Noise Reduction Technique for Images using Radial Basis Function Neural Networks

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RECEIVED ON 21.11.2013 ACCEPTED ON 19.03.2014

ABSTRACT

This paper presents a NN (Neural Network) based model for reducing the noise from images. This is a RBF (Radial Basis Function) network which is used to reduce the effect of noise and blurring from the captured images. The proposed network calculates the mean MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio) of the noisy images. The proposed network has also been successfully applied to medical images. The performance of the trained RBF network has been compared with the MLP (Multilayer Perceptron) Network and it has been demonstrated that the performance of the RBF network is better than the MLP network.

Key Words: **Image Processing, Noise Reduction, Neural Networks, Radial Basis Function**

1. INTRODUCTION

As the system under goes transmission process, it transmits images which are composed of packets, bits in its simplest form. These bits are usually affected by impulse noise which can change these bits in either value, which results in error or false information. The approach in this paper is to reduce the noise from images and to enhance the approximation of the received image with the original image to avoid the encounter of false information. Reduction of Noise is considered as the continuous process of mapping the noisy data to the noise reduced data. This results in an enhanced image which can be considered as the approximation with least error or error free image and thus improves the performance of the system [1]. Use of ANN (Artificial Neural Networks) is the best possible way to achieve this goal which is to have a good approximation for mapping of input bits, output bits. Reviewing from the conventional methods ANNs are good because of their learning from the previous experiences. The approximation is based on the supervised method in order to synthesis almost the same input-output bit mapping.

In this paper RBF architecture is employed. The use of RBF is preferred over MLP because of its local approximations to non-linear input output mappings which result in fast learning and reduced sensitivity to the order of presentation of training data [2].

The training of the designed ANN assumes the input signal to be the rectangular/square box in which pixels are confined with the addition of additive white Gaussian noise. The employed ANN generalizes the model by learning from the noisy image with corresponding desired output. This ANN can be employed for reducing the noise as well as enhancing the images from the corrupt image signal. The steps for achieving this goal are:

- As the designed ANN is trained for the assumption of composite image with additive white Gaussian noise, the learning process gets faster and the approximation gets better.
- Comparison of original image with the image produced after the reduction of the noise.

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- Calculation of MSE between the original image and the image produced after the reduction of the noise as well as the PSNR of the output image in comparison with the input image [3].

2. ARTIFICIAL NEURAL NETWORKS

ANNs are very useful in solving signal processing problems. Unlike conventional methods ANN can adapt and track continuous changes in signal over time and possesses the ability to learn from noisy data to solve complex problems which produces better results than the conventional statistical techniques. ANNs consist of two phases i.e. Learn and test. Learning is a process which is stimulated by the environment on continuous basis so that it can adapt the variable parameters of any neural network embedded in the system. Adaptation of weights in response of learning is determined by the training algorithm. Testing refers to the mode of application where the process is being tested in accordance with the pattern provided in the input layer and the desired output which is created at the output layer.

Designing an application oriented ANN, the architecture of the neural network and the optimal size of the network must be determined i.e. the total number of layers, the number of hidden layers and output layers and the training algorithm used in the learning phase. There are two types of network architecture commonly used in Neural Networks to perform the desired task (filtration in this case) from a noisy training set to filter the image and enhancement of the image. Multilayer Feedforward networks and Recurrent or Feedback networks. As this paper takes RBF into consideration so only Multilayer feed forward networks will be discussed in the following section.

3. MULTILAYER FEEDFORWARD NETWORKS

The most popularly used ANN is multilayer feedforward network. A multilayer feedforward network mainly consists of more than two layers of units, all of which are adaptive. Number of artificial neurons or nodes in a layer of multilayer feedforward networks is random or arbitrary. Same activation function is used in a single particular layer but different activation functions can be used by neurons in different layers. In feedforward networks the signal always travels in the forward direction to other layers, it cannot be transmitted to the other neurons in the same layer or in backward direction, this is the reason for which this network is named as feedforward network.

