PRESERVING FINE DETAILS IN HIGHLY CORRUPTED IMAGES BY REDUCTION OF IMPULSIVE NOISE USING MULTILAYER PERCEPTRON NEURAL NETWORKS

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ABSTRACT

Impulsive noise occurs frequently in image processing. This problem gets an importance especially when the important details in images having highly intensive impulsive noise are required to be retrieved. In this work, a multilayer perceptron neural network was developed for the purpose of reducing impulsive noise in images without removing the fine details. Using a back propagation algorithm, we are able to obtain fine details from noisy image effectively. The process of noise reduction is successfully realized by using generalization property of neural networks and learning algorithm in approximating pixel values with high amplitude of corrupted image to an average value.

I. INTRODUCTION

Impulsive noise is one of the frequently faced problems in image processing. It may be caused by many reasons such as transmission channel error (e.g., binary symmetric channel noise), sensor faults, edge sharpening procedures, engine sparks, ac power interference and atmosphere electrical emissions. The impulsive noise having strong amplitude can be noticed visually, and thus, the removal of such noise is an important issue in image processing [1].

There are many types of impulsive noise. Let I_{ij} be the gray level of a true image I at pixel location (i;j) and [n_{min}; n_{max}] be the dynamic range of I. Let X_{ij} be the gray level of the noisy image X at pixel (i;j), then

$$X_{ij} = \begin{cases} R_{ij}, & \text{with probability} \quad r, \\ I_{ij}, & \text{with probability} \quad 1-r, \end{cases} \qquad (1)$$

Where Rij $\in$ [n_{min}; n_{max}] are random numbers and r is the noise ratio [2].

Efficient removal of noise from digital image data is of key importance in many image processing applications because the performances of subsequent operations performed on the image are purely dependent on the success of the noise removal operation. This is a difficult task since the details and texture within the image must be reserved while removing the noise. Most conventional noise removal filters distort the uncorrupted regions of the image while restoring the corrupted regions [3].

In literature, different approaches have been used to reduce impulsive noise in images [4-8]. There are also some works aiming to reduce the noise of highly corrupted images while retaining the details [9-13]. Although most of these works seem to have good visual quality, they are not tried for the highly corrupted input images where the fine details may be important.

In this paper, we propose an approach for reducing impulsive noise in images without removing the fine details using artificial neural networks. Here, the system is also simulated with highly corrupted input images having important fine details. The results of the system are given by Peak Signal to Noise Ratio and Mean Square Error values numerically for the given test images which can also be visually seen by the figures. Statistical analysis and comparison of the proposed method with traditional filters (e.g., median and order-statistic filters) are also provided.

II. PROCESS OF NOISE REDUCTION

A. Neural Network Approach

There has been some effort to apply artificial neural networks (ANN) to the task of image noise suppression. In fact, there are possibilities that ANNs might perform noise suppression more effectively than conventional approaches, not least in adapting to specific types of noise, and in eliminating the image distortion which is a characteristic of the widely used median filter [14].

Our purpose in this work is the reduction of impulsive noise in images. For this purpose a three-layer feed forward neural network has been used. Input layer, hidden layer with 8 neurons, and output layer with 1 neuron. Various back propagation algorithms have been applied for the training process. Among all results, the best ones to update weights and bias values of the network are obtained by using Levenberg-Marquardt (LM) algorithm. To achieve the training input values and target values are necessary to be introduced to the network so that the suitable behavior of the network could be learned. The image pixels should be gray level values. Image matrix is reformed into a column vector and applied to the input of the neural network through the input layer. The process of noise reduction is successfully realized by using generalization property of neural networks and learning algorithm in approximating pixel values with high amplitude of corrupted image to an average value. For training the network, the 256x256 pixels Cameraman image has been employed. The structure of the noise reduction system using Multilayer Perceptron Neural Network is shown in Figure 1.

