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IMPULSE NOISE REMOVAL FROM HIGHLY CORRUPTED IMAGES USING NEW HYBRID TECHNIQUE BASED ON NEURAL NETWORKS AND SWITCHING FILTERS

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Abstract: One well-studied image processing task is the removal of impulse noise from images. Images are often corrupted by impulse noise due to errors generated in noisy sensors, communication channels, or during storage. It is important to eliminate noise in the images before some subsequent processing, such as edge detection, image segmentation and object recognition. For this purpose, many approaches have been proposed. In the past two decades, median-based filters have attracted much attention because of their simplicity and their capability of preserving image edges. Nevertheless, because the typical median filters are implemented uniformly across the image, they tend to modify both noise and good pixels. To avoid the distortion of good pixels, the switching approach is introduced by some published works, In this case the impulse detection algorithms are employed before filtering and the detection results are used to control whether a pixel should be modified or not. This approach has been proved to be more effective than uniformly applied methods when the noise pixels are sparsely distributed in the image. However, when the images are very highly corrupted, a large number of impulse pixels may connect into noise blotches. In such cases, many impulses are difficult to be detected, thus can't be eliminated. In addition, the error will propagate around their neighborhood regions. In this paper, we propose a technique based on impulse noise detection by means of a self-organizing neural network and a class of the switching filters 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.

INTRODUCTION

Image noise suppression is a highly demanded approach in digital imaging systems. Impulsive noise is one such noise, which is frequently encountered problem in acquisition, transmission and processing of images. In the area of image restoration, many state-of-the art filters consist of two main processes, classification (detection) and reconstruction (filtering). Classification is used to separate uncorrupted pixels from corrupted pixels. Reconstruction involves replacing the corrupted pixels by certain approximation techniques.

Possible sources of image noise include photoelectric exchange, photo spots, errors in image communication, etc. Such noise causes speckles, blips, ripples, bumps, ringing, and aliasing that not only affects the visual quality, but also degrades the efficiency of data compression and coding. Developing robust de – noising and smoothing techniques is consequently important.

A popular used noise model is Gaussian, since it is susceptible to linear (stationary) analysis. In practice, many physical noise environments are more accurately modeled as impulsive, which is characterized by heavy – tailed, non – Gaussian distributions. Such noise includes atmospheric noise (due to lightening or spurious radio emission in radio communication), ice cracking and aquatic animal activity in sonar and marine communication, and relay – switch noise in telephone channels. Moreover, a great variety of synthetic noise sources (such as automatic ignitions, neon lights, and other electronic devices) are also impulsive. Impulsive interference may be broadly defined, as random signal corruption, which spares of high or low amplitude relative to nearby uncorrupted signal values [1].

To reduce the impulse noise level in digital images various filters were introduced amongst which (SAM) Simple Adaptive Median is one of the method, which uses hybrid technique of adaptive median filter and switching median filter. Based on local noise level on digital images size of filter is changed i.e. square filter technique is used basically in SAM. SAM was compared with three derivatives namely Weighted SAM (WSAM), Circular SAM (CSAM) and Weighted CSAM (WCSAM) and images were restored maximum of impulse noise, but as Circular filter has complicated implementation that resulted in increase of execution time. [2], [3], [4], and [5].

A large variety of filtering algorithms have been proposed to perform effective noise cancellation while preserving the image structure [6],[7]. Typical examples include the neighborhood mean and median filter. Most of the classical linear digital image filters, such as averaging low pass filters have low- pass characteristics and they tend to blur edges and to destroy lines, edges and other fine image details. One selection to this problem is the use of median filter, which is the most popular order statistics filter under the nonlinear filter classes [7]. This filter has been recognized as a useful filter due to its edge preserving characteristics and its simplicity in implementation. Applications of the median filter require caution because median filtering tends to remove image details such as thin lines and corners while reducing noise. One way to improve this is the weighted median (WM) filter [7], which is an extension of the median filter that gives more weight to some values within the window. The special case of the median filter is the center – weighted median (CWM) filter, which gives more weight to the central value of the window. It is also reasonable to give emphasis to the central sample, because it is one that is the most correlated with the desired estimate.

A new switch median filter is presented for suppression of impulsive noise in image [8]. The filter is Modified Adaptive Center Weighted Median (MACWM) filter with an adjustable central weight obtained by partitioning the observation vector space.