The first layer is the input layer in multilayer feedforward networks which accepts the input patterns based on the data samples which are fed as shown in Fig. 1. There is no processing involved in this layer as this layer works as passive unit which just fan outs the input patterns to the next layer. Input layer passes the signals based on input patterns to the hidden layer which can be one or more than one and as the name indicates it is hidden so it cannot be accessed from outside the network. Learning takes place in this hidden layer which learns the complex tasks and extracts the information associated with the input patterns. Output layer is the final layer which accepts the signal from the hidden layer and processes it according to the given condition. The output for the given input pattern can be read out at this layer. As the feedforward network is a supervised learning method so the training phase compares the computed results passed from activation function with the target value to calculate the error associated with these units. After the error has been calculated the weights are updated accordingly and the error is distributed from output layer to the next lower layer as we move forward the error is computed and passed forward by updating the weights.

4. RADIAL BASIS FUNCTION

RBF network is the powerful alternative of MLP network. RBF has the similar architecture but the difference is that it contains only single hidden layer. Gaussian activation function is used by all the neurons in the hidden layer which are inversely proportional to the distance from the centre of the neuron. Though the concept is similar to KNN (K-Nearest Neighbor) model but the implementation is very different. It assumes that all the items which have close values to the predictor variables are likely to have same predicted target values; this is the basic concept behind RBF NN.

Gaussian activation function is applied in the hidden layer of the RBF network which is defined as follows:

$$f_j(\vec{x}) = \exp\left(-\frac{\left\|\vec{x}-\vec{c}_j\right\|^2}{\sigma_j^2}\right) \tag{1}$$

Where $\vec{x}$ is the input vector $\vec{c}_j$ is the centre of jth RBF and σ_j^2 is its variance. The third layer computes the output function for each class as follows:

$$y_j(\vec{x}) = \sum_{j=1}^{M} W_j f_j(\vec{x}) \qquad (2)$$

Where M is the function of RBF and W_j is the weight associated with j^{th} RBF. RBF takes the radius as their argument to update the weights accordingly. RBF architecture is shown in Fig. 2.

The reason of using RBF network is that unlike MLP networks RBFs performs fast learning due to the construction of local approximations of input-output mapping and thus reduces the sensitivity to the order of the training data presented.

5. TRAINING RBF NETWORK

The literature about computational power tell us what an RBF can do, but nothing about how to find its parameters. The training process of RBF is determined by the following parameters:

- Number of neurons in the hidden layer
- Coordinates of the centre of each hidden layer [4]
- Spread of each RBF function in each dimension
- Weights of RBF function which are passed to the summation layer [5]

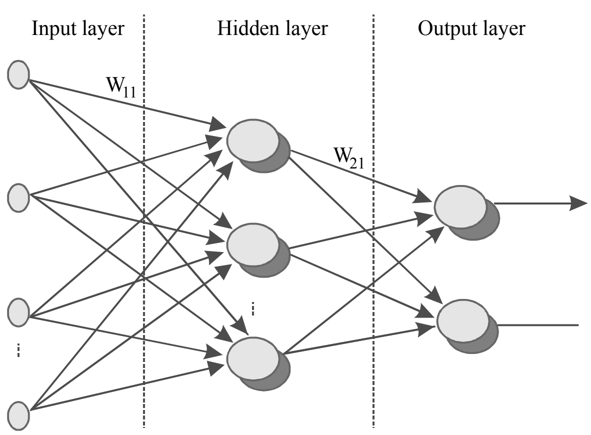


FIG. 1. A SIMPLE THREE LAYER FEEDFORWARD NETWORK

the space spanned by the basis vectors Φ_k such that Φ=YA. The solution of radial basis function using the above orthogonal representation is given by:

$$T = \Phi W = YG \qquad (3)$$

$$G = (Y^tY)^{-1}\,Y^tT \qquad (4)$$

$$g_t = \frac{q_i^t T}{q_i^t q_i} \qquad (5)$$

This is precisely what makes orthogonal least squares method most suitable and efficient implementation. Where T is the Target vector, W represents weight, G is the weight vector in orthogonal space, q_i is the i^{th} orthogonal vector and g_i is the forward regression. However, the selection of basis function is done with the energy of the desired vector or sum of the squares which can be defined by:

The selection of the RBF centres is the most crucial problem in designing the RBF network. This problem could be overcome by using the popular algorithm known as Orthogonal Least Squares Method. It constructs a set of orthogonal vectors in the spaces spanned by the vectors of hidden unit activations for each pattern in the training set. This algorithm automatically selects number of neurons in a hidden layer [6].