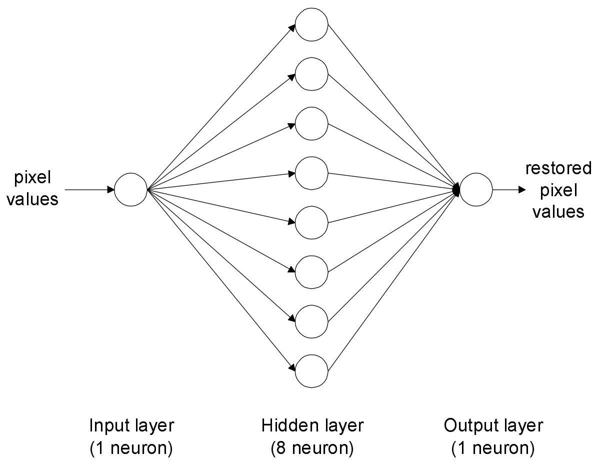


Figure 1. The feedforward neural network structure for impulsive noise reduction.

B. Training and Test Algorithm

The basic steps of neural network algorithm can be described as follows;

1. Convert the original noisy image to a column vector.
2. Apply the same process in step 1 for the target matrix.
3. Choose a suitable learning algorithm and parameters to start training.
4. Train and simulate the network with the input and target values.
5. Obtain the output vector of the output layer.
6. Convert the output vector to a matrix.
7. Convert the test matrix to a column vector.
8. Simulate the network with the test values.
9. Repeat to step 5 and step 6.

III. SIMULATIONS AND RESULTS

Figure 2a shows the corrupted 256-by-256 pixel Cameraman training image. From the simulations performed, it is observed that the histogram of the training image is important and the performance of the network in test increases with wider histogram of the training image. Thus, the choice of the training image should be significant in impulsive noise reduction. The image shown in Figure 2b is the target image. The image in Figure 2c is the output image. Levenberg-Marquardt optimization is used to minimize the learning error since the best results are obtained from this algorithm. The network is trained with training image. For new test images there is no need of training process.

(a)

(b)

(c)

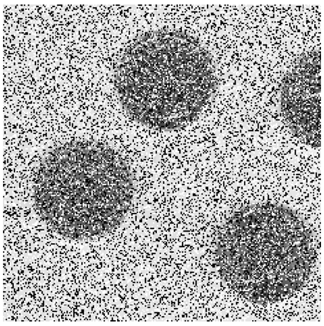
Figure 2. (a) Corrupted Cameraman image (%8 impulsive noise)– training image, (b) Target image, (c) Output image.

The performance of the system is evaluated on popular test images having different image properties and under %40 noise densities. The experimental image is a gray level image having a size of 240-by-240 pixels. This image is especially chosen because of its rich details and texture. Figure 3a shows the corrupted 240-by-240 pixel test image1. The image shown in Figure 3b is the output image after simulation of the network with the test image. The other test image is a gray level image having a size of 256-by-256 pixels and under %25 noise densities. Figure 4a shows the corrupted test image2. The image shown in Figure 4b is the output image after simulation of the network with the test image. The Table 1 shows PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error) performance of our algorithm and median filter under different conditions for different images. Here PSNR and MSE are defined as

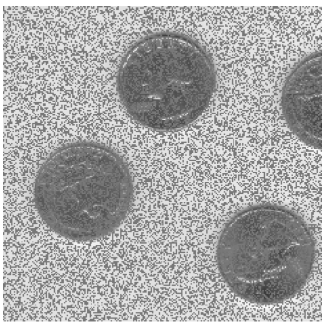
$$MSE = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} \left[I(x,y) - I'(x,y) \right]^2 \qquad (2)$$

$$\text{PSNR} = 20 * \log10\,(255 / \text{sqrt(MSE)}) \qquad (3)$$

Where I(x,y) is the original image, I'(x,y) is the approximated version and M,N are the dimensions of the images.

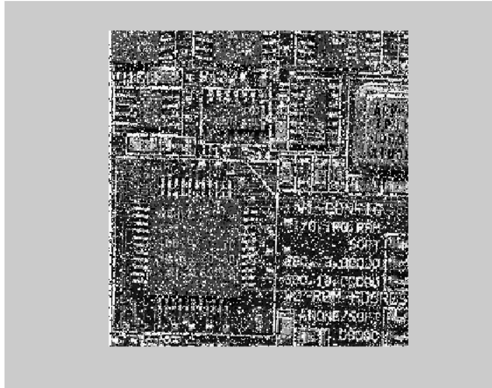


(a)

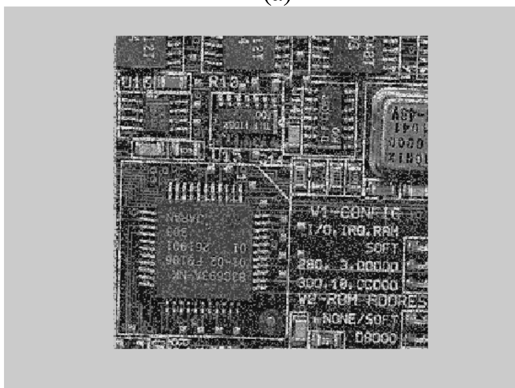


(b)

Figure 3. (a) Corrupted test image1 (% 40 impulsive noise), (b) Output image.