Dominant points of the approach are partitioning of observation vector space using clustering method, training procedure using LMS algorithm then freezing weights in each block are applied to test image. In the training phase, Least Mean Square (LMS) algorithm use to train center weight in each block then obtained weights used in testing phase. Final results shows better performance in the impulse noise reduction over standard images.

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.

One known technique is α - trim filter, in which the median is calculated first, and then the pixels in a neighboring window are ordered according to their absolute difference from the median value (from minimum to maximum). The first three (or several) pixels close to the median are weighted and averaged to substitute for the observed pixel luminance.

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 the literature there are polynomial approximation (PA) filter and adaptive-order polynomial approximation (AOPA) filter that depend heavily on that approach [7].

In [9], [10] a comparative study is present on six methods such as median filter, Progressive switching median filter, Fuzzy switching median filter, Adaptive median filter, Simple adaptive median filter and its modified version i.e. Modified Simple Adaptive median filter. Objective evaluation parameters i.e. mean square error; peak signal-to-noise ratio is calculated to quantify the performance of these filters.

One obvious observation in the literature is that the success of impulse noise removal that depends on the neural network to detect the impulses and locate their positions in the image, then replacing the impulses by the best estimates using only the uncorrupted pixels.

In this paper, we 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. 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 is applied 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; Noise model is presented in Section 2. Section 3 introduces the proposed work. Section 4 reports the experimental results to demonstrate the performance of the proposed system. Finally, conclusions are drawn in Section 4.

NOISE MODEL

The principal sources of noise in digital images arise during image acquisition (digitization) and / or transmission. 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. Images are corrupted during transmission principally due to interference in the channel used for transmission [7]. We assume that noise is independent of spatial coordinates, and that it is uncorrelated with respect to the image itself (that is, there is no correlation between pixel values and the values of noise components).

The PDF of an Impulse (salt-and-pepper) noise of random variable, z, is given by:

$$\mathbf{p(z)} = \begin{cases} p_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

if b > a , gray – level b will appear as a light dot in the image. Conversely, level *a* will appear like a dark dot. If either P_a or P_b is zero, the impulse noise is called unipolar. If either probability is zero, and especially, if they are approximately equal, impulse noise values will resemble salt-and-pepper granules randomly distributed over the image. For this reason, bipolar impulse noise also is called salt-and-pepper noise. Shot and Spike noise are also terms used to refer to this type of noise. Normally, impulse noise is a result of a random process such that the value of the corrupted pixel is either the minimum or a maximum value of a display instrument. The noise could be positive (maximum), negative (minimum) or a mixture (salt and pepper). Scaling is usually a part of the image digitizing process. Because impulse corruption usually, is strongly compared with the strength of the image signal, impulse noise generally is digitized as extreme (pure black or white) values in an image. Thus, the assumption usually is that a and b are "saturated" values, in the sense that they are equal to the minimum and maximum allowed values in the digitized image. As a result, negative impulse appears as black (pepper) points in an image. For the same reason, positive impulses appear white (salt) noise. For an 8-bit image this means that a = 0 (black) and b = 225 (white).

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.

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 noises 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 depends on the whole corrupted pixels, but in the second part the processing depends 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 can also be properly filtered. Fig. (1) shows the system block diagram:

