# Image Reconstruction and Edge Detection based upon Neural Approximation Characteristics

Manoj Kumar Singh
Manuro Tech Research, Bangalore, India
mksingh@manuroresearch.com

***Abstract*—In image processing based applications there are very important requirements of noise removal and edge detection. In this paper universal approximation characteristic of feedforward neural is taken to achieve both of these requirements in a simple but very efficient way. Concept of local pattern generated by small region pixels which define the possibility of relation among pixels is presented. This approach facilitates the solution as universal solution for different types of noise removal compare to conventional solutions which are based on noise characteristics. Same model of neural network with little extension can also be utilized as edge detector has also presented. Another benefit of proposed model is contrast enhancement without any extra computation cost. In effect this solution can be considered as universal solution for noise reduction, edge detection and contrast enhancement. Comparison has made with well established solution like median filter and adaptive Wiener filter for noise reduction where as Canny and Prewitt detectors have taken for edge detection comparison.**

***Index Terms*—noise reduction, edge detection, contrast enhancement, neural network, universal approximation.**

## I. INTRODUCTION

In the field of digital image processing, image recovery define a process which recovers the original image data from the degraded image (noise in the acquisition, transmission problems, etc.). Its use is of utmost importance for several disciplines such as: Medicine, Biology, Physics, and Engineering. If conventional solutions are analyzed, it can be noticed that there exist specific filters for each type of noise [1], [2]. For instance, in the "salt and pepper" noise, the mean filter is the mostly used [3], [4]; in the case of the Gaussian noise, Weiner filter is used. It is important to notice that the application of a low-pass filter, like Weiner, despite being an effective way of reducing Gaussian noise in an image, does not produce good results with impulsive noise. This leads to the analysis of the noisy signal and considering, in each case, the solution to apply [5]. On the other hand, through adaptive solutions efforts have given to fix the problem [6], [7].

Edge detection is a very important area in the field of Computer Vision. Edges define the boundaries between regions in an image, which helps with segmentation and object recognition. They can show where shadows fall in an image or any other distinct change in the intensity of an image. The edge detection process serves to simplify the analysis of images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries. There is certainly a great deal of diversity in the applications of edge detection, but it is felt that many applications share a common set of requirements. Edges are quick changes on the image profile. These quick changes on the image can be detected via traditional difference filters [8]. Also it can be also detected by using canny method [9] or Laplacian of Gaussian (LoG) method [10]. In these classic methods, firstly masks are moved around the image. The pixels which are the dimension of masks are processed. Then, new pixels values on the new image provide us necessary information about the edge.

This paper presented the unified concept to remove various types of noise efficiently with the use of artificial neural network. With same concept solution has defined for edge detection and contrast enhancement. In the section II concept of universal approximation posed by neural network presented. In section III definition of local pattern defined whereas section IV method to remove the noise given. Section V carries the information of experimental results in noise removal process. Contrast enhancement method explains in section VI. Edge detection and corresponding experiments are given in section VII and in section VIII. Conclusion is defined in section IX.

## II. UNIVERSAL APPROXIMATION CAPABILITY OF ANN

The approximation capability of the network is closely related to Kolmogorov's superposition theorem, which states that any continuous function with multiple inputs is representable by sums and superposition of continuous functions of only one variable [11].Because the mapping between vector pairs can be considered as a superposition of n mapping networks with n inputs and one single output for each coefficient. The signal representation at the outputs of the hidden layer units is a nonlinear function of a weighted sum of the inputs plus an additive constant term. The desired output function is finally obtained from a linear combination of the weighted outputs of the hidden units. The relation between the



doi: 10.12720/joig.1.1.8-12

input vector and the output for one coefficient in a network with hidden layer units is given by (1).

$$f\left(\bar{x}\right)=\sum_{j=1}^{h}v_j\psi\left(\sum_{i=1}^{n}w_{ji}x_i+b_i\right) \qquad (1)$$

With x' as input vector, $W_{ji}$ as connection weights between input and hidden layer, the offset $b_i$ as the additional input to the hidden units, Ψ( ) as the nonlinear hidden layer activation function, and $V_j$ as weights from the hidden units to the output. A common choice for Ψ ( ) is e.g. a sigmoid-type function. Contribution of single hidden layer unit to the whole network is the calculation of the nonlinear activity function of the weighted sum of its inputs plus an additional offset. Some important hints for the practical realization of an appropriate network topology can be found in [12]. The units of subsequent layers should be fully connected with each other, and three layers are - at least theoretically - sufficient. An upper limit for the number of hidden units h is $h \lesssim 2n+1$.