(a)



(b)

Figure 4. (a) Corrupted test image2 (% 25 impulsive noise), (b) Output image.

The median and order-statistic filters were also applied to the corrupted test images to remove the noise for comparison with the proposed model. 3x3, 5x5 and 7x7 masks are applied to the corrupted images but, best result which gives the fine details is obtained with 3x3 kernel. The reconstructed test image2 is shown in Figure 5.

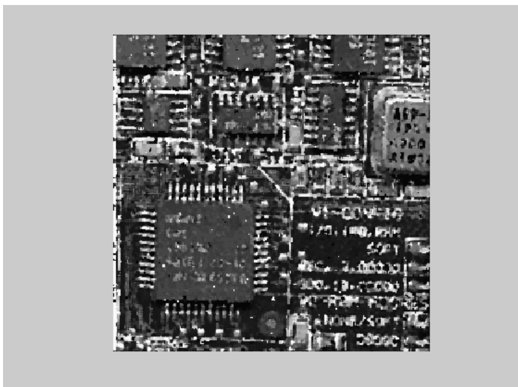
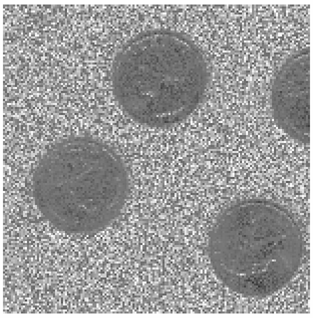


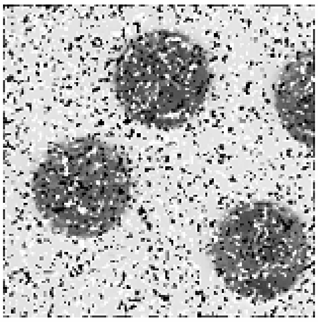
Figure 5. Median-filtered test image2 using a 3 x 3 kernel.

As can be seen from Table 1, for the proposed method, the PSNR value becomes higher as the density of the noise increases. And also, as can be seen from the output images given in figure 3b and 4b, the details of the output image are preserved by using the method proposed for highly corrupted images.

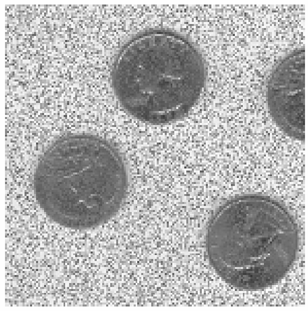
The details which are filtered with median filter are disappeared in corrupted images. In this respect, the method proposed here has certain advantages in applications that require fine details. Both the median filter method and the method used in this work are applied to remove the noise in the test image1 which have different noise densities. The images are shown in Figure 6. Thus, when the corrupted images having noise density higher than %30, are filtered with median filter, the details are disappeared.



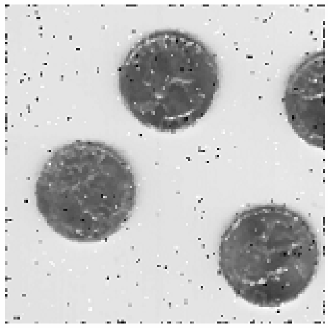
(a) % 60 impulsive noise (new approach)



(b) %60 impulsive noise (median filter)



(c) % 30 Impulsive noise (new approach)



(d) %30 impulsive noise (median filter)

Figure 6. Reconstruction using new approach and 3x3 median filter for test image1 (different noise density impulsive noise)

Table 1. Comparative filtering results for corrupted images.

