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Image Denoising using Adaptive Wiener Filters with Radial Basis Function and its comparison with Wavelet transform based methods

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Abstract: Removal of noise from images is the fundamental process of computer vision and image processing. The basic purpose of image denoising is to restore the noisy images and to enhance the image for better understanding to other systems (or humans). Since many different approaches of image denoising have been proposed for a decade, amongst them removal of noise by wavelet transform produces some desired results. This paper proposes the integration of adaptive wiener filter and Radial Basis Function Neural Networks (RBFNN) for image denoising. Furthermore, a comparison between the proposed method and wavelet transform based methods has been carried out on the basis of Mean Square Error and PSNR. Separation results fetched from the tested images demonstrates the feasibility of the approach presented in this paper.

Keywords: Radial Basis Function Neural Network, Adaptive Wiener Filter, Wavelet Transform, Image Denoising, and Peak Signal to Noise Ratio.

1. INTRODUCTION

In this era digital images are the highest stake holders in multimedia communications and thus play an important role not only in our daily life applications but also in research and technology (Raja, and John 2009). Pre-processing is always performed on images due to the addition of noise which decreases the quality of images and thus results in loss of information. This is a very sensitive issue in image processing and a lot of research has been carried out to develop a sophisticated way to remove the noise from the images. Noise is added to images at the time of acquisition or at the time of transmitting the image, the reasons could be many but some of them are faulty hardware, lens faults, channel errors or error in storage media (Parmar, and Patil 2013). Removal of noise from the images is still a real challenge for the researchers.

There are different types of noises associated with the images which can be characterized in three general categories i.e. substitutive noise, additive noise and multiplicative noise. To be specific salt and pepper noise and random valued impulse noise etc., can be classified as substitutive noise, Gaussian noise and additive white Gaussian noise can be classified as additive noise and speckle noise can be classified in multiplicative noise (Arivazhagan, *et al*,.) In this paper images having different types of noises will be tested. Main goal of any image denoising method is to preserve the low level details along with the edges of image while suppressing the noise at the maximum extent (Parmar, and Patil 2013).

Most popular and most widely used method for image denoising is the wavelet transform method (Nasri, and Nezamabadi-pour 2009). **(Fig. 1)** shows the block diagram which illustrates the working of image denoising using wavelet transform. As shown, the input image is combined with noise which is added intentionally for testing purposes, upon application of wavelet transform, the image is decomposed, thresholding and adaptive wiener filter is then applied to the decomposed image and finally after applying inverse wavelet transform the denoised image is obtained (Nasri, and Nezamabadi-pour 2009).

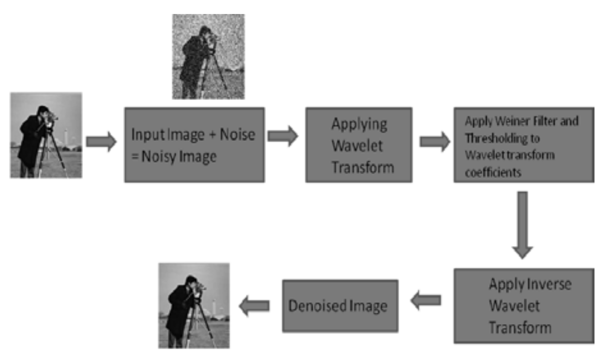

Fig. 1 Block diagram of Image Denoising using WaveletTransform

The method proposed in this paper for image denoising uses the Radial Basis Function Neural Network (RBFNN). **(Fig. 2)** shows the block diagram which illustrates the working of image denoising using Adaptive Wiener Filter (AWF) and RBFNN. As shown,

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noise is added to the input image, after applying the adaptive wiener filter and Radial Basis Function Neural Networks the noisy image is compared to the original image constantly and weights are updated to reduce the error in the noisy image. When the error reaches the goal provided to the system, the denoised image is obtained.