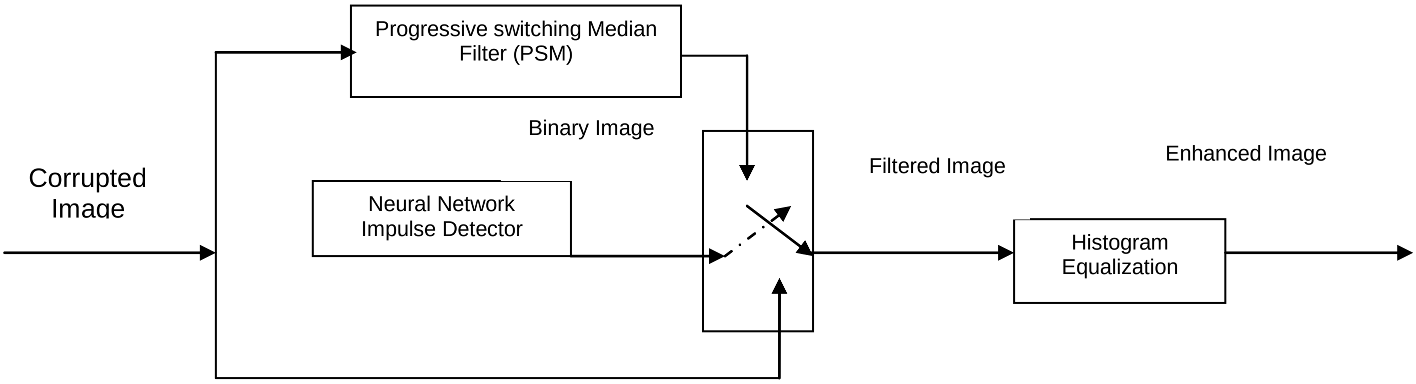

Figure. (1): The system block diagram

The histogram equalization filter is dedicated to enhance the visual quality of the filtered image

Neural Network Impulse Noise Detection:

The objective of segmentation is to divide a given image into meaningful regions that are homogeneous according to certain properties [11],[12] and [13]. Two basic categories of classification methods exist for machine learning: supervised and unsupervised. In supervised learning, the user supervises the process by initially selecting features from sample patterns for each possible class. In this way, the classification algorithm determines what each class looks like and then assign each testing pattern to one of the predefined classes. It is necessary to have some prior knowledge to form the basis of learning. In contrast to supervised learning, the unsupervised learning method is used when there is little or no available classification information.

The noise detection part is performed using neural networks. The field of neural networks has a long history and the field is still developing rapidly. Neural networks are composed of many simple elements operating in parallel. These elements are inspired by biological nervous systems. The network function is determined largely by the connections among elements. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Neural networks have been trained to perform complex functions in various fields. It serves the purpose of cluster discovery. Similar to networks using a single Kohonen layer with competitive learning neurons, this network learns clusters in an unsupervised mode. The novel property of the ART1 network is the controlled discovery of clusters. In addition, the ART1 network can accommodate new clusters without affecting the storage capabilities for clusters already learned. The network produces clusters by itself, if such clusters are identified in input data, and stores the clustering information about patterns or features without a priori information about the possible number and type of clusters. Essentially the network "follows the leader" after it originates the first cluster with the first input pattern received. It then creates the second cluster if the distance of the second pattern exceeds a certain threshold; otherwise the pattern is clustered with the first cluster. This process of pattern inspection followed by either new cluster origination or acceptance of pattern to the old cluster is the main step of ART1 network production. The control part of the ART1 network computes the matching score reflecting the degree of similarity of the present input to the previously encoded clusters.

The proposed technique integrates the already existing systems [12], [13]. The noise considered by our algorithm is only salt-pepper impulsive noise which means: (1) only a proportion of all the image pixels are corrupted while other pixels are noise-free and (2) 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 ($0 \le R \le 1$) to represent how much an image is corrupted. For example, if an image is corrupted by R = 30 % impulse noise, then 15 % of the pixels in the image are corrupted by positive impulses and 15 % 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 [12]. If we use Ω_i^{WD} to represent the set of the pixels within a WxW window centered about i

$$\Omega_i^{WD} = \{ j=(j_1,j_2) | i_1-(W-1)/2 \le j_1 \le i_1+(W-1)/2,\ i_2-(W-1)/2 \le j_2 \le i_2+(W-1)/2 \} \quad (2)$$

Where W is the window size

Thus:

$$Z = (P_1, P_2) \quad (3)$$

Where :

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

$$P_2=\text{Median}\{V_j | j \in \Omega_i^{WD}\} - V_i \quad (4)$$

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:

$$W_i = (W_{i1}, W_{i2}) \quad (5)$$

Building up the clusters is performed as follows:

a. Initialize the weight vectors with random values.

b. Present a new sample to the input layer of the network, and compute the Euclidean distance D_i between the sample and all the weight vectors using

$$D_i = \sqrt{\sum_{j=1}^{2} (Z_j(t) - W_{ij}(t))^2} \quad (i=1,\ldots,K) \quad (6)$$

Where K is the number of clusters.

c. Select the wining node i^* with minimum D_i.

$$D_i^* = \min\{D_i\} \quad (7)$$

If

$$D_i^* <= T \quad (8)$$

Where T is the predefined threshold then assigns Z to the i^{th} cluster.

