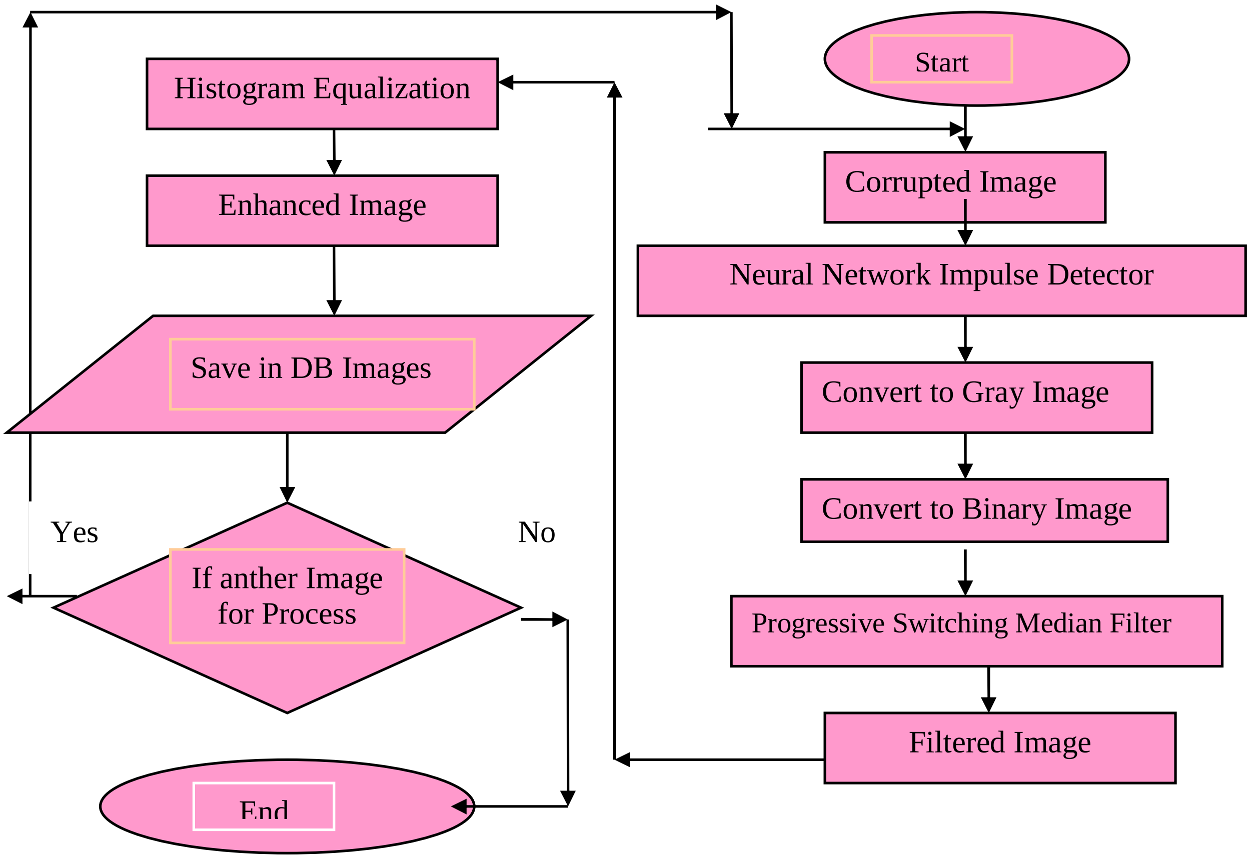
