Neural Networks Applied for impulse Noise Reduction from Digital Images

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Abstract. This paper proposes the use of a new method for detecting and removing impulse noise from digital images based on the combination of two Artificial Neural Networks (ANN). The training algorithm of the ANNs is based on the technique of backpropagation. The first ANN is used to the detection of impulse noise, known as salt and pepper, and the second ANN is used to replace it by an estimated value. The proposed method is compared with other methods on literature in terms of visual judgment and also using a quantitative measure of PSNR - Peak Signal To Noise Ratio. The numerical and visual results obtained demonstrate the feasibility of the proposed method, which can be used as part of a tool for treatment of images.

Keywords: Artificial Neural Networks, Impulse noise, Impulse Detector, Impulse estimator, Digital images.

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1 Introduction

Most image processing algorithms, such as feature selection and recognition, depend on the performance of the image filter which aims to remove impulse noises from the image. Impulse noise or salt and pepper in digital images usually happen because of the data transmission process [17]. Images are often corrupted by impulse noise at the time it is captured or when they are being transmitted by some type of channel. In many applications it is necessary to remove noise without affecting the fine details in the image, i.e., it should preserve the edge like fine details, while removing the noise.

A great number of methods have been proposed to remove impulse noise, for example Standard Median Filter [21], Adaptive Median Filter [21], [13], [9], [15], [1], [10] and [4], fuzzy techniques [20] and [14], Laplacian Operator [28], and some other methods relying on previous training [1]. Most methods use an impulse noise detector to determine if a pixel must be modified or not, and then the filter is applied only on the pixels identified as noise. This process is known as Switching technique and it has the advantage of being simpler and more efficient than the methods applied to all pixels [4].

Recently, an impulse detector and filter-based Rank-Ordered Absolute Differences (ROAD) statistic has been proposed [7]. This detector considers that high ROAD factor implies that the pixel is corrupted and low ROAD factor implies that the pixel is uncorrupted.

In the last years, advanced techniques based on computational methods have been applied to image filtering by considering it as a nonlinear problem. In this way, ANN can be potentially applied due to the excellent performance in solving various problems involving image processing. Recently, G. Kalirajet et al. [11]

used ANN as a tool for detecting noise, but, for its removal, they used two algorithms based on the mean as a means of estimating the value of noisy pixel.

In this paper, a new method for detection and removal of impulse noise based on the combination of two ANN is proposed. The first ANN is used as noise detector [11] and the second is used as estimator of a new value for noisy pixel reducing the noise present in the original image. The estimator performance is compared with various filtering methods in various set of images, and it found good among the others in terms of PSNR [6] and [12].

The rest of the paper is organized as follows. In Section II, a brief description of impulse noise will be given. In Section III, it will be showed the scheme of the proposed method as well as details of its implementation. Section IV presents the results of the proposed method, and finally the main conclusions are presented.

2 Noise (Salt and Pepper)

By definition, noise is considered any type of unwanted information blocking the acquisition and processing of information desired. There are many types of noise that may be present in images. The types can be determined by the shape of the histogram of noise [16].

Some types of noise that can be found in digital images are uniformly distributed noise, Gaussian distribution, negative exponential distribution, and impulse noise. In this work, the focus is on impulse noise. For details on other types of noise see [16].

The impulse noise which generally occurs due to defects in the image systems contains two levels of gray. The white noise pixels and and black noise pixels are called salt and pepper, respectively. In this work, the values of salt and peppers are 255 and 0, respectively.

There are two ways through which an image can be corrupted by noise. The first is called additive noise, which is simply added some kind of noise to an image free of noise so far. The second way is called a multiplicative noise, which consists in multiplying each pixel of the image by a random noise term. In this work, we will work with the first way, i.e, the images are corrupted by a noise simulation done on a data channel, where noise is added in percentage terms in the images as follows:

1) Choose the picture you want to work, for example, order 256;

2) Order 256 means that the picture has 65536 pixels;

3) Select the percentage of impulse noise, for example, 30% means that 19661 are pixels randomly chosen to be modified (corrupted pixel) and the rest of the image remains without changing (uncorrupted pixel);

4) The selected pixels will have 50% probability of begin 0 or 255.