Update the weight vector W_i according to the following learning rule:

$W_i(t+1) = W_i(t) + \eta\, [Z(t) - W_i(t)]$, where η is the learning rate; $0 < \eta < 1$. (9)

Else Form a new cluster starting with Z.

d. Repeat by going back to step 2:

In step 3, if the distance D_i between the sample and one of the cluster centers is less than the predefined threshold T, the pixel values are further compared. If the difference is small, a very small value is given to the learning rate η to update the weight vector of the pixel values and a value in the range of 0.5 to η to change the weight vector of the median deviations. Otherwise, η is set to 0.5 for both the weight vector of the pixel values and that of the median deviations.

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.

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. In the n^{th} iteration (n=1 , 2 , . . .) , for each pixel $V_i^{(n-1)}$, we compute its median value $m_i^{(n-1)}$ 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 $G_i^{(n)} = 0$ in the $W_F * W_F$ window. If M is odd, then:

$$m_i^{(n-1)} = \text{Median}\{V_j^{(n-1)} | G_j^{(n-1)} = 0, j \in \Omega_i^{WF}\} \quad (10)$$

if M is even but not 0, then :

$$m_i^{(n-1)} = (\text{Med}_L\{V_j^{(n-1)} | G_j^{(n-1)} = 0, j \in \Omega_i^{WF}\} + \text{Med}_R\{V_j^{(n-1)} | G_j^{(n-1)} = 0, j \in \Omega_i^{WF}\}) / 2 \quad (11)$$

Where Med_L and Med_R denote the left and the right median values, respectively [13]. 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 $V_i^{(n)}$ is modified only when the pixel i is an impulse and M>0 :

$$V_i^{(n)} = \begin{cases} m_i^{(n-1)} & \text{if } G_i^{(n-1)} = 1,\ M > 0 \\ V_i^{(n-1)} & \text{else} \end{cases} \quad (12)$$

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

$$G_i^{(n)} = \begin{cases} G_i^{(n-1)} & \text{if } V_i^{(n)} = V_i^{(n-1)} \\ 0 & \text{if } V_i^{(n)} = m_i^{(n-1)} \end{cases} \quad (13)$$

The procedure stops after the NF^{th} iteration when all the impulse pixels have been good pixels, i.e.,

$$\Sigma_i G_i^{(NF)} = 0$$

Then obtain the image $\{V_i^{(NF)}\}$ that is the filtered image.

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 r_k is the kth gray level and n_k is the number of pixels in the image having gray level r_k . we assume that r_k has been normalized to the interval [0,1], with r_0 representing black and r_1 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 [7]:

$P_r(r_k) = n_k/n$ for k=0,1,2,……,L-1. (15)

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

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

$$= \sum_{j=0}^{k} \frac{n_j}{n}, \qquad k = 0,1,..,L-1 \qquad (16)$$

That produces a level s_k for every pixel value r_k in the original image. For reasons that we assume that the transformation function $T(r_k)$ satisfies the following conditions:

(a) $T(r_k)$ is single –values and monotonically increasing in the interval $0 \le r_k \le 1$; and

(b) $00\le T(r_k) \le 1$ for $0\le r_k \le 1$. (17)

Thus, 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 as shown in equation (16). As known, a plot of $P_r(r_k)$ versus r_k is called a histogram. The transformation (mapping) given in equation (16) is called histogram equalization or histogram linearization.

SIMULATION RESULTS

In our experiments, the original test images are corrupted with fixed valued salt and pepper impulses, where the corrupted pixels take on the values of either 0 or 255 with equal probability. Normalized Mean Square Error (NMSE), which is used to evaluate the restoration performance.

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

Where F_{ij} is the original image, Y_{ij} is the filtered image and NxN is the size of the image.

Referring to the traditional techniques, which used only the median [2], PSM [13], and NEN [12]. The proposed technique integrates the ART1 network s a detector & the PSM filtering part Matlab (Image Processing Toolbox) benefits very well to easily test for our proposed technique for more advancement in the impulse noise removal in image enhancement. The NMSE is calculated for different percentages of impulse noise (10% - 90%) and the results are shown in Table (1). Fig. (2) shows NMSE applied by different filters and the proposed technique to “lenna” image. From this, it is evident that the proposed technique has a lower NMSE and it is stable over very large range of the noise. Table (2) show “lenna” image corrupted by different percentage of impulse noise , the enhancement results done by different filters, and the proposed one. It is obvious that the proposed technique realizes more enhancement over other techniques in the visual quality especially at high percentages of impulse noise.