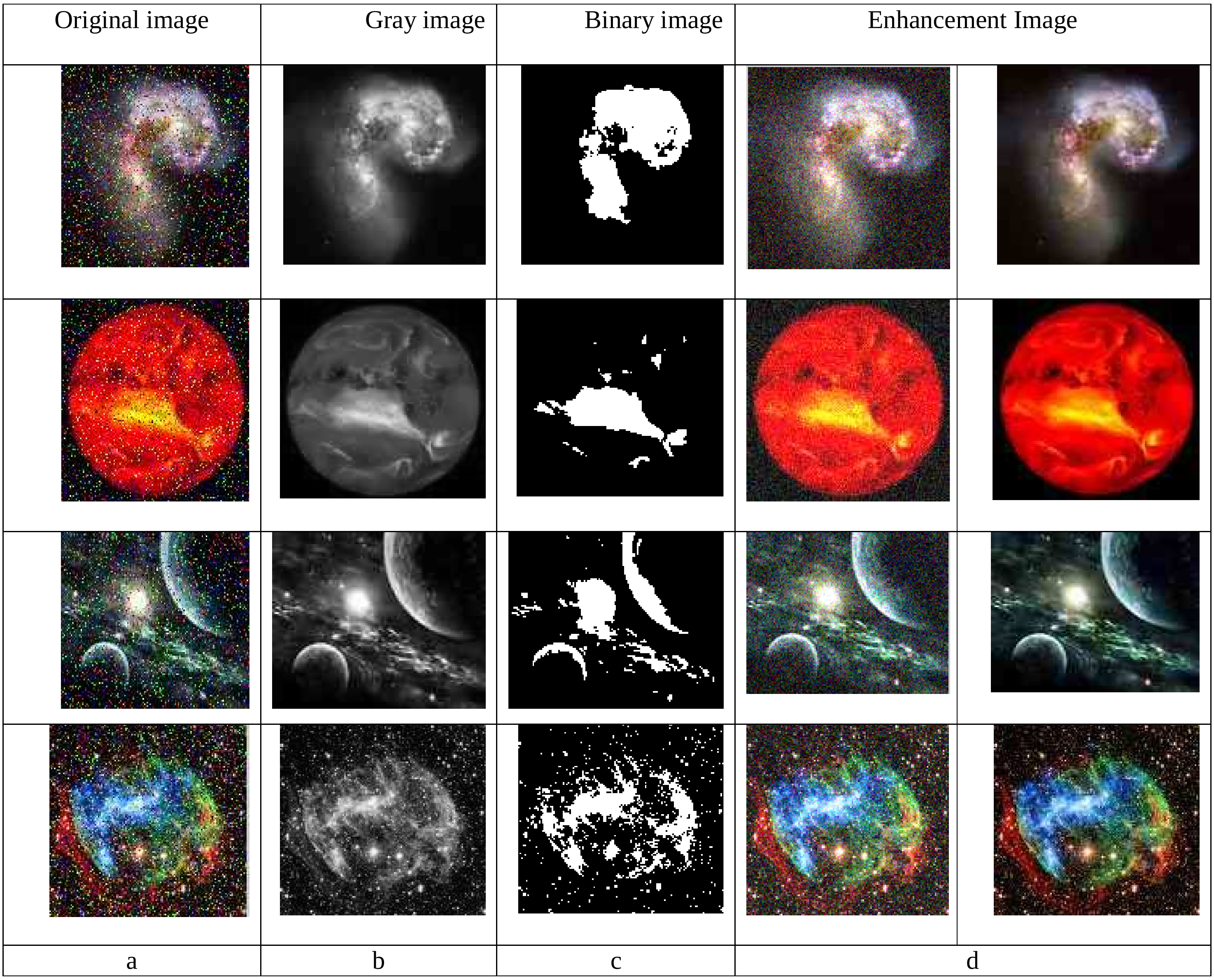


