ITERATIVE DENOISING USING NON LINEAR FILTER IN WAVELET DOMAIN

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Abstract

Digital images are prone to different noise during acquisition and transmission. Noise reduction is a traditional problem in image processing. This paper explores a novel neural network-based non-linear filter in wavelet transform domain for image denoising. In this method, using wavelet transformation a noisy image is decomposed into four subbands. A simple procedure is suggested to extract the training patterns from these four subbands. Using a layered neural network architecture denoising is performed. The denoised image is thereafter obtained through the inverse transform on the noise-removed wavelet coefficients. Simulation results demonstrate that this method is very efficient in removing the noise. Compared with other methods performed in wavelet domain, it requires no a priori knowledge about the noise and needs only one level of signal decomposition to obtain very good denoising results.

Keywords: *Wavelet transform, Neural Network Filter, White Gaussian noise,Iimage denoising*

1. INTRODUCTION

An image is degraded by noise due to various factors during its acquisition and transmission phases. Image denoising is aimed to remove or reduce the noise so that a good-quality image can be obtained for various applications. This paper investigates the problem of image denoising when the image is corrupted by additive white Gaussian noise. Traditionally, linear processing methods such as wiener filter, mean and median filters are employed for this purpose. However, mean filters tend to blur the edges in the images and median filters are ineffective in dealing with non-impulse noise components. To preserve the edges, non-linear methods have become the mainstream approaches in the field of image denoising.

Wavelet transform provides excellent properties for image processing. Non-linear denoising methods performed in the wavelet transform domain have received wide research attention. One of the standard non linear methods is wavelet thresholding. In this method a threshold value is chosen for each subband of the image. The better result depends on the choice of the thresholding parameters. It is difficult to find the optimum threshold value. In wavelet thresholding, the local space-scale information is not considered adaptively. In order to overcome these drawbacks here a Neural network based Non linear method is developed for image denoising.

A layered neural network (LNN) is properly designed and trained to explore the learning capability of the neural network to learn the correlation among the noisy wavelet coefficients, thus removing noise from them. The LNN filter method generates better results than the linear processing methods. Traditional wavelet thresholding methods which usually require three or more levels of wavelet decomposition and need the accurate estimate of the noise to obtain good denoising results. But this method needs only one level of wavelet decomposition and can adapt itself to the various noise environments by learning.

2.DENOISING IN IMAGES

Applied scientists and engineers who work with data obtained from the real world know that signals do not exist without noise. There are several fact that noise into an image depending on how image is created. For example:

- If the image is scanned from a photographic made on film, the film grain is source of noise. Noise can also be the result of damage to the film, or be introduced by the scanner itself.
- If the image is acquired directly in a digital format, the mechanism for gathering the data (such as a CCD detector) can introduce noise.
- Electronic transmission of image data can introduce noise.

There are different types of noises like gaussian noise, salt and pepper noise and speckle noise.

2.1.IMAGE DENOISING

Denoising is the process of removing/reducing noise from the noisy image and retaining the original image. The general additive noise reduction problem can be formulated as follows[1]:

$$y=x+v$$

where, y is the corrupted image.

x is the original uncorrupted image

v is the additive noise

The objective of noise reduction is to reduce the noise in y and to make the estimate $\hat{x}$ from y which is as close to x as possible. Here it is assumed that the noise is Gaussian zero mean and variance σ^2 $_{,ie.,}$ N $(0,\sigma^2)$.

3.LAYERED NEURAL NETWORK FOR IMAGE DENOISING

An artificial neural network (ANN or NN for short) is an artificial intelligence closely modeled after a human brain[5]. Such a neural network is composed of computer-programming objects called nodes. These nodes closely correspond in both form and function to their organic counterparts, neurons. Individually, nodes are programmed to perform a simple mathematical function, or to process a small portion of data. A node has other components, called weights, which are an integral part of the neural network. Weights are variables applied to the data that each node outputs. By adjusting a weight on a node, the data output is changed, and the behavior of the neural network can be altered and controlled. By careful adjustment of weights, the network can learn. Networks learn their initial behavior by being exposed to training data. The network processes the data, and a controlling algorithm adjusts each weight to arrive at the correct or final answer(s) to the data. These algorithms or procedures are called learning algorithms.