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

filter / Noise %	*MEDIAN*	*PSM*	*NEN*	*PROPOSED*
10%	0.0213	0.0029	0.0026	0.0016
20%	0.0258	0.0100	0.0049	0.0032
30%	0.0324	0.0148	0.0077	0.0051
40%	0.0452	0.0224	0.0103	0.0076
50%	0.0687	0.0335	0.0153	0.0099
60%	0.0974	0.0629	0.0259	0.0129
70%	0.1536	0.1257	000.06	0.0165
80%	0.2072	0.2176	0.1508	0.0382
90%	0.2830	0.3096	0.4058	0.2153

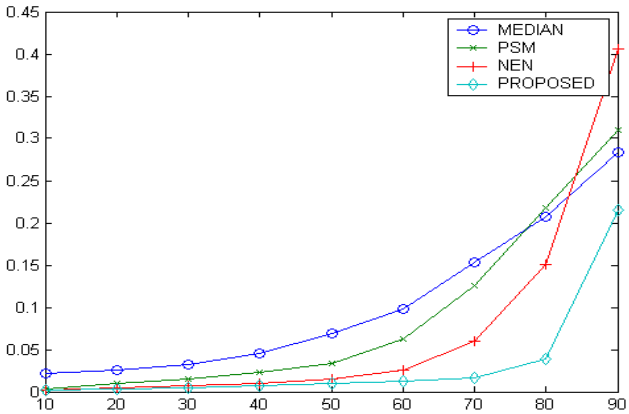

Figure.(2): The performance comparison of filters and the proposed technique .

Fig. (3) shows the comparison among different techniques and the proposed one at different signal to noise ratios (30% up to 90%). Then we applied the histogram equalizing filter to out proposed techniques we get better results compared to the other techniques. The comparison between the proposed and the modified proposed technique is shown in Fig. (4).

CONCLUSIONS

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 method 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.

FUTURE WORK

Nowadays the RGB-based images are widely used with added features. These features need more processing time in real time to meet the majority of applications. This demand needs less complexity in algorithm development. So the future work will be a trivial to enhance noise –removal based system by getting less order for the proposed algorithm.