## III. Local Pattern in an Image

Any image technically describe as variation of light intensity which form a set of patterns in spatial domain. These patterns may be simple or complex depends upon style of variation in light intensity. Digitally these patterns are embedded in pixels values. It is very difficult to define these patterns through pixels globally but it is possible to observe and understand the characteristics of these patterns in small region where pixels are highly correlated and it can be consider as a local pattern defined by pixels in that region as shown in Fig.1.complexity and information available within the patterns not only depends upon the position of local region but also size of local region. Small size of region will not deliver high informative pattern where as very large size will carry to many information. These local patterns can be expressed as some kind of function. Hence an image can be taken as collection of number of local function. If available image having good diversity of patterns there is possibility that through local function as an input data set, approximation capability of neural network can acquire the possible knowledge necessary to define the local pattern as an output. If noise is included with the image, effect of any types of noise over the local patterns fundamentally destroy the correlation available within pixels in the local region as shown in Fig2 and Fig3.

## IV. Noise Removal by ANN

Assume a kind of intelligent solution which is able to understand the normal relationship involve within the pixels in a small region through learning. If for such solution any abnormal relationship in form of pattern appears as an input, it can utilize the learned knowledge to correct the input pattern through approximation basis. The important advantage of this approach is correction will not depends upon the what kind of abnormalities available within the input pattern. This type of solution can achieve by use of artificial neural network where training data set is a set of normal pattern generated by pixels in small region over an image having good spatial diversity and target is the same as input. With concept of universal approximation three layer feedforward architecture is optimal choice for this. Quality of learning is improved with large number of nodes in hidden layer but reduce the capability of correction if some abnormalities are appeared at the input pattern whereas if number of hidden node is very less learning will difficult.

## V. Experimental Analysis

Various parameters defined for this experiment have shown in table1.gray scale of Lena image having size 512*512 pixels has taken as a training image. After pre-processing as normalization and division into number of sub block of size 5*5 learning has applied with Back-propagation algorithm with architecture size of 25 input nodes 5hidden nodes and 25 output notes. Once learning completed, with the trained weights, architecture applied for testing over various different type of image with different types of additive noise. Performances have shown inFig1 and in Fig.2.Noise reduction by Neural network (ANN) & wiener filter (AWF) over Gaussian noise and Median filter over salt and pepper, have given in Table1.GNVR is the noise variance, NL is the PSNR of image with noise,SPDEN represent the density of salt & pepper noise in image.MNR is % mean noise reduction form noisy image.

TABLE I. Performance over Different Types of Noise and Images

| **LENA + GN** | | **MNR (%)** | | **PSNR(db)** | |
|---|---|---|---|---|---|
| **GVR** | **NL(db)** | **ANN** | **AWF** | **ANN** | **AWF** |
| 0.02 | 17.18 | 57.7 | 58.7 | 24.18 | 24.36 |
| 0.04 | 14.43 | 59.16 | 59.16 | 21.85 | 21.69 |
| 0.06 | 12.99 | 59.41 | 59.41 | 20.44 | 20.30 |
| 0.08 | 12.03 | 59.53 | 59.53 | 19.53 | 19.37 |
| 0.10 | 11.32 | 59.75 | 59.75 | 18.84 | 18.70 |

| **LENA + S&P** | | **MNR (%)** | | **PSNR(db)** | |
|---|---|---|---|---|---|
| **SPDEN** | **NL(db)** | **ANN** | **MF** | **ANN** | **MF** |
| 0.005 | 28.43 | 83.06 | 95.85 | 30.25 | 29.17 |
| 0.01 | 25.56 | 82.80 | 95.94 | 29.29 | 29.16 |
| 0.02 | 22.49 | 82.8 | 96.02 | 27.82 | 29.12 |
| 0.04 | 19.39 | 82.26 | 95.94 | 25.71 | 29.10 |
| 0.10 | 15.43 | 80.92 | 95.94 | 22.42 | 28.93 |