6. METHODOLOGY

As the RBF network follows the supervised method so the image with the noise is compared with the original image to reduce the errors and produce the desired result. Reducing errors is accomplished by the algorithm used in the previous section. As it was mentioned earlier that orthogonal least squares method constructs a set of orthogonal vectors let's say Y for

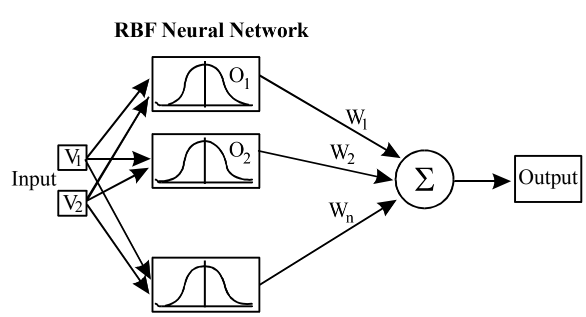


FIG. 2. RADIAL BASIS FUNCTION NETWORK ARCHITECTURE

$$T^tT = \sum_{i=1}^{M} g_i^1 q_i^t q_i + E^t E \quad (6)$$

In Equation (6) variable E is the predicted error vector. Assuming that the mean of the desired target T has been removed, then the variance of T is given by:

$$[err]_i = \frac{g_i^2 q_i^t q_i}{T^t T} \quad (7)$$

If some residual error falls below some specified tolerance ρ which is a threshold set by the developer to stop the iterations:

$$1 - \sum_{j=1}^{M} [err]_j < \rho \quad (8)$$

If this condition is satisfied the iteration process will be halted or stopped.

7. RELATED WORK

Many techniques have been proposed to reduce the noise from images, some are based on wavelet transforms, FIR filter design, Adaptive non-linear filter and Neural Networks (MLP). The results are very attractive though the mean square error still demands to be improved. As in normal images the errors can be tolerated but when it comes to medical images this error gets very crucial as very small noise or a very minor change can create a great difference in diagnosis. This method works very well with the Gaussian noise but the results with other noises are also very impressive as compared to the techniques which are applied so far [1,3,7-11].

8. EXPERIMENTAL RESULTS

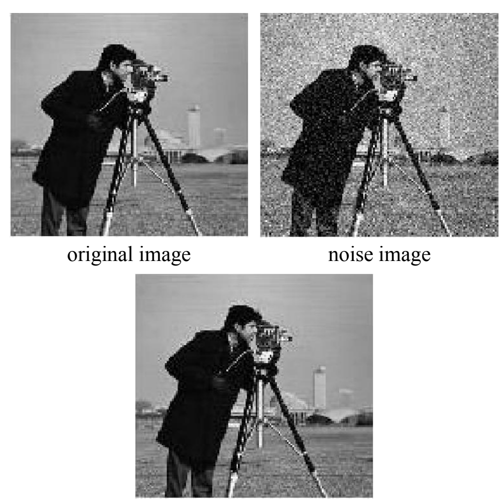
Initially the images with additive white Gaussian noise were used to train the RBF network. Gaussian noise is characterized by energy spectrum of all available frequencies. That's why the value of pixels will be different at every instant whenever the image is captured and whenever this type of problem arises.

This effect changes the real gray level values and the new values will be independent of those taken by the image. The results are evaluated and simulated using MATLAB. In this experiment the image is added with the additive white Gaussian noise, this noise is added with the use of "imnoise" function in MATLAB, the neural network then compares the pixels of original image and the noisy image and calculates the residual error distance. The neural network updates the weights and reduces the error by using the algorithm which is discussed in the methodology section.

Following are the results obtained by noise reduction with RBF.

It is shown in Fig. 3 that the results after Gaussian noise reduction is approximately same as the original image, but it does not mean that radial basis function networks can only remove Gaussian noise efficiently. RBF networks can remove other noise very efficiently as well. The blurring effects and other noises which can be removed by RBF networks and these results are compared with that of MLP networks which prove that RBF networks are well suited for noise removal in images in contrast to MLP networks (Figs. 4-9).