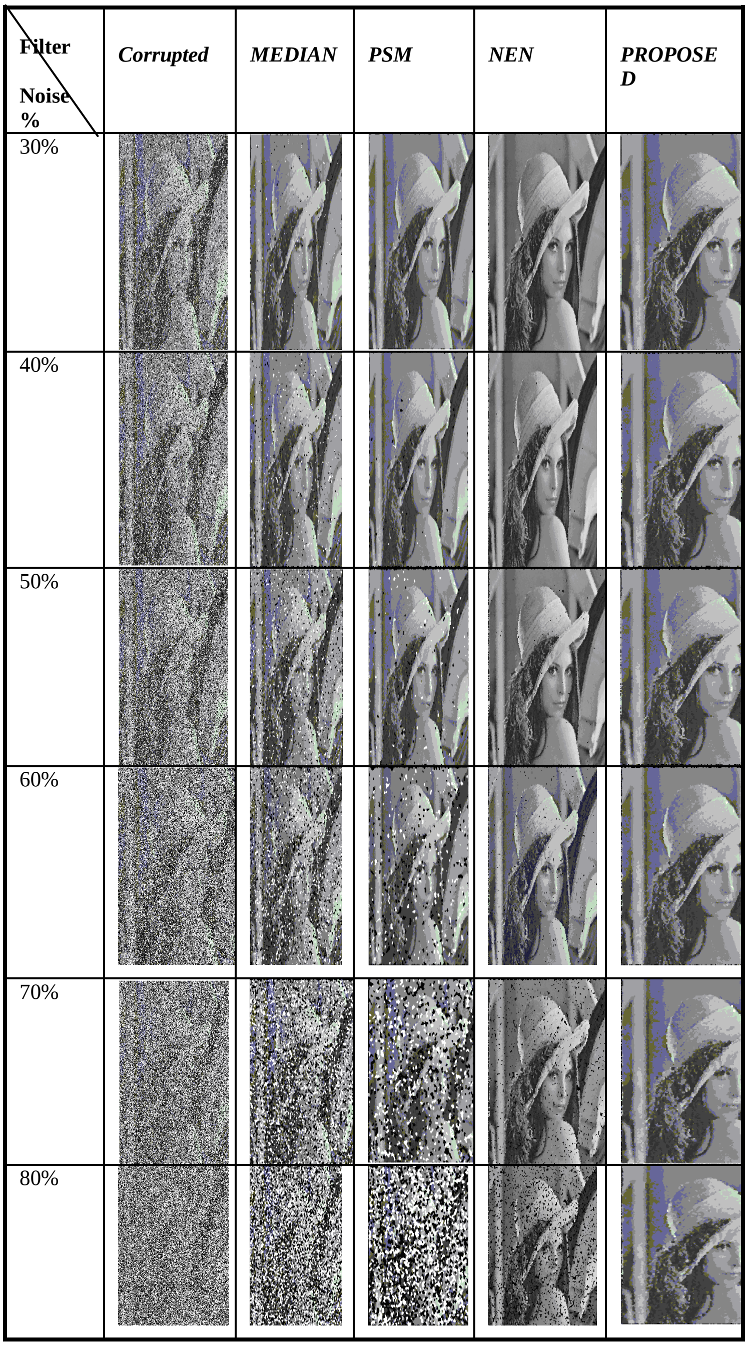

Figure. (3): Comparison between different techniques and the proposed one. At different signal to noise ratios.

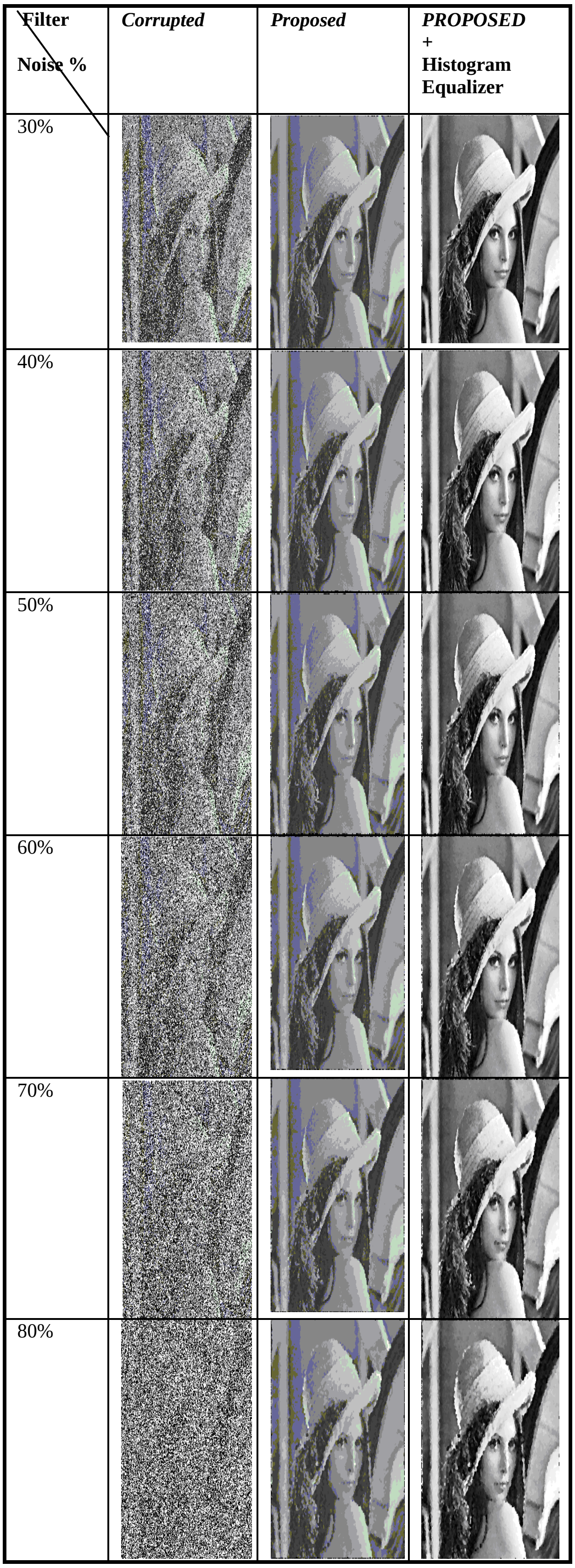

Figure. (4): Comparison between the proposed one and its modification.

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