Military Technical College
Kobry Elkobbah,
Cairo, Egypt

ICEENG 99

2nd International Conference
on Electrical Engineering
ICEENG 99

DETECTION AND REMOVAL OF IMPULSE NOISE IN DIGITAL IMAGES

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ABSTRACT

A new method is proposed to eliminate impulsive noise in digital images. The method is based on impulse noise detection by means of a self-organizing neural network and a class of noise-exclusive filters. The filtering scheme presented can suppress impulse noise effectively while preserving image edges and fine details. Experimental results demonstrate that the performance of the noise-exclusive filters is superior to that of the traditional median filter family.

KEYWORDS

Self-organizing neural network, Impulse noise removal, Noise-exclusive filtering, Digital image processing.

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1. INTRODUCTION

The Chinese proverb "*One picture is worth a thousand words*" expresses correctly the amount of information contained in a single picture. Most media (e.g. newspapers, TV, cinema) use pictures (still or moving) as information carriers. The tremendous volume of optical information and the need for its processing and transmission paved the way to image processing by digital computers [1].
The past twenty years in particular were characterized by massive increase in the speed, power and availability of digital computers. Accordingly, one area of information technology that has grown rapidly is imaging science. This subject has become increasingly important because of the growing demand to obtain information about the structure, composition and behavior of objects without the need to inspect them visually [2].

Digital images are corrupted by noise either during image acquisition or during image transmissions. The type of noise, which usually appears during image and TV picture transmissions, is the salt-pepper noise. It appears as black and / or white impulses on the image. It is impulsive noise and its source is either atmospheric or man-made (e.g. car engines). It can be modeled as follow [1]:

$$G(i,j)=\begin{cases} N(i,j) & \textit{with probability } p \\ F(i,j) & \textit{with the probability } 1-p \end{cases} \qquad (1)$$

Where:

F (i , j) denotes the uncorrupted pixels values. The noise impulses are denoted by N (i , j) which appear with probability p and whose value may be:

$$N(i,j)=\begin{cases} V_p & \textit{denotes the fixed value of the positive impulses} \\ V_n & \textit{denotes the fixed value of the negative impulses} \end{cases} \qquad (2)$$

And G (i , j) denotes the pixel values of the degraded image.

Digital image enhancement techniques are concerned with the improvement of the quality of the digital image. The principal objective of enhancement techniques is to process an image so that the result is more suitable than the original image for a specific application.

The aim of all noise-reducing processes is to suppress noise without blurring or degrading the digital image quality. Median filters possess some interesting properties. They have low-pass characteristics and they remove additive white noise. Since the median is a robust estimator of location, it is very suitable for impulse noise filtering. The principal function of the median filter is to force points with distinct intensities to be more like their neighbors. The median filter not only smoothes noise in homogeneous image regions but tends to produce regions of constant or nearly constant intensity as well. Thus it removes very fine details and changes signal structure that causes streak or blotch effects in the image. [1], [3], [4]. To improve the performance of the median filter, many generalized median filters such as the center weighted median (CWM) filter [5], the maximum/median (max/med) filter and the multistage median filter have been proposed

[6]. The generalized median filters tend to have better detail preserving characteristics than the median filter but they preserve more details at the expense of poor noise suppression.
In this paper, we propose a novel spatial approach for effectively suppressing impulsive noise from images while preserving image integrity. Our strategy is that if we can detect the impulses and locate their positions in the image, then we are able to replace the impulses by the best estimates using only the uncorrupted pixels.

2. IMPULSE NOISE DETECTION

2.1 Image Segmentation by an Unsupervised Learning Algorithm

The objective of segmentation is to divide a given image into meaningful regions that are homogeneous according to certain properties [7]. Segmentation is achieved by pixel classification method based on a self-organizing neural network.

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 assigns 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 [8].

The neural network proposed in this paper has a structure similar to that of ART1 (Adaptive Resonance Theory). This net clusters input patterns by using unsupervised learning. Each time a pattern is presented, an appropriate cluster unit is chosen and the cluster's weights are adjusted to let the cluster unit learn the pattern. As is often the case in clustering nets, the weights on a cluster unit may be considered to be a model for the patterns placed on that cluster [9] [10].

2.2 Feature Selection

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 noise degraded image. The size of the window is arbitrary. However, a 3x3 window is good enough in most applications. From the small window, useful local features are obtained such as mean, median, variance, range, etc.

Assume that M features are measured from each input pattern. Each set of M features is considered as a vector in the M-dimensional feature space. The problem of classification is to assign each possible vector to a proper pattern class.