Figure 1 shows the image free of noise and the image corrupted with 30% of impulse noise.

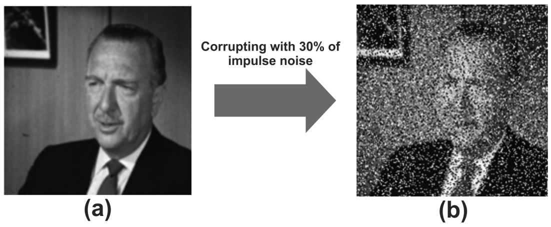

Figure 1: Man (a) Without noise. (b) Corrupted with 30% noise

3 Proposed Method

The method applied in this paper is based on two phases; each phase is processed by neural networks (NN). The first phase works as an impulse noise detector, using an artificial image of the first neural network for training (NN-1). Details of NN-1 are shown in the section 3.1. In the second phase, the new value of pixel considered noisy is estimated by using values of neighboring pixels as input to a second neural network (NN-2). A general scheme of the proposed method is shown in Figure 2.

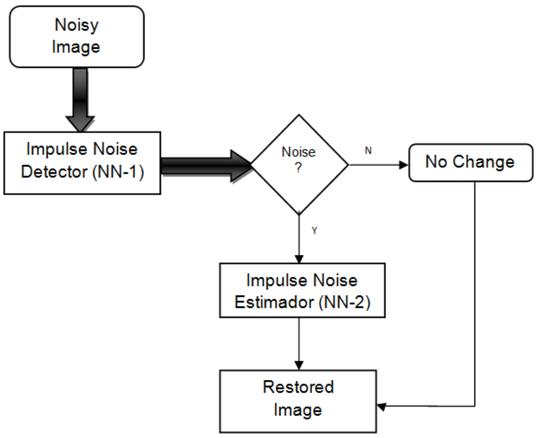

Figure 2: General scheme of the proposed method

3.1 Impulse Noise Detector

The structure of the impulse noise detector is shown in Figure 3. It consists of a neural network, NN-1, and a decision maker. The neural network takes three inputs, current pixel value, median, and the ROAD value of the 3 x 3 window, as shown in Figure 4, with the center as the current pixel. The neural network's output is given to the decision maker which converts the output to either 0 or 1 to classify whether the pixel is uncorrupted or corrupted, respectively.

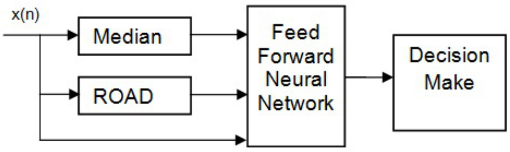

Figure 3: Impulse noise detector

x(i-1,j-1)	x(i-1,j)	x(i-1,j+1)
x(i,j-1)	x(i,j)	x(i,j+1)
x(i+1,j-1)	x(i+1,j)	x(i+1,j+1)

Figure 4: Elements of 3 x 3 window of around current pixel x(i, j).

The median filter [16] has great importance in image processing because of its excellent performance in removing noise, allowing a clear view or almost clear image. The median filter used in impulse noise detector in Figure 3 follows the standard of 3 x 3 window. The window is scanned throughout the image by raster scan fashion.

Let **n** = *(i, j)* be the location of the current pixel under consideration, and let $W_{\mathbf{n}}$ be the 3 x 3 window as shown in Figure 4.

$$W_n = \{x\,(n+b) : -1 \leq b \leq 1\} \tag{1}$$

Where x(**n**) is the pixel value of the corrupted image, and $W_{\mathbf{n}}$ consists of elements in 3 x 3 window. The median filter is governed by Eq. (2).

$$m(n) = median(W_n) \tag{2}$$

The ROAD factor is proposed by [11] which is a very useful factor to distinguish corrupted and uncorrupted pixels. ROAD factor is high for noisy pixels, and low for uncorrupted pixels. Here, the same 3 x 3 window is considered to calculate the ROAD factor (the second input) for neural network-1. The ROAD factor is calculated as follows:

1) The absolute deleted difference between the center pixel and the remaining pixel is calculated and denoted by $d_{\mathbf{n}}$ (for a 3 x 3 window, $d_{\mathbf{n}}$ consists of eight elements);
$$d_n = |W_n - x(n)| \tag{3}$$

2) Sort $d_{\mathbf{n}}$ values in the increasing order and let the sorted values as $r_{\mathbf{n}}$;
$$r_n = sort(d_n) \tag{4}$$

3) The ROAD factor is calculated by summing up the first four values of $r_{\mathbf{n}}$.