These results are efficient as any error less than 0.01 has no major impact in the results but when it comes to medical images and in today's era where sophisticated computers are used to diagnose the results on the basis of X-Rays and CT Scans it can leave a major impact on the diagnose results, but RBF networks assure that it can produce the results with error very much less than 0.00001 as the number of neurons in this function is exactly the same as the number of Gaussian functions used to reduce the errors so the Gaussian functions performs the local approximations unlike the MLP networks which performs global approximations. Some medical images are shown in Figs. 10-13. Figs.11-12 and Figs. 14-15 show that the RBF network successfully removes noise from these images. A comparison of MLP and RBF network has been presented in Table 1.



original image noise image

filtered image

FIG. 3. GAUSSIAN NOISE REDUCED BY USING RBF NETWORKS (PICTURE COURTESY: MATHWORKS)

FIG. 4. BLURRING EFFECT IS REMOVED BY USING RBF NETWORKS (PICTURE COURTESY: MATHWORKS)

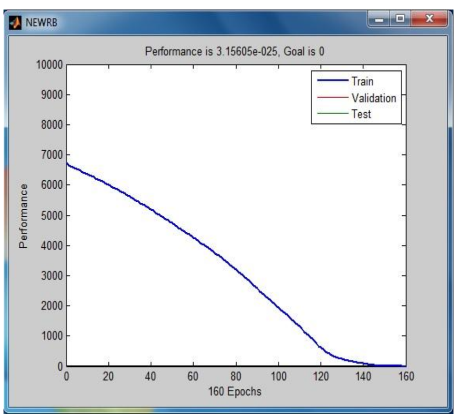


FIG. 5. TRAINING GRAPH AND ITERATIONS USED BY RBF NETWORKS

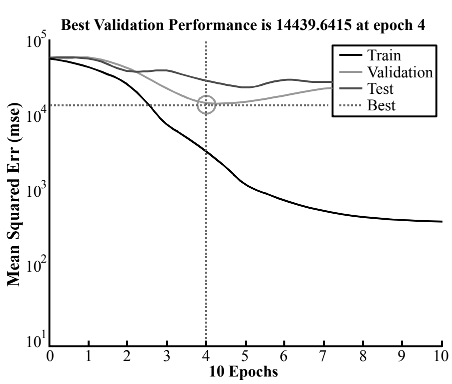


FIG. 6. TRAINING GRAPH AND ITERATIONS PERFORMED BY MLP NETWORKS

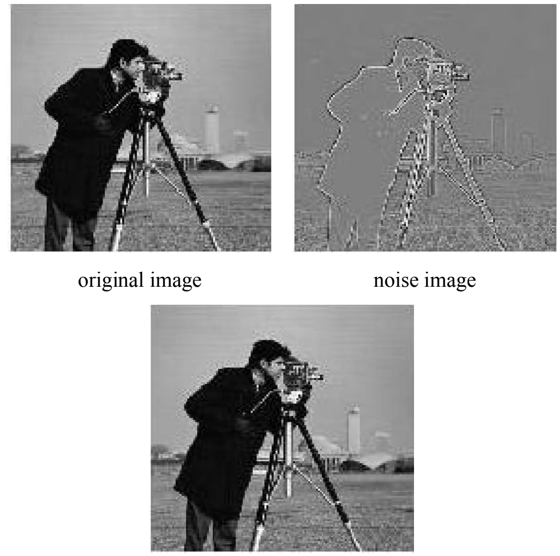


FIG. 7. DIFFERENT TYPES OF NOISE REDUCED BY RBF NETWORKS (PICTURE COURTESY: MATHWORKS)