Fig. (1): The system block diagram

Table (1): Comparison of filters values on Astronomy Images by different percentages of impulse noise

Filter Noise %	MEDIAN	MPSM	NEN	Proposed
10%	0.0115	0.0020	0.0019	0.0009
30%	0.0220	0.0135	0.0086	0.0059
50%	0.0543	0.0321	0.0142	0.0090
70%	0.0 650	0.1244	0.1 019	0.1170
90%	0.2930	0.2096	0.2058	0.2169

Fig. (2): (a) Original image , (b) Gray image, (c) Binary image , (d) Enhancement Image



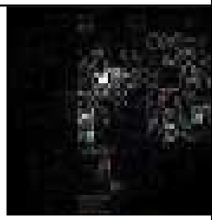
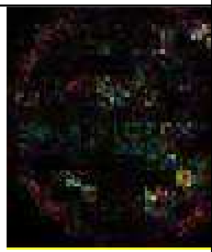
Filter Noise %	Corrupted	Median	MPSM
30%			
60%			
90%			

Fig.3 (a) Original Image (b) Median Image (c) MPSM Image

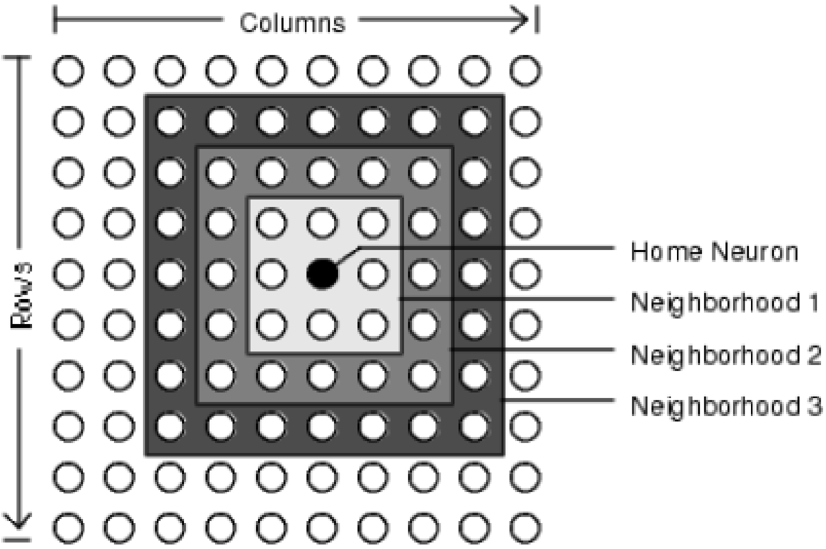


Fig 4. regular neuron grid is the base of the SOFM algorithm[14]

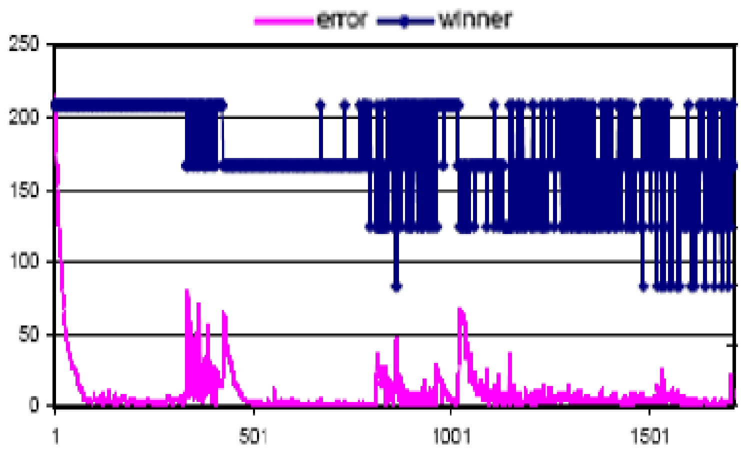


Fig. 5 The behavior of the SOM with a different learning rate

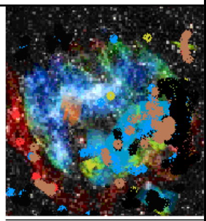
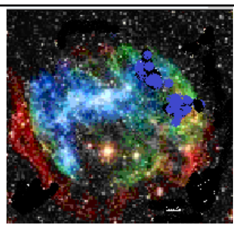
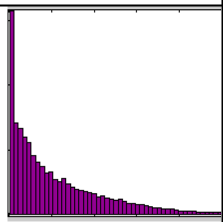
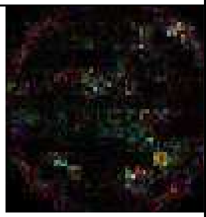
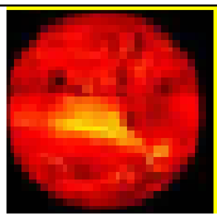
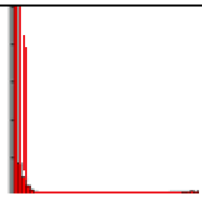
Filter Noise %	Corrupted	Proposed	Histogram	Proposed And Histogram Equalizer
30%				
90%				

Fig. (6): Comparison between the proposed one and its modification.

Filter **Noise %**	***Corrupted***	***MEDIAN***	***MPSM***	***NEN***	***PROPOSED***
30%					

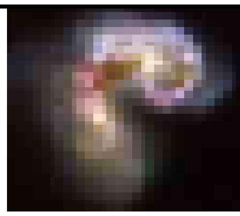
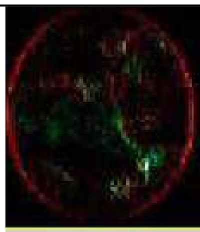
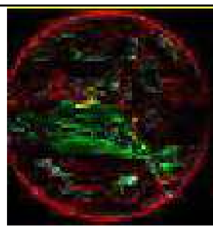
60%					
90%					

Fig. (7): Comparison between different techniques and the proposed one.
At different signal to noise ratios.