In our experiments, 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 [11]. Thus

$$Z = (Y_1 , Y_2) \tag{3}$$

Where

$$Y_1 = X_i \tag{4}$$

X_i is the value of the pixel in the center of the window.

$$Y_2 = \text{median}(X_{i-w/2}, \ldots, X_i, \ldots, X_{i+w/2}) - X_i$$

w is the size of the window.

2.3 Unsupervised Learning Algorithm

The essential point of this algorithm is to build up the clusters using the Euclidean distance measure between the input Z and the weights W_i assuming:

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

The algorithm is summarized as follows:

Step 1:

Initialize the weight vectors with random values (we simply take the first sample as representative of the first cluster).

Step 2:

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

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

Where K is the number of clusters.

Step 3:

Select the wining node i^* with minimum D_i.

$$D_i^* = \min \{ D_i \} \tag{7}$$

If

$$D_i^* \le T \tag{8}$$

Where T is the predefined threshold then assign Z to the i^{th} cluster.
Update the weight vector W_i according to the following learning rule:

$$W_i (t+1) = W_i (t) + \alpha [Z (t) - W_i (t)] \tag{9}$$

Where α is the learning rate; $0 < \alpha < 1$.

Else

Form a new cluster starting with Z.

Step 4:

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 α to update the weight vector of the pixel values and a value in the range of 0.5 to α to change the weight vector of the median deviations. Otherwise, α 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.

2.4 Noise Exclusive Filters

Since the cluster centers, which represent the impulse noise, have been detected, the recovery of image becomes the process of matching pixels with the cluster centers.

Several noise exclusive filters are introduced, the noise-exclusive arithmetic mean (NEAM) filter, the noise-exclusive median (NEM) filter, the noise-exclusive neighbors (NEN) filter, and the noise-exclusive mean-median (NEMM) hybrid filter are used to restore the impulse corrupted images. The window size of these filters may vary, as does the traditional median-type filters (3x3 window size is used). By noise-exclusive we mean that all the impulses in the window do not participate in the operation of order sorting or do not count in the operation of the mean calculation. It is different from the conventional median-type filtering in that all noisy pixels inside the window are involved in the operation of ordering.

The NEAM filter and the NEM filter take the mean value and the median of the uncorrupted pixels respectively. The NEN filter takes the nearest neighbor. The NEMM replaces the impulses with the mean value in the window, then takes the value of the median.

3. EXPERIMENTAL RESULTS AND ERROR ANALYSIS

The proposed adaptive filter has been extensively tested on simulated examples. In this paper, one example is illustrated to discuss the performance of the filter.

"Lenna" image 256x256 size shown in Fig. 1(a) is corrupted by 60% positive and negative impulse noise, as shown in Fig. 1(b). The images processed by the median filter, the CWM filter, the max/med filter and the multistage median filter are given in Figs. 1(c), 1(d), 1(e) and 1(f) respectively. In Figs. 1(g), 1(h), 1(i) and 1(j), the proposed NEAM, NEM, NEN, and NEMM process the images respectively.
Fig. 2(a) shows the distribution of the input vectors (Y_1, Y_2) fed to the neural network for "Lenna" images. Fig. 2(b) shows the clusters classification done by the neural network.

The corresponding normalized mean square errors (NMSE) are calculated from the following formula:

$$\mathrm{NMSE} = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(F_{ij} - Y_{ij})^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(F_{ij})^2} \qquad (10)$$

Where F_{ij} is the original image, Y_{ij} is the filtered image and NxN is the size of the image.
The NMSE of our example are also calculated for different percentages of impulse noise.Table 1. and Fig. 3 show the NMSE applied by each filter (F) to "Lenna" image corrupted by different percentages of impulse noise (%I).
The NMSE of the noise-exclusive median filters are compared to the NMSE of the median filters as a sample of the traditional median-type filters according to the following formula:

$$\delta\mathrm{NMSE} = \frac{\mathrm{NMSE}_M - \mathrm{NMSE}_N}{\mathrm{NMSE}_M} * 100 \qquad (11)$$

Where:

NMSE_M is the NMSE of the median filter.
NMSE_N is the NMSE of the noise-exclusive median filter.
δNMSE is the relative NMSE reduced by the noise-exclusive median filter.