The decision maker rounds off the output of the neural network NN-1 with the threshold 0.5. That is, the output y(n) = 0 if the output of NN-1 $\leq$ 0.5 and y(n) = 1 if the output of NN-1 $>$ 0.5. Thus, the decision maker checks whether a pixel is noisy or not. An NN-1 used in the scheme consists of two hidden layers with seven and two neurons in each layer, respectively. It is important to note that there is no analytical method to choose the number of layers and neurons, and hence they are determined experimentally on trial and error basis.

For the generalization of the noise detector, selecting the training image is the most important task. In [11], [8] and [26], the artificially generated training image which has more generalization capability is used. The base training image, The input image and target image are shown in Figure 5(a), 5(b) and 5(c). The first image is the base training image of size 100 x 100 pixels and it consists of square boxes each of size 2 x 2 pixels. All the pixels inside the square box have the same gray level value which is randomly chosen between [0 - 255], as shown in Figure 6. The second image is obtained by corrupting the first image with impulse noise of density 50%, as shown in Figure 5b. The process of creating the final ones occurs as follows:

1) Create an image of the same size as the base training image with all pixels of value 0, i.e, a black image;

2) At the same instant the image of Figure 5(a) is corrupted with 50% impulse noise (see section 2), the black image is also changed. The difference is that the black image receives only the value 255 (white

dots), which denotes the presence of noise and acts as a target image for the proposed detector.

The set of input/output for training the NN-1 is obtained as follows. The image of Figure 5(b) and 5(c) are completely scanned through by the window of Figure 4. The median values, ROAD factor and current pixel are calculated from Figure 5(b) to form the set input to the neural network, and the desired output is taken form the current pixel value of the target image, Figure 5(c). Each pixel value comprises 8 bits represented by the level of gray scale.

The NN-1 used in this paper was a feed-forward MLP (Multilayer Perceptron) with the following structure in its architecture: 3-7-1. The Input layer in the MLP networks does not perform any computation. It is not necessary to assign activation function. In turn the hidden and output layer were configured with hyperbolic tangent (tansig) activation function. The neural network-1 was trained by using the back propagation algorithm with a maximum of 100 times, and learning rate of 0.05 and error 1^{-6}.

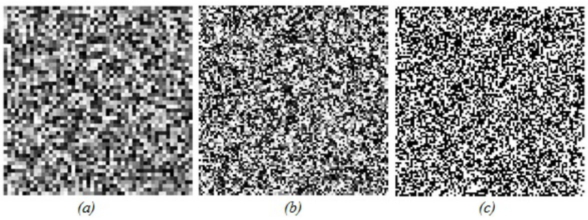

Figure 5: (a) Base training image. (b) Image in (a) corrupted by 50% impulse noise. (c) Target image.

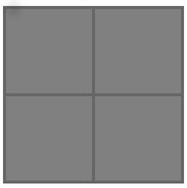

Figure 6: Example cell composed 2 x 2 pixels with same gray level

3.2 Impulse Noise Estimator

In the second phase the detected noisy pixel is replaced to a new value estimated by a neural network NN-2 which is called The Impulse Noise Estimator. In this method, unlike traditional methods [6], [5] and [25], uncorrupted pixels are left unchanged. The NN-2 estimates precisely the value by using neighbors of noisy pixels, as shown in Figure 7. x_C is the corrupted pixel and x_1, x_2, ..., x_8 are the neighbors.

x1	x2	x3
x4	xC	x5
x6	x7	x8

Figure 7: 8-neighborhood of xC

In [24] and [27], for training network, the authors used the artificial training images like the ones in Figure 4, but, based on the Correlation Theorem [8], they believe that these methods are not reasonable. In [18] the authors compare the performance of the neural network using real and artificial images for training network, and good results were found by using real images.