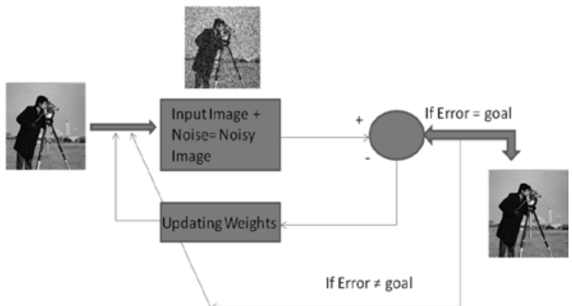

Fig. 2 Block diagram of Image Denoising using RBFNN (Ruikar. et al)

Most of the work done in image denoising through wavelet transform (WT) methods depends on the thresholding and shrinking of coefficients (Hongqiao, and Shengqian 2009). Wavelet transform decomposes the image while image denoising is performed by adaptive wiener filter. Still many techniques which are proposed are either improvements or enhancements to the mentioned technique or fusion of other techniques with the wavelet transform method. However, in the proposed paper two different methods for denoising the image are taken into consideration. One technique is the adaptive wiener filter along with the wavelet transform which is used to remove the noise from the image, though this method gives good results but varying different noises in the image shows the limitations of this method and the denoised image has greater mean square error which of course is not desired in the output. To overcome these drawbacks the second method which is the proposed one is tested on the images with different noises which shows negligible mean square error when compared to the existing techniques which are used to denoise the image. These results are carried out using MATLAB and techniques are evaluated on the basis of Mean Square Error and PSNR.

2. WAVELET BASED IMAGE DENOISING

Wavelet thresholding in Time-Frequency Domain (TFD) plays a vital role in image denoising using wavelet transform. Using the threshold the process of denoising an image based on wavelet transform is considered to be the optimal estimation of noise data in the input image. Wavelet based threshold for denoising of an image works in the following hierarchal fashion (Bijalwan, *et al.*, 2012).

1. Obtain the wavelet coefficients by applying wavelet decomposition method on the input image with noise.

$$\mathrm{wc} = \mathrm{W}(\mathrm{I} + \mathrm{N}) \qquad (1)$$

Where W is the wavelet transform, I is the input image, N is the noise data and wc are the wavelet coefficients obtained.

2. Based on the rule of wavelet thresholding the wavelet coefficients are modified and thus results in optimal estimations.

$$\mathrm{We} = \delta_{\mathrm{T}}(\mathrm{wc}) \qquad (2)$$

Where T is the threshold, δ_T (wc) the wavelet threshold function and We is it[he] optimal estimation of wavelet coefficient.

3. By applying inverse wavelet transform on the above modified coefficients, the denoised image can be obtained.

$$\mathrm{I}' = \mathrm{W}^{-1}.\mathrm{wc}' \qquad (3)$$

On the basis of these three steps it is clear that the denoising of an image can be efficient by choosing the appropriate thresholding function as well as appropriate threshold(Hongqiao, hengqian 2009), (Ray *et al*. 2013).

Until now wavelet transform was a widely used method for image denoising because it overcomes some of the limitations of Fourier transform as wavelet transform represents a function in both time and frequency domain simultaneously. Once the wavelet coefficients are calculated by wavelet transform it is easy to filter out these coefficients by using wiener filter (Saini, *et al.* 2012). The main purpose of denoising the image is not only removing the noise but also preserving the edges and other fine details in the image. However using adaptive wiener filter to remove noise does not give satisfactory results and the image suffers from ripple like artifacts and thus provides low Peak Signal To Noise Ratio (PSNR), this decreases the visual quality of the denoised image and this will affect our goal to reduce the noise from the noisy image while preserving the fine details and edges of the image (Ben, *et al.*, 2011). To overcome this problem the image denoising method using adaptive wiener filter with radial basis function is proposed in this paper.