Table 2. shows the δNMSE for different percentages of impulse noise.
The projection mean square error (PMSE) is the mean square error projected along the image axis and is described mathematically by:

$$\mathrm{PMSE}(i) = \frac{\sum_{j=0}^{N-1}(F_{ij} - Y_{ij})^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(F_{ij})^2} \qquad (12)$$

Fig. 4 shows the PMSE calculated for median filter, as a sample of the traditional median-type filters, and the NEAM filter, as a sample of the noise-exclusive median filters, applied on "Lenna" corrupted by 60% impulse noise. It is evident that the NEAM has a lower PMSE and consistent overall the image as well (Due to zero padding, peak values are shown at PMSE(1) and at PMSE(256)).

Table 1. The performance comparison of filters with window size 3x3 applied on Lenna image 256x256 size corrupted by different percentages of impulse noise.

F / %I	Median	CWM	Max / Med	Multistage	NEAM	NEM	NEN	NEMM
20%	0.0103	0.0098	0.111	0.1222	0.0020	0.0016	0.0045	0.0016
40%	0.0577	0.0616	0.340	0.3614	0.0053	0.0063	0.0103	0.0056
60%	0.2269	0.2163	0.6037	0.6087	0.0113	0.0148	0.0259	0.0132
80%	0.5833	0.5141	0.8606	0.8417	0.0275	0.0319	0.1508	0.0306
95%	0.9478	0.7876	1.0572	1.0173	0.1161	0.1175	0.6456	0.1173

Table 2. The δNMSE reduced by the noise-exclusive filters versus the traditional median filter

%I \ F	NEAM	NEM	NEN	NEMM
20%	80.58 %	84.47 %	56.31 %	84.47 %
40%	90.81 %	89.08 %	82.15 %	90.29 %
60%	95.02 %	93.48 %	88.59 %	94.18 %
80%	95.29 %	94.53 %	74.15 %	94.75 %
95%	87.75 %	87.60 %	31.88 %	87.62 %

4. CONCLUSIONS

A neural network guided median filter is introduced to remove impulse noise in images. This is done by detecting the positions of the noisy pixels and then applying a number of noise-exclusive median filters. 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 noise removal, edge and fine detail preservation, as well as minimal signal distortion. However, the traditional median-type filters have smaller time calculations than the proposed method. Therefore, the proposed filters are 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 percentages of impulse noise at the expense of minimum noise removal and signal distortion occurrence.

REFERENCES

[1] Pitas I., Digital Image Processing Algorithms, Prentice Hall, UK, (1993).

[2] Blackledge J., Quantitative Coherent Imaging, Academic Press, UK, (1989).

[3] Pitas I., Venetasanopoulos A., Nonlinear Digital Filters: Principles and applications, Kluwer Academic, (1990).

[4] Hampel F., Ronchetti E., Rousseevw P., Stahel W., Robust Statistics: An approach based on influence functions, Willey, (1986).

[5] Ko S., Lee Y., "Center weighted median filters and their applications to image enhancement" IEEE Trans. Circuits Syst., Vol.38, no.9, pp 984-993, Sept. (1991).

[6] Gonzalo R., Russell E., "Detail-Preserving ranked-order based filters for image processing", IEEE Trans. Acoustics, Speech, and Signal Processing, Vol. 37,no.1, pp 83-98, Jan. (1989).

[7] Ballard D., Brown C., Computer Vision, Prentice Hall, UK, (1982).

[8] Kong H., Guan L., "A self-organizing neural network for image segmentation", Proc. 2nd Australian and New Zealand Conf. on Intelligent Information Systems, pp 27-31, Brisbane, Australia, Dec. (1994).

[9] Carpenter G., Grossberg S., "The ART of adaptive pattern recognition by a self-organizing Neural Network", IEEE Computer, pp 77-88, March (1988).

[10] Fausett L., Fundamentals of Neural Networks, Prentice Hall, UK, (1994).

[11] Kong H., Guan L., "A neural network adaptive filter for the removal of impulse noise in digital images", Neural Networks, Vol. 9, no. 3, pp 373-378, (1996).