For the training of NN-2, it was used the picture in Figure 8, that has the size of a matrix of order 256. The image in Figure 8(b) was obtained by corrupting the image in Figure 8(a) with 40% of impulse noise. The input was obtained of corrupted pixel's neighbors of Figure 8(b) and the output was obtained from current pixel of Figure 8(a).

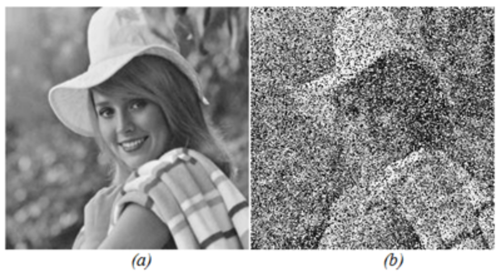

Figure 8: (a) Base training image. (b) Image in (a) corrupted by 40% of impulse noise.

The NN-2 used in this work has three layers, the input layer has 8 neurons which correspond to the eight-pixel neighborhood considered noisy in Figure 8(b). The output layer has only one neuron corresponding to the new estimated value for NN-2, and the hidden layer, which was obtained through some experiments, used 16 neurons. Thus, the architecture of the NN-2 that had the best performance for estimating the new value of noisy pixel has the following structure: 8-16-1. The proposed structure is shown in Figure 9. The hidden and output layers were configured with sigmoid (logsig) and linear (purelin) activation function, respectively. The NN-2 was trained using the back-propagation algorithm with a maximum number of 100 times, learning rate of 0.47 and desired error of 10^{-3}.

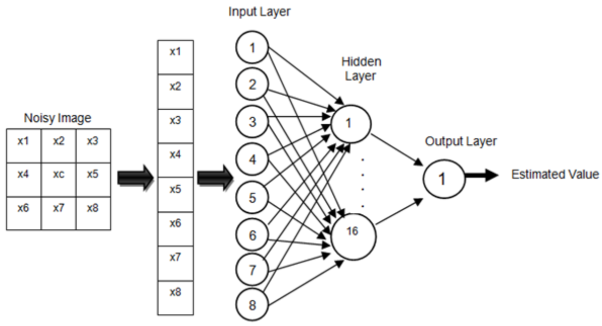

Figure 9: Structure for impulse noise estimator

4 Result

The performance of the method is analyzed both quantitatively and qualitatively. The PSNR is the quantitative measure filtering performance. The PSNR value is defined by Eqs. (5) and (6).

$$PSNR = 10 \log \frac{Max(X(i,j))^2}{MSE} \tag{5}$$

where MSE is the mean squared error and it is defined by Eq. (6)

$$MSE = \frac{1}{NM} \sum_{i=1}^{N} \sum_{i=j}^{M} (X(i,j) - Y(i,j))^2 \tag{6}$$

where X(i, j) is the original image, Y(i, j) is the restored image and N x M is the image size.

A larger PSNR indicates good signal strength. In [11] and [26], after detecting the impulse noise, various filter algorithms were implemented and compared with various standard filters, since the performance of the proposed method is good compared to [11] and [26].

The performance of the method is tested under various noise conditions on ten popular test images from the literature, including *Baboon, Blood, Boats, Bridge, Cameraman, Goldhill, Lena, Pentagon, Peppers, and Rice images*. All test images are 8-bit gray level images. The experimental images used in the simulations are generated by contaminating the original images by impulse noise with an appropriate noise density depending on the experiment. For comparison, the corrupted experimental images are also restored by using several conventional and state-of-the-art impulse noise removal operators, the progressive switching median filter, (PSMF) [22], the modified peak and valley filter (MPVF) [3], the two-output nonlinear filter (TONF) [19], the threshold boolean filter (TBF) [2], the adaptive fuzzy switching filter (AFSF) [23], Yuksel [26] and the latest NNBID [11].