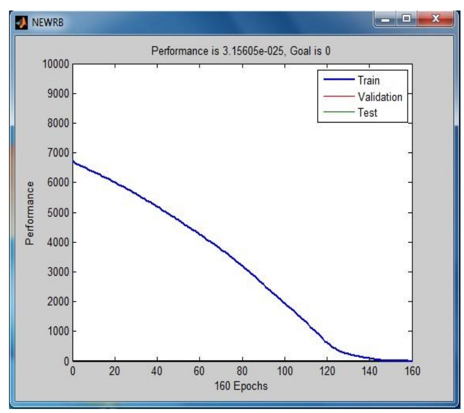


FIG. 8. TRAINING GRAPH AND ITERATIONS PERFORMED BY RBF NETWORKS

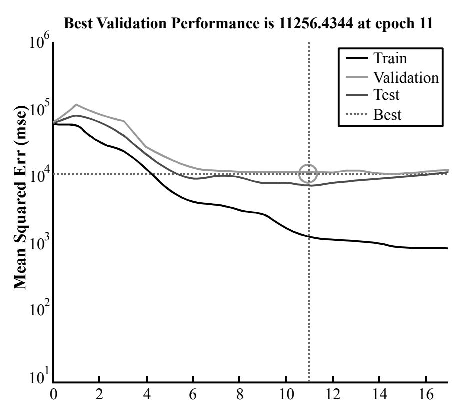


FIG. 9. TRAINING GRAPH AND ITERATIONS PERFORMED BY MLP NETWORKS

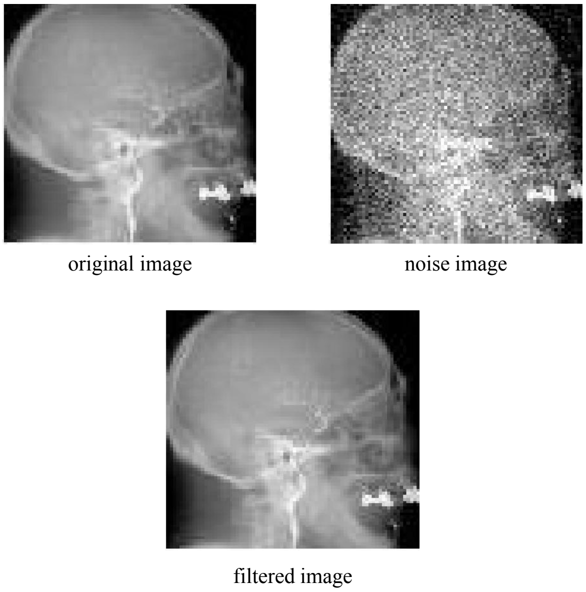


FIG. 10. NOISE REDUCTION IN X-RAY IMAGE USING RBF NETWORKS (PICTURE COURTESY: MATHWORKS)