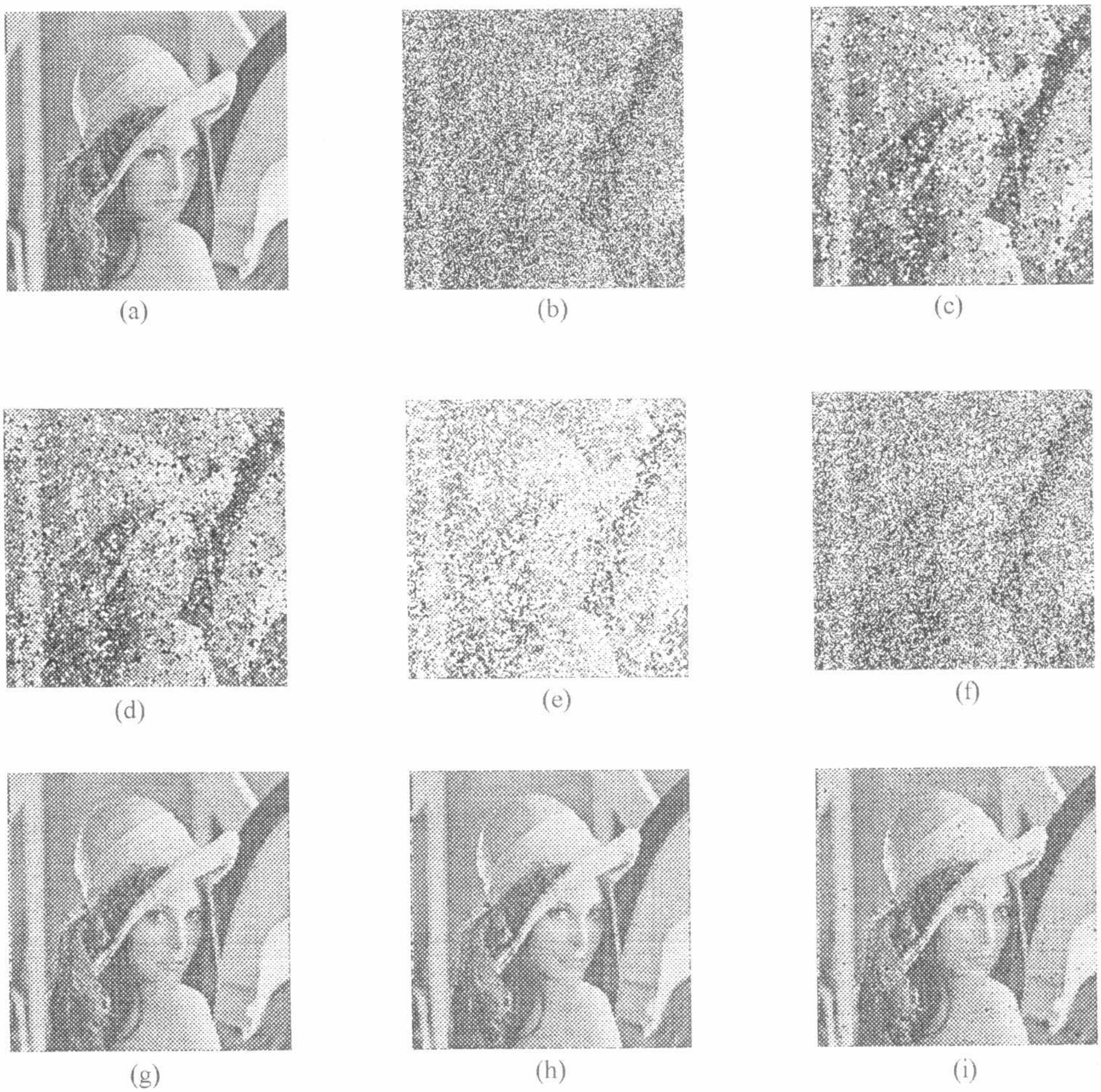

Fig. 1. a) Lenna image; b) Lenna image corrupted by 60 % impulse noise; c) Median-filtered Lenna; d) CWM-filtered Lenna; e) Max/median filtered Lenna; f) Multistage-median filtered Lenna; g) NEAM filtered Lenna; h) NEM filtered Lenna; i) NEN filtered Lenna; j) NEMM filtered Lenna.