The experimental procedure to evaluate the performance of a given method is as follows: The noise density is varied from 5% to 90% with 5% of increments. For each noise density step, the ten test images are corrupted by impulse noise with that noise density. This produces ten different experimental images, each one with the same noise density. These images are restored by using the operator under experiment, and the PSNR values are calculated for the restored output images. This produces ten different PSNR values representing the filtering performance of that operator for different image properties. These values are then averaged to obtain the representative PSNR value of that operator for that noise density. This procedure is separately repeated for all noise densities from 5% to 90% to obtain the variation of the average PSNR value of that operator as a function of noise density. Finally, the overall experimental procedure is individually repeated for each operator.

Table 1 lists the variations of the average PSNR values of the operators as a function of noise density. The performance of all algorithms is taken from Yuksel [26], because he performed the same experiment described above using the same set of images.

Table 1: Average PSNR Values Versus Noise Density

	Prop.	NNB.	Yuk.	TONF	MPVF	AFSF	TBF	PSMF
5%	39.23	39.30	33.96	33.58	32.06	30.50	30.26	29.15
10%	36.56	36.25	32.03	31.72	30.40	29.02	28.80	27.77
15%	34.83	34.40	30.30	30.03	28.86	27.69	27.49	26.51
20%	33.53	33.05	28.87	28.62	27.55	26.62	26.41	25.50
30%	31.40	30.99	26.54	26.27	25.29	24.64	24.46	23.84
40%	29.74	29.05	24.45	24.15	23.16	22.90	22.70	22.30
50%	28.21	27.81	22.32	21.98	21.00	20.98	20.78	20.58
60%	26.71	26.48	19.92	19.57	18.64	18.72	18.54	18.50
70%	25.24	25.13	17.35	16.99	16.14	16.18	16.05	16.14
80%	23.36	23.61	14.53	14.21	13.49	13.34	13.28	13.48
90%	20.33	21.63	11.37	11.12	10.58	10.31	10.28	10.40

From Table 1, it can be seen that the average PSNR value for the proposed method is high compared with other proposed algorithms. To clearly show the results, Figure 10 shows the graph of the proportion of noise density to the PSRN values obtained for the *Lena* image retrieval methods. Figure 10 indicates that the average PSNR value is high when compared to Yuksel [26] and NNBID [11].

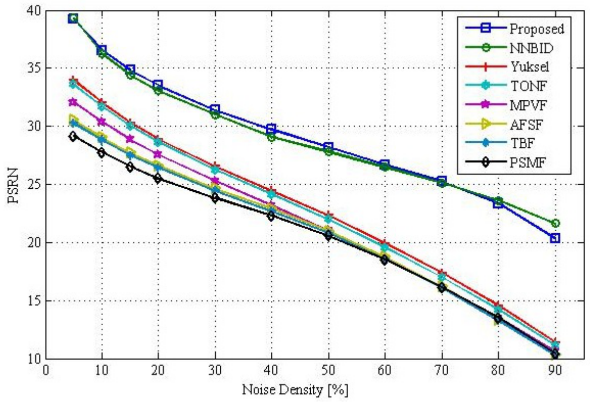

Figure 10: Average PSNR vs % noise density of the Proposed method: NNBID, Yuksel, TONF, MPVF, AFSF, TBF and PSMF

The difference in detail preservation performances of the operators may be better observed by looking at the output images of the operators. For this purpose, the *Baboon* test image shown in Figure 11(a) is corrupted by 25% impulse noise and the noisy image is restored by using the operators. This image is especially chosen for comparison because of its rich detail and texture. Figure 11(b) shows the output images of the operators. Here, zoomed portions of the output images are presented for better visual comparison.

5 Discussion and Conclusion

In this paper we present a new method based on two neural networks for detection and reduction of impulse noise in digital images. The results of the method were compared with other methods in technical literature by using a numerical measure based on the PSNR and visual observations. It can be observed, according to the graph of Figure 10, that the proposed method achieved better results compared to other methods. This result was observed, because the proposed method has a different way of dealing with noisy pixels, i.e, it uses two neural networks to detect and estimate the noisy pixels. And in comparison with the NNBID, there is a similarity in the curve of the graph, because both methods used the same neural network (NN-1) in first phase for detecting noisy pixels. However, the filter used to replace it in the second phase is different.