| BOAT + GN | | MNR (%) | | PSNR(db) | |
|---|---|---|---|---|---|
| **GVR** | **NL(db)** | **ANN** | **AWF** | **ANN** | **AWF** |
| 0.02 | 17.19 | 51.2 | 56.34 | 23.07 | 23.94 |
| 0.04 | 14.45 | 54.84 | 57.21 | 21.10 | 21.40 |
| 0.06 | 12.95 | 56.26 | 57.65 | 19.86 | 20.02 |
| 0.08 | 12.00 | 56.84 | 57.86 | 19.0 | 19.1 |
| 0.10 | 11.28 | 57.55 | 58.24 | 18.4 | 18.4 |
| **BOAT + S&P** | | **MNR (%)** | | **PSNR(db)** | |
| **SPDEN** | **NL(db)** | **ANN** | **MF** | **ANN** | **MF** |
| 0.005 | 28.48 | 81.94 | 93.4 | 27.19 | 25.23 |
| 0.01 | 25.52 | 82.23 | 93.57 | 26.70 | 25.22 |
| 0.02 | 22.43 | 82.16 | 93.62 | 25.79 | 25.22 |
| 0.04 | 19.47 | 81.44 | 93.42 | 24.39 | 25.19 |
| 0.10 | 15.54 | 79.98 | 93.46 | 21.76 | 25.13 |
| **Elaine + GN** | | **MNR (%)** | | **PSNR(db)** | |
| **GVR** | **NL(db)** | **ANN** | **AWF** | **ANN** | **AWF** |
| 0.02 | 17.17 | 55.64 | 57.57 | 24.0 | 24.19 |
| 0.04 | 14.43 | 58.11 | 58.41 | 21.71 | 21.58 |
| 0.06 | 12.96 | 58.76 | 58.83 | 20.36 | 20.20 |
| 0.08 | 11.99 | 59.3 | 59.01 | 19.45 | 19.27 |
| 0.10 | 11.30 | 59.45 | 59.37 | 18.76 | 18.64 |
| **Elaine + S &P** | | **MNR (%)** | | **PSNR (db)** | |
| **SPDEN** | **NL(db)** | **ANN** | **MF** | **ANN** | **MF** |
| 0.005 | 28.40 | 82.40 | 95.69 | 29.99 | 31.15 |
| 0.01 | 25.50 | 82.53 | 95.79 | 29.05 | 31.13 |
| 0.02 | 22.41 | 82.66 | 95.87 | 27.58 | 31.12 |
| 0.04 | 19.32 | 82.01 | 95.72 | 25.66 | 31.06 |
| 0.10 | 15.48 | 80.69 | 95.74 | 22.39 | 30.91 |

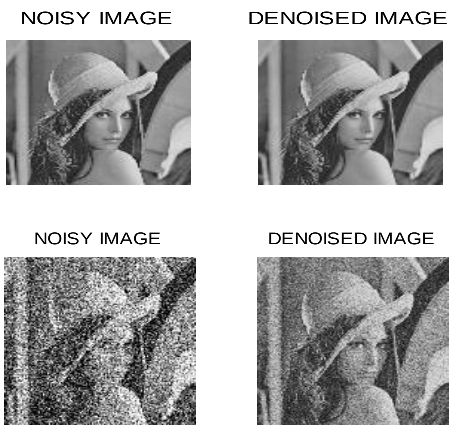
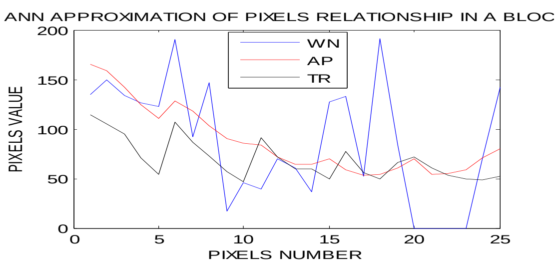