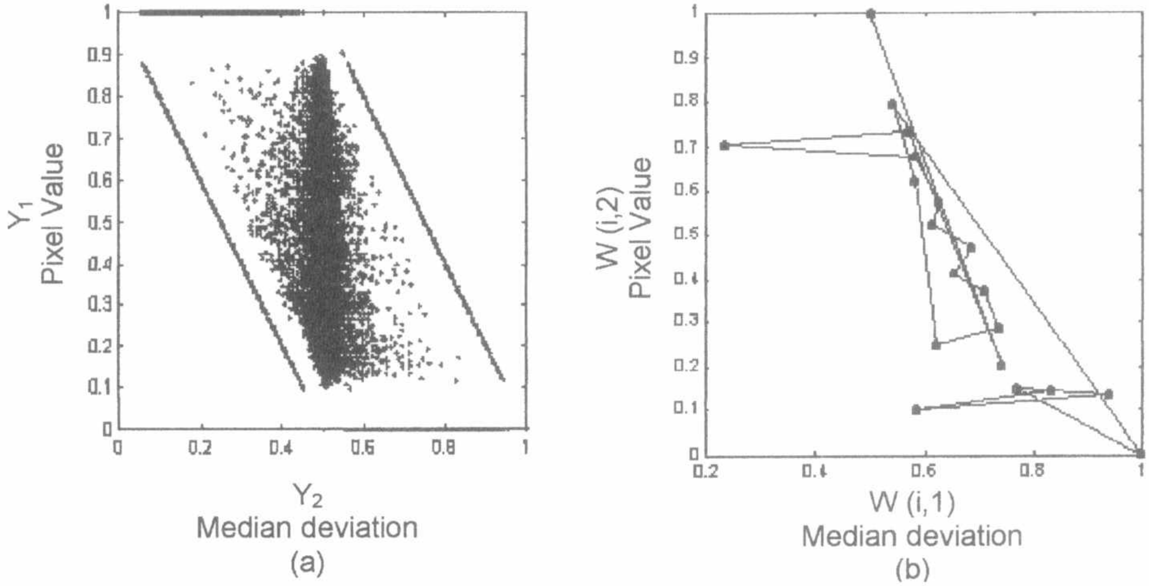

Fig. 2. (a) Distribution of the input vectors for Lenna Image
(b) Classification of the clusters done by the neural network

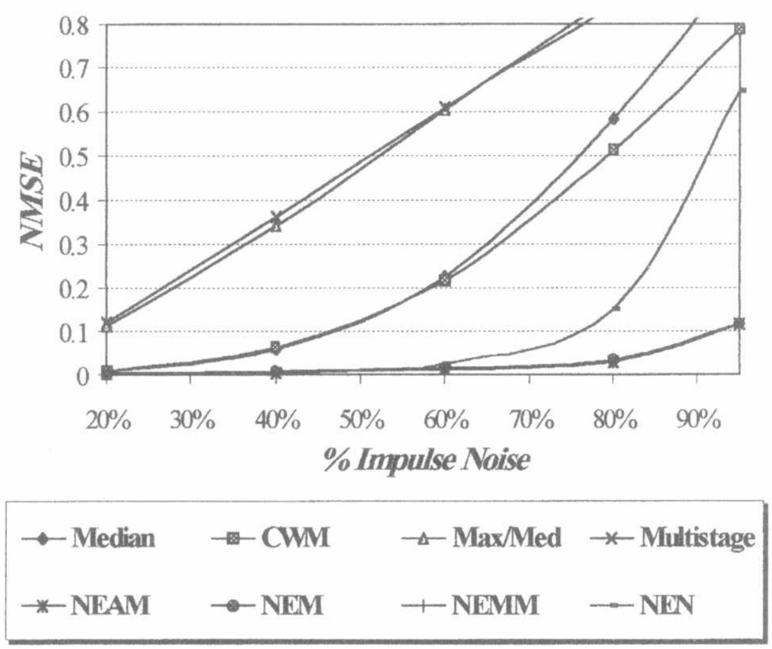

Fig. 3. The performance comparison of filters with window size 3x3 applied on Lenna image 256x256 size corrupted by different percentages of impulse noise

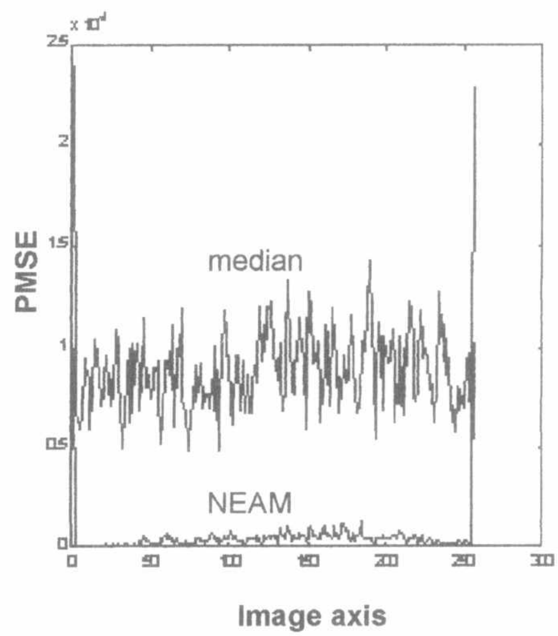

Fig. 4. The PMSE calculated for the NEAM filter and the median filter