3. ADAPTIVE WEINER FILTERING

Adaptive wiener filter is popularly used in the enhancement of signals; its basic purpose is to filter the signal from that corrupted by the Gaussian or additive noise. Let's consider a corrupted image; the resultant image can be modeled as in equation (4).

$$Z(m,n) = I(m,n) + N(m,n) \quad (4)$$

Where $N(m,n)$ is the noise (can be Gaussian noise, additive white Gaussian noise etc.), $I(m,n)$ is an input image and Z (m, n) is the noisy image. The main purpose of the filter is to reduce the noise from the image having minimum MSE. Adaptive wiener filter minimizes the MSE between the filtered image and the original image. The error between these two images can be calculated by the expression in equation (5).

$$e^2 = E\left[\left(I(m,n) - I^\wedge(m,n)\right)^2\right] \quad (5)$$

Here adaptive wiener filter initially assumes the noise with zero mean and σ^2n variance which are uncorrelated with the original image *I (m, n).* On the basis of these assumptions the variance and local mean is estimated by wiener filter as given in equation (6) and equation (7).

$$\mu = \frac{1}{XY} \sum\nolimits_{m,n,\varepsilon,k} Z(m,n) \quad (6)$$

and

$$\sigma^2 = \frac{1}{XY} \sum\nolimits_{m,n,\varepsilon,k} Z^2(m,n) - \mu^2 \quad (7)$$

Thus the estimated image using wiener filter is given by (8).

$$I^{(m,n)} = \mu + \left[\frac{\sigma^2 - \sigma^2 n}{\sigma^2}\right](Z(m,n) - \mu) \quad (8)$$

4. RADIAL BASIS FUNCTION NEURAL NETWORK

Radial basis function is a type of feed forward network embedded in a two layer neural network, where each unit implements Gaussian activation function. RBF is much better and is able to model complex mappings due to its non-linear approximation properties. RBF uses Gaussian activation function in the hidden layer by all neurons which is inversely proportional to the distance from the center of the neuron (Khowaja *et at.*, 2014). Reason for preferring radial basis function over other methods is its robust learning which is possible due to its local approximations to the input-output map. Radial Basis Function takes following parameters into account.

1. Neurons in the hidden layer
2. Coordinates of center in each layer
3. Spread in each dimension for each RBF function
4. Weights which are passed to the summation layer

In all the above mentioned parameters the crucial stage is the selection of neurons in the hidden layer and that is the most crucial part when designing the radial basis function. The selection of neurons can be determined by the method known as Orthogonal Least Squares Method.

5. METHODOLOGY

Radial basis function is a type of supervised learning method. It takes the original image and the error is calculated by comparing the noisy image with the original image, reduction of error is done by the algorithm given in equation (9).

$$f_j(\bar{x}) = \exp\left(-\frac{\|\bar{x} - \bar{c}_j\|^2}{\sigma_j^2}\right) \quad (9)$$

And the output function is given by

$$y_j(\bar{x}) = \sum_{j=1}^{M} W_j f_j(\bar{x}) \quad (10)$$

After calculating the error, orthogonal least squares method creates a set of orthogonal vectors for the space spanned by basis vectors such that ϕ = AY, using this representation solution of RBF is given by equation (11).

$$T = \phi W = YG \quad (11)$$

This is precisely what makes OLSM method as an efficient implementation. The energy of the sum of squares is defined as given in (12).

$$T^t T = \sum\nolimits_{i=1}^{M} g_i^2 q_i^t q_i + E^t E \quad (12)$$

The residual error can be given as in (13)

$$[err]_i = \frac{g_i^2 q_i^t q_i}{T^t T} \quad (13)$$

A predefined threshold T can be set so as if error falls below the provided threshold the iterations should stop which is illustrated in equation (14).

$$1 - \sum\nolimits_{j=1}^{M} [err]_j < T \quad T \quad (14)$$

If the above provided condition is fulfilled the iteration process is stopped.