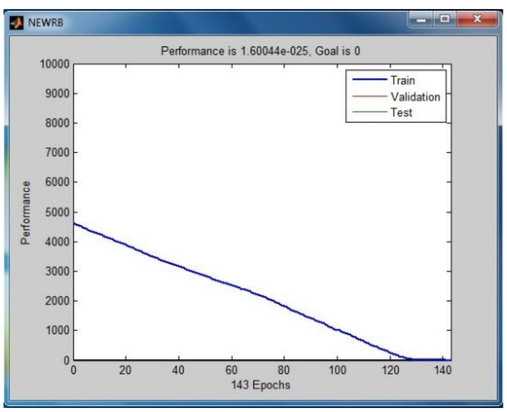


FIG. 11. TRAINING GRAPH AND ITERATIONS PERFORMED BY RBF NETWORKS

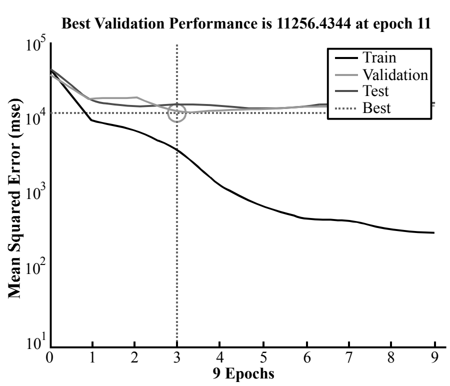


FIG. 12. TRAINING GRAPH AND ITERATIONS PERFORMED BY MLP NETWORKS

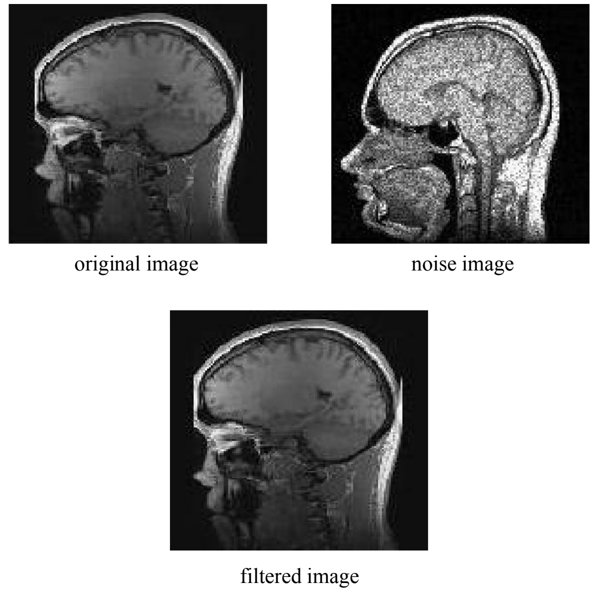


FIG. 13. CT SCAN IMAGE NOISE REDUCED BY RBF NETWORKS (PICTURE COURTESY: MATHWORKS)

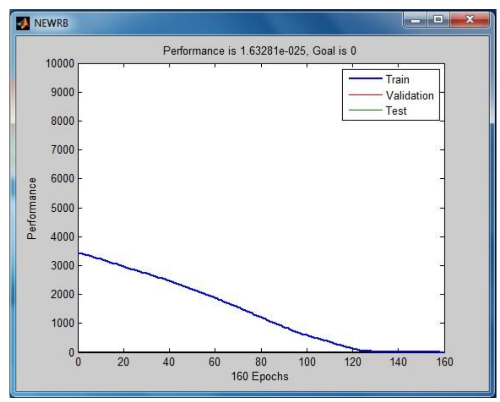


FIG. 14. TRAINING GRAPH AND ITERATIONS PERFORMED BY RBF NETWORKS

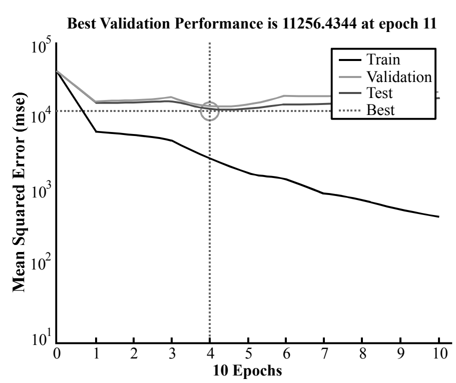


FIG. 15. TRAINING GRAPH AND ITERATIONS PERFORMED BY MLP NETWORKS

TABLE 1. COMPARISON OF RBF IMAGE FILTERING WITH MLP IN TERMS OF PSNR

Image	Radial Basis Function		Radial Basis Function	
	MSE	PSNR (dB)	MSE	PSNR (dB)
Fig. 3	5.3743×10^{-25}	99	250.37	24.1450
Fig. 4	3.1561×10^{-25}	99	794.563	19.1925
Fig. 7	3.15605×10^{-25}	99	852.54	18.8237
Fig. 10	1.60044×10^{-25}	99	749.36	19.3839
Fig. 13	1.63281×10^{-25}	99	836.93	18.9039

8. CONCLUSIONS

In this paper a method of reducing the noise has been presented based on RBF Neural Network and is compared with the MLP networks which are popularly used in Noise reduction techniques. The above table validates the results for removal of noise from images, threshold was set to 10^{-20} therefore, MSE less than 10^{-20} will show the maximum PSNR value i.e. 99dB. It can be concluded from above table that MLP works well only with Gaussian noise, it can't handle other type of noises very well, though visually the images with less information could be retrieved but applications associated with medical imaging and images with greater information cannot tolerate the degree of noise reduced by MLP. We are currently working on making this method also work with colour images to reduce the errors in colours and making the images more qualitative in terms of vision. Also we are working to construct a method for such type of filtering with unsupervised method which can give us the results approximately same as the results shown in this simulation.

ACKNOWLEDGEMENTS

Authors are indebted to acknowledge with thanks to Prof. Dr. Mukhtiar Ali Unar, Director, Institute of Information & Communication Technologies, for his moral support and Mehran University of Engineering & Technology, Jamshoro, Pakistan, for providing necessary facilities to complete this research work and valuable suggestions of anonymous reviewers for improving the readability of this paper.

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