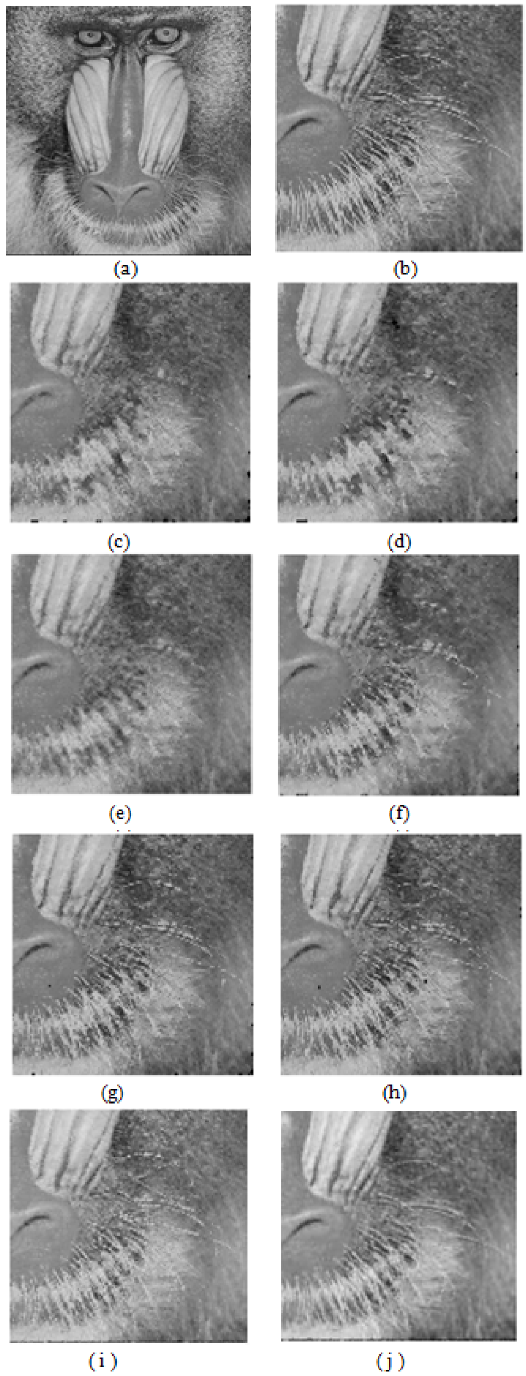

Figure 11: Output images of the operators for the Baboon image corrupted by impulse noise with 25% noise density. (a) Baboon test image. (b) Lower right portion zoomed. (c) PSMF. (d) TBF. (e) AFSF. (f) MPVF. (g) TONF. (h) Yuksel. (i) NNBID. (j) Proposed.

Thus, the proposed method that uses other neural network (NN-2) obtained slight improvement in noise ratios ranging from 10% - 70%. The advantages of the new method may be summarized as follows.

1) The training of NN-1 is easily accomplished by using very simple artificial images that can be generated in a computer and the NN-2 may be used for efficiently filtering any image corrupted by impulse noise in any density;

2) An even better performance may be obtained by repetitive application of the proposed operator to the corrupted image.

On the other hand, it should be pointed that the computational complexity of the proposed operator is higher than most of the other impulse noise filters in the literature. This is because neural networks need training. This is an inherent property of neural networks, but the training section was performed just for one time. Once the training is completed, the parameters of the operator are fixed and the response time of the trained system is very short, that is virtually instant.

The results obtained through simulations demonstrate the feasibility of the proposed method, especially through self-adaptation of the ANN to avoid destroying uncorrupted pixels and the ANN has the main characteristic pattern recognition. It is concluded that the proposed operator can be used as a powerful tool for efficient removal of impulse noise from digital images without distorting the useful information within the image. For future work, the authors intend to adapt the method for recognition of noise present in images of oil known as ground roll noise.

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