Figure 1. Performance with training image



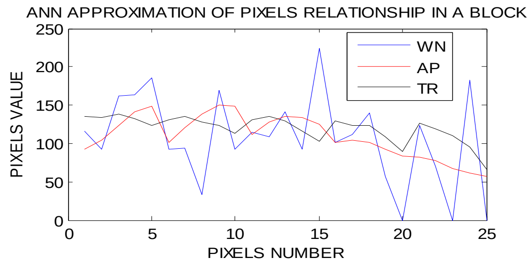




Figure 2. ANN approximation for two blocks of imagehaving gauussian noise,WN:with noise,AP:approximated,TR:actual

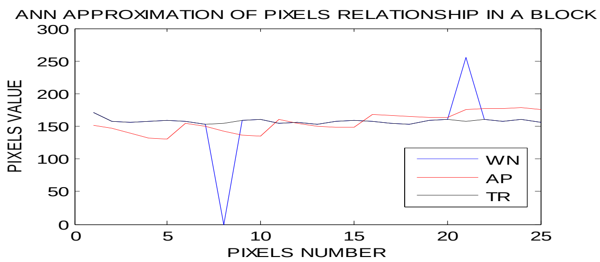



Figure 3. ANN approximation with salt &pepper noise

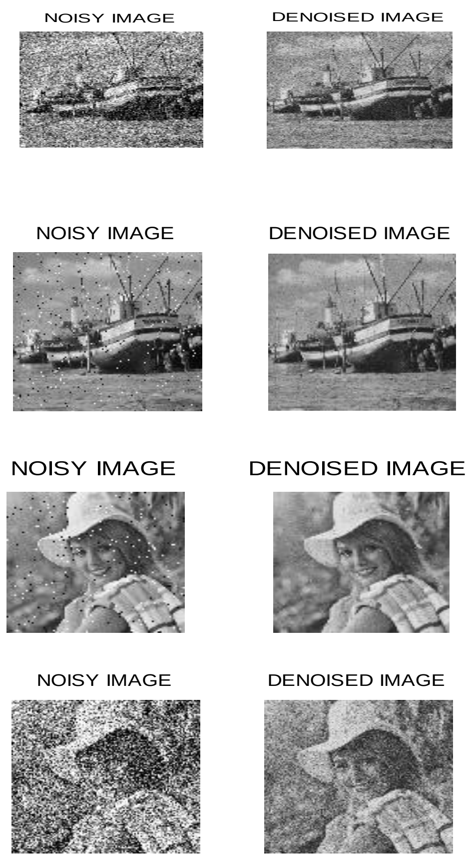



Figure 4. Performance with test images

## VI. CONTRAST ENHANCEMENT

Presented model of noise removal using neural network can also utilize to enhance the contrast without any extra comutation model by simply changing the slope of sigmoid function at output layer by assigning higher value of constant K in the (2).in the example below after noise reduction,result for three different vlue of k: 1,1.5 and 2 has shown in Fig5.

$$S=1 / (1+e^{-k\,x}) \qquad (2)$$

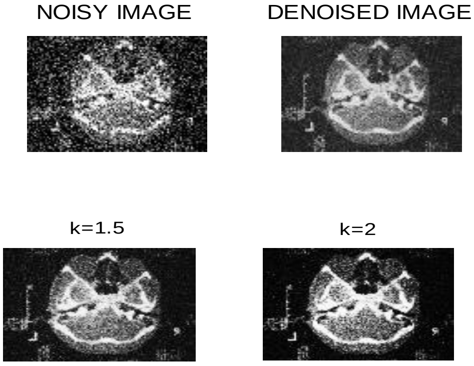



Figure 5. Contrast enhancement after noise reduction

## VII. Edge Detection by ANN

Pixels over the edge in an image having high value of variation compare to their neighbors.if there is low passfilter available then output from this image will carry the information about less variation.if difference between original and generated low variation output is taken it will carry the information about the edges.in the proposed method efficient low filter has generated by taking the single node in hidden layer of feedforward neural achitecture.initially this architecture involves in getting training with standard image to produce the same as an output.but because of single node in hidden layer it will acquire the knowledge maximally to produce the output having low variation in result started to behave like low passfilter.use of this trained neural network for any test image has in Fig6.thresholding applied to normalized the variation of intensity over the length of edge into two different class only.