Neural networks are often used for image denoising and compression. Their adaptability and learning capabilities make them excellent choices for removing noisy coefficients. Image processing using neural networks is a very broad field, but one of the common use for an NN is image denoising. This neural network based non linear filter removes the noise effectively than the standard filters. There are different types algorithms to train the network. Here we used the Back propagation Neural Network for image denoising.

In image denoising, filtering is a common technique. In this paper, neural network is used as a non linear filter. Their adaptability and learning capabilities make them excellent choices for removing noisy coefficients.

The LNN filter is a three-layer neural network with inputs derived from an NxN neighborhood of the transformed image and appropriately selected neuron activation functions. As shown in Figure(1), the network takes Y_P and ΔY_k as the inputs, where Y_P is the wavelet transform coefficient under consideration, which is the center of a N x N processing window, and $\Delta Y_k = Y_k - Y_P$ is the difference value between Y_P and the coefficient Y_k (k=0,1,2………N^2 -1, k≠p) of the other points in the N x N window, Figure(2) shows an example of a processing window with a size of a 5 x 5 pixels. In this example, Y_{12} is the center of the window, and $\Delta Y_k = Y_k - Y_{12}$ (k=0,1,……..24, k≠ 12).

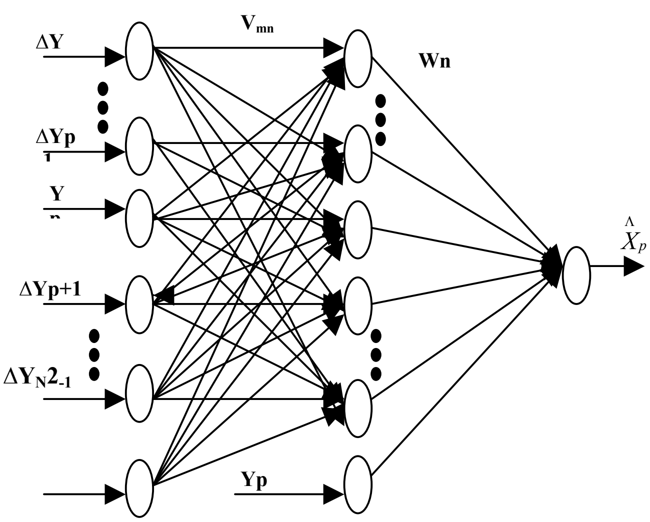

Figure.1 Structure of the neural network

In this figure v_{mn} is the weight of the connection between the m-th neuron in the input layer and n-th neuron in the hidden layer and is initialized randomly between -1 to 1. w_n is the weight connecting the n-th neuron in the hidden layer to the neuron in the output layer and is initialized as randomly between -1 to 1.

Y_0	Y_1	Y_2	Y_3	Y_4
Y_5	Y_6	Y_7	Y_8	Y_9
Y_{10}	Y_{11}	Y_{12}	Y_{13}	Y_{14}
Y_{15}	Y_{16}	Y_{17}	Y_{18}	Y_{19}
Y20	Y_{21}	Y_{22}	Y_{24}	Y_{25}

Fig.2 5 x 5 processing window

3.1 TRAINING THE LAYERED NEURAL NETWORK

In this paper, neural network is trained using back propagation algorithm. In this algorithm, first error is calculated between the noise free coefficients and the output of the neural network. Error is back propagated to output and hidden layer. According to the error weights are updated. This algorithm minimizes the output error by updating the weights based on the gradients of the output error. The proposed algorithm is as follows: The input 25 elements are normalized using the formula as given:

$$NV = \frac{2(y - y_{\min})}{y_{\max} - y_{\min}} - 1 \qquad (1)$$

Where y_{min} is minimum value among the 25 values. y_{max} is the maximum value among the 25 values. NV is the normalized value between -1 to 1. The net input to the hidden layer is calculated as[7]:

$$net_{hn} = \sum_{m=0}^{N^2+1} i_m v_{mn} \qquad (2)$$

The output of the hidden layer is calculated as:

$$z_n = f_h\,(net_{hn}) \qquad (3)$$

where i_m is the m-th input of the input layer and takes its from set ($\Delta y_0, \Delta y_1, \ldots \ldots \ldots \Delta y_{24}, y_P, 1$), and activation function of the hidden layer is selected as:

$$f_h\,(x) = \frac{2}{1+e^{-\lambda x}} - 1 \qquad \lambda > 0 \qquad (4)$$

In this work, the λ value is taken as 1.