6. RESULTS

The performance of both the methods for denoising the image was tested on a set of pictures as shown in **(Figs 3 to7)**. These tests are divided in two categories one category is of the visual quality, the image will be compared on the basis of visual quality and then the image will be tested on the analytical results based on Mean Square Error and Peak Signal to Noise Ratio. Mean square error is mathematically defined in equation (5), another important aspect to measure the quality of the image is Peak signal to noise ratio. Peak signal to noise ratio (PSNR) is a ratio of peak signal power to noise power; mathematically the PSNR is defined as given in equation (15).

$$PSNR = 10 \log 10 \frac{M.N.255^2}{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [I(i,j) - I'(i,j)]^2} \quad (15)$$

On the basis of MSE and PSNR the below table is constructed which comprises of the results from both methods. We can clearly see that the Radial basis function has higher PSNR as compared to the Wavelet based denoising method. However the visual quality is also based upon the PSNR value, higher the PSNR value higher will be the visual quality of the image though increasing the noise value will affect the PSNR value in Wavelet based denoising method but it will not affect the PSNR value in RBFNN denoising method.
Following are the test results which are conducted on different images using both methods.

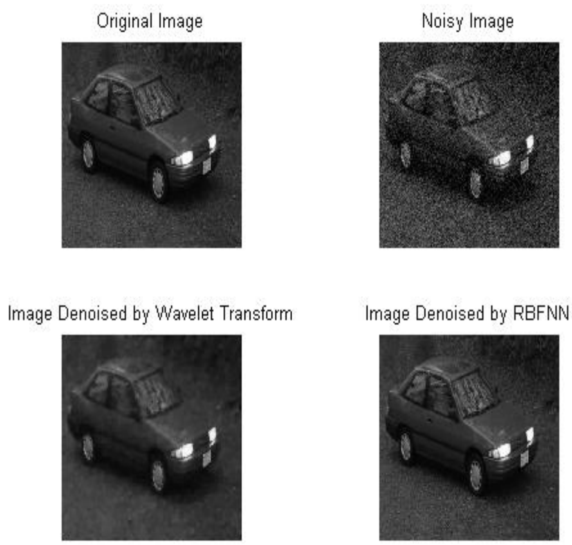

Fig. 3. Car Image tested by both methods

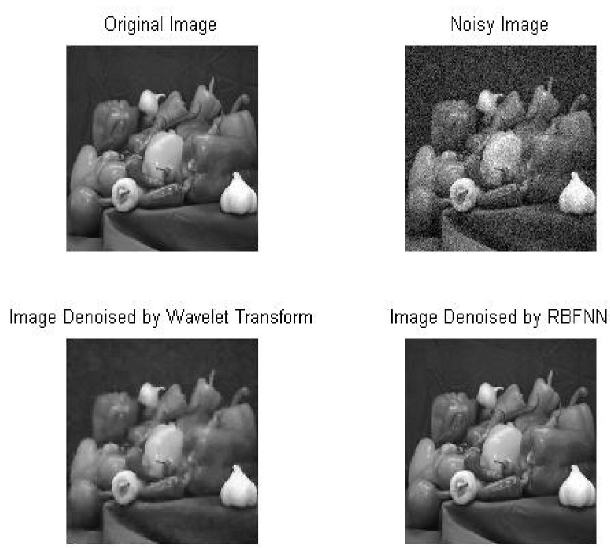

Fig. 4. Pepper image tested by both methods

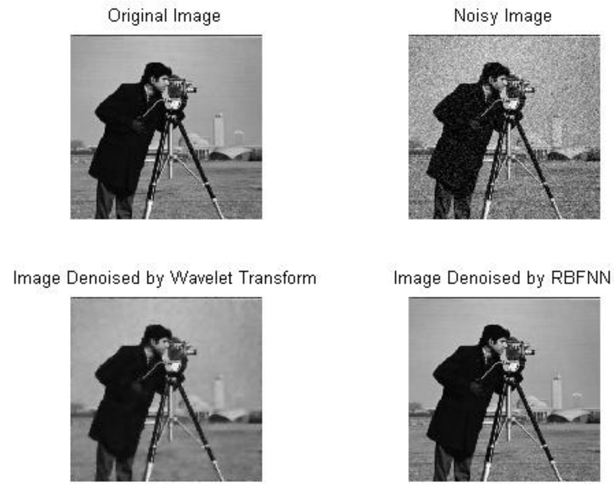

Fig. 5. Camera man Image tested by both methods