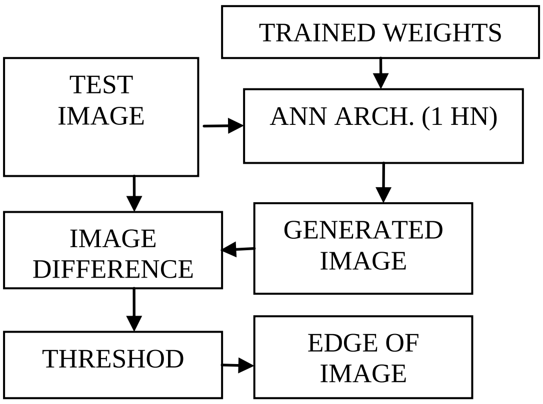



Figure 6. Edge detection procedure

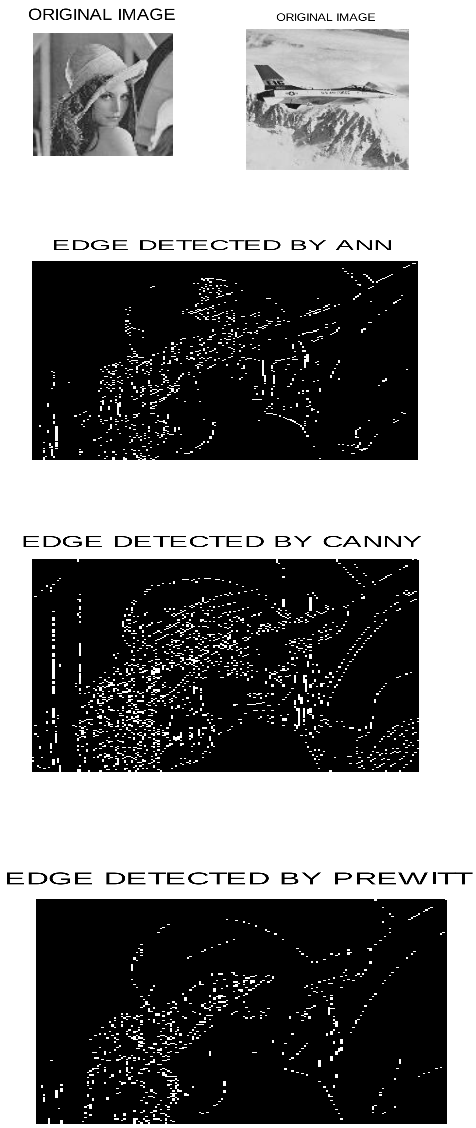
## VIII. Experimental Setup

Standard training input is taken as Lena of 512*512 pixels and divided into number of blocks each one have size of 3*3 pixels. a feedforward architecture having size of 9 input nodes,1 hidden node and 9 output nodes is taken to involve in learning by back propagation algorithm to produce same output as values are available at input. Learning constant and momentum constant both are equal to 0.1.bias has also applied and learning iterated up to 200 iterations. Threshold is taken as function of difference in pixels shown in (3).

$$TH = \text{mean}\,(|D|) + 1.5{*}\text{Std .Dev}\,(|D|) \qquad (3)$$

For comparison purpose two well established methods for edge detection namely “Canny” and “Prewitt’ have taken .Performance for two different images have shown in Fig7.It is clear from the performance that proposed solution given competitive detection for other two methods.