	Corrupted Images		Restored using New Approach		Restored using 3x3 Median Filter	
	PSNR(dB)	**MSE**	**PSNR(dB)**	**MSE**	**PSNR(dB)**	**MSE**
Training image- %8 impulsive noise corrupted	16,03	1608	23,20	313,6	26,33	152,6
Test image1 %40 impulsive noise corrupted	8,42	9429	12,86	3392	16,99	1310
Test image1 %50 impulsive noise corrupted	7,42	11870	11,93	4211	13,72	2782
Test image1 %60 impulsive noise corrupted	6,60	14337	11,09	5099	10,99	5217
Test image2 %30 impulsive noise corrupted	9,65	7103	14,88	2130	12,62	3584
Test image2 %40 impulsive noise corrupted	8,43	9407	13,73	2776	11,48	4661

IV. CONCLUSION

A neural network is introduced to reduce impulsive noise in images. In this approach, a multilayer feedforward neural network trained by Levenberg-Marquardt algorithm is used to obtain effectively appearing of fine details from noisy image. For the proposed method, the PSNR value becomes higher as the density of the noise increases. Particularly, reduction of impulsive noise using neural networks helps to preserve fine details in highly corrupted images.

REFERENCES

1. Lin, H.-M., Willson, A.N., Jr.: Adaptive-length median filters for image processing., IEEE International Symposium on Circuits and Systems, Vol.3. Espoo, Finland, (7-9 June 1988) 2557 – 2560.
2. Chan, R.H.; Chen Hu; Nikolova, M. : An iterative procedure for removing random- valued impulse noise. IEEE Signal Processing Letters, Volume 11, Issue 12, Dec. 2004, Page(s):921- 924 .
3. M. E. Yüksel, E. Beşdok, A. Baştürk, M.T. Yıldırım: Efficient Blur Reduction of Impulse Noise Removal Operators from Digital Images by a Simple Neuro-Fuzzy Impulse Detector. International XII. Turkish Symposium on Artificial Intelligence and Neural Networks – TAINN, Çanakkale-Turkey (2003).
4. P. S. Windyga, "Fast impulsive noise removal," IEEE Transactions on Image Processing, vol. 10, pp. 173–179, 2001.
5. T. Chen and H. R. Wu, "Space variant median filters for the restoration of impulse noise corrupted images," IEEE Transactions on Circuits and Systems II, vol. 48, pp. 784–789, 2001.
6. M. E. Yüksel, "A simple neuro-fuzzy method for improving the performances of impulse noise filters for digital images," International Journal of Electronics and Communications, vol. 59, no. 8, pp. 463-472, 2005.
7. M. Nikolova: A Variational Approach to Remove Outliers and Impulse Noise. Journal of Mathematical Imaging and Vision, Volume 20 , Issue 1-2, January-March 2004, pages: 99 - 120. 2004 Kluwer Academic Publishers. Manufactured in The Netherlands.
8. E. Beşdok ve M. E. Yüksel, "Impulsive noise suppression from images with Jarque-Bera test based median filter," International Journal of Electronics and Communications, vol. 59, no. 2, pp. 105-110, 2005.
9. Zhou Wang; Zhang, D. : Restoration of impulse noise corrupted images using long-range correlation. IEEE Signal Processing Letters, Volume 5, Issue 1, Jan. 1998, Page(s):4 - 7 .
10. Jiang, X.D. : Image detail-preserving filter for impulsive noise attenuation. IEE Proceedings on Vision, Image and Signal Processing, -Volume 150, Issue 3, 20 June 2003, Page(s):179 - 185.
11. Li, W.; Ogor, B.; Haese-Coat, V.; Ronsin, J.: Detail-preserving morphological filters in noise suppression. 3rd International Conference on Signal Processing, Volume 1, 14-18 Oct.1996, Page(s):527 – 530.
12. C.K. Chui, R. Garnett, T. Huegerich: A universal noise removal algorithm with impulse detector. IEEE Transactions on Image Processing, Nov. 2005 Volume: 14, Issue: 11, on page(s): 1747- 1754.
13. N. Alajlan, M. Kamel and E. Jernigan, Detail preserving impulsive noise removal. Signal Processing: Image Communication, Volume 19, Issue 10, November 2004, Pages 993-1003.
14. Greenhill, D., Davies, E.R.: How do neural networks compare with standard filters for image noise suppression?. Applications of Neural Networks to Signal Processing, IEE Colloquium, (15 Dec. 1994), 3/1 -3/4.