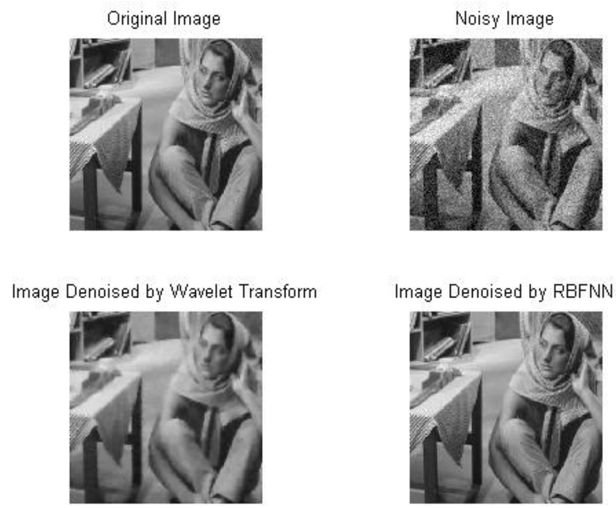

Fig. 6. Woman Image tested by both methods

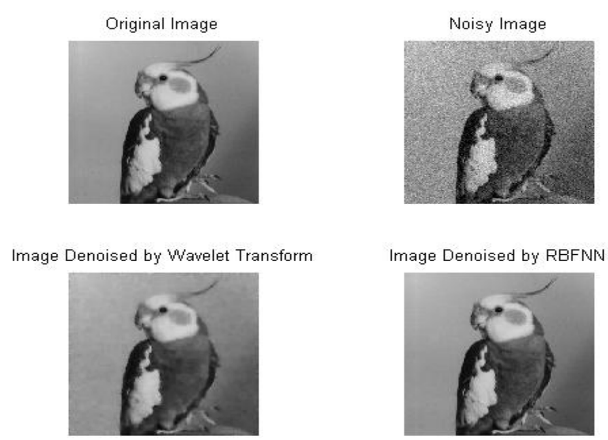

Fig. 7. Parrot Image tested by both methods.

Table. 1 Comparison for both methods based on MSE, RMSE & PSNR

S. No	Name	Image Denoising by Haar Wavelet		Image Denoising by proposed method	
		MSE:RMSE	PSNR (dB)	MSE:RMSE	PSNR (dB)
1	Car	72.3645 : 8.5	29.5355	0.0122:0.1105	67.2647
2	Pepper	49.3862 :7.0275	31.1948	0.0033:0.0571	72.9915
3	Camera man	101.928 : 10.1	28.05	0.0011:0.0327	77.845
4	Woman	114.548 : 10.70	27.5409	0 : 0	99
5	Parrot	40.921 : 6.937	32.0113	0 : 0	99

Table. 2 Comparison for both methods based on MSE, RMSE & PSNR

S. No	Name	Image Denoising by Daubishes Wavelet		Image Denoising by proposed method	
		MSE:RMSE	PSNR (dB)	MSE:RMSE	PSNR (dB)
1	Car	66.36 : 8.14	29.9115	0.0122:0.1105	67.2647
2	Pepper	47.9614 : 6.9	31.3219	0.0033:0.0571	72.9915
3	Camera man	79.96 : 8.94	29.10	0.0011 : 0.0327	77.845
4	Woman	84.58 : 9.19	28.851	0 : 0	99
5	Parrot	38.22 : 6.18	32.30	0 : 0	99

7. CONCLUSION

Denoising of an image is an important aspect and previously many methods have been proposed to denoise the image but more effective and popularly used method is Wavelet denoising method using adaptive wiener filtering but by taking the above observations and results into account on the basis of mean square error and PSNR it is clear that image denoising method by using adaptive wiener filter with radial basis function neural network by far yields better results. Thus the images after denoising by the proposed method have a better visual quality and also preserve the fine details of image.

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