Test case1: Lena, Threshold value TH= 50.7674




Test case2: Airoplane,Threshold value TH=53.68

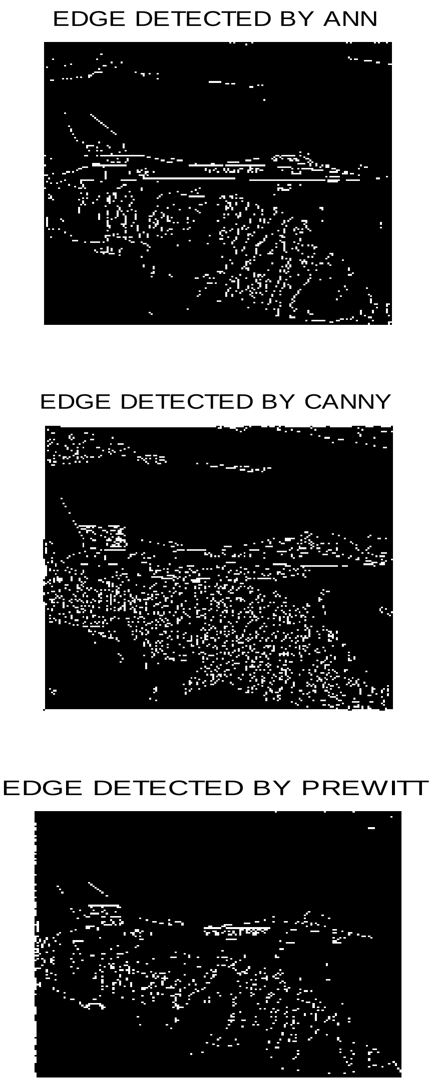



Figure 7. Edge detection performance

## IX. CONCLUSION

With the use of feedforward neural network an efficient universal solution for different types of noise removal and edge detection has presented in the work. Proposed solution is not only having good efficiency but also having simplicity in nature. With the single image as a training data set it is having generalized capabilities for both noise as well as edge detections. Contrast of image can be enhancing without any extra effort. Comparison between existing and proposed solution shows that presented work having improvement over wiener filter at high level of Gaussian noise where as at low level of salt &pepper noise it is better compare to median filter. Edge detection performance are competitive to canny and prewitt performance.

## ACKNOWLEDGMENT

This research is completed at Manuro Tech Research and author expresses his thanks to associated members.

## REFERENCE

[1] Chung-Changwu, Wang, "Speckle noise reduction for ultrasonic images," *Systems, Man and Cybernetics, 2003. IEEE,International Conference on Volume* 5, 5–8 Oct.

[2] S. Kwang Lee and Yo-Song Ho, "Edge-preserving image restoration using adaptive constrained optimization," TENCON '98. 1998 IEEE Region 10 *International Conference on Global Connectivity in Energy, Computer, Communication and Control*. vol. 1, 17-19 Dec. 1998, pp. 70–73, Vol. 1

[3] A. R. Forouzan and B. N. Araabi, "Iterative median filtering for restoration of images with impulsive noise," *Electronics, Circuits and Systems, 2003.ICECS 2003. Proceedings of the 2003 10th IEEE International Conference* on Volume 1, 14-17 Dec.2003, pp. 232–235, vol. 1.

[4] T. Chen and H. Ren Wu, "Space variant median filters for the restoration of impulse noise corrupted images," *Circuits and Systems II: Analog and Digital Signal Processing, IEEE Transactions on* , Volume 48, Issue 8, Aug. 2001,pp. 784–789.

[5] F. Russo, "A method for estimation and filtering of Gaussian noise in images," *Instrumentation and Measurement, IEEE Transactions* on vol. 52, Issue 4, Aug. 2003 pp. 1148–1154.

[6] T. Mélange, M. Nachtegael, and E. E. Kerre, "Fuzzy random impulse noise removal from color image sequences," *Image Processing, IEEE Transactions on*, Volume: 20 Issue:4,pp:959-970,2011.

[7] R. E. Patino-Escarcina, J. A. F. Costa, " An evaluation of MLP neural network efficiency for image filtering, "*IEEE-ISDA*, pp. 335 – 340, 20-24 Oct. 2007

[8] M. Norgaard, N. K. Poulsen, and O. Ravn, "Advances in derivative-free state estimation for non-linear systems," *Technical Report IMM-REP-1998-15 (revised edition), Technical University of Denmark,Denmark,* April 2000.

[9] L. Canny, "A computational approach to edge detection," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 8 no. 1, pp. 679-698, 1986.

[10] D. Marr and E. Hildreth, "Theory of edge detection," *Proc. of Royal Society Landon*, B(207): 187-217, 1980.

[11] V. Kurkova (1991) Kolmogorov's Theorem Is Relevant. *NeuralComputation* 3, pp. 617-622,The MIT Press

[12] Hecht-Nielsen R., *Neurocomputing*, pp. 132, Addison-Wesley Publishing Company, 1990

**Manoj Kumar Singh** is currently holding the post of director in Manuro Tech. research, Bangalore, India. He is also actively associated with industry and academic as expert in advanced intelligent technology. He is having background of R&D in advanced intelligent computing and solution in various fields. His field of research include Nature inspired computation, Nano-computing, Soft computing, Machine learning, Optimization, etc. He has number of publications in international journals and conferences.