The net input to the output layer is calculated as[7]

$$net_o = \sum_{n=0}^{N^2+1} z_n\, w_n \qquad (5)$$

The output of the output layer can be formulated as:

$$\hat{X}_p = f_0\,(net_o) \qquad (6)$$

Where $\hat{X}_p$ is the output of the neural network at pixel under consideration and the activation function of the neuron in the output layer is of the following form:

$$f_o\,(x) = \frac{2}{1+e^{-\lambda x}} - 1 \qquad \lambda > 0 \qquad (7)$$

The value of the λ here is 1.

The update equations of the weights and function coefficients are as follows[7] :

$$v_{mn}^{k+1} = v_{mn}^{k} - \alpha \frac{\partial E}{\partial v_{mn}}$$

$$= v_{mn}^{k} - \alpha \frac{\partial E}{\partial o} \frac{\partial o}{\partial net_o} \frac{\partial net_o}{\partial z_n} \frac{\partial z_n}{\partial net_{hn}} \frac{\partial net_{hn}}{\partial v_{mn}^{k}}$$

$$= v_{mn}^{k} + \alpha(d-o) f_o^{'}(net_o) w_n f_h^{'}(net_{hn}) i_m \qquad (8)$$

$$w_n^{k+1} = w_n^{k} - \beta \frac{\partial E}{\partial w_n} = w_n^{k} + \beta(d-o) f_o^{'}(net_o) z_n \qquad (9)$$

In the above equations, $E = (d_i - o_i)^2 /2$ is the square error, d_i is the Noise free coefficients, o_i is the output of the neural network, and α, β are the learning factors. Here α, β are initialized as 0.8 and 0.6. Weights are updated based on error accordingly. Finally neural network will give the noise removed coefficients. They are value between -1 to 1. It should be denormalized to obtain the original value. The equation for denormalization is as follows:

$$DNV = \frac{(NV+1.0)*(x_{\max} - x_{\min})}{2.0} + x_{\min} \qquad (10)$$

Where DNV is the denormalized value. NV is the noise free coefficients from the neural network.The LNN filter explores the strong correlation between the pixel under consideration and its neighbors and utilizes the mapping function of the layered network to remove the white Gaussian noise.

3.2. PROCEDURAL STEPS INVOLVED IN LNN FILTER METHOD

The steps involved in this method are as follows[6] :

Step 1: A noisy image is decomposed into four subbands using a wavelet transform. Here Daubechies wavelets family is applied.

Step 2: For each subband, a layered neural network is properly designed.

Step 3: Each of the LNNs is trained using one of the four subbands of the decomposed image. All the four LNN have same structure.

Step 4: The inputs to the neural network are derived from an NxN neighborhood of the transformed image. Here we have taken 5x5 window. It consists of

25 elements. They are given as inputs to the neural network. Before applying to the network the inputs are normalized.

Step5: Back propagation is used to train the network. The activation functions used are bipolar activation for both hidden and output layer. Weights are updated according to the error criterion. This algorithm minimizes the error by adjusting weights accordingly.

Step 6: After the training process, the four LNNs are applied to the corresponding subband of the wavelet transformed noisy image.

Step 7: The outputs of the networks are normalized noise-removed coefficients. Hence it is denormalized using original image to obtain original value of the noise removed wavelet coefficients.

Step 8: The denoised image is obtained by performing an inverse wavelet transform on the noise free wavelet coefficients.

4. SIMULATION AND RESULTS

This algorithm is implemented using Matlab6.5. The LNN filter was implemented and the computer simulation results are presented. We used cameraman and parrots image of size 256 x 256 are used as the test image. Noises of different decibels are added and the denoised images are produced. The Daubechies wavelet family(db2) is used and one level 2D DWT of noisy image is taken.

The noisy images of above are used for training the neural network.PSNR(in dB) is used as performance measure for comparing the quality of denoising. The PSNR is calculated using the formula

$$PSNR = 10 * \log 10 \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} Original\ image^2}{\sum_{i=1}^{M}\sum_{j=1}^{N} (Original - noise)^2} \quad ......(11)$$

Where NxN is the size of the image.

Table 1 - shows the PSNR values of the Noisy image of cameraman image and PSNR value obtained from proposed method and standard denoising methods. It shows that the PSNRs of the images are improved at all of the noise levels. The table also shows that the proposed method outperforms all of the standard methods.

The Figure 3 shows that output images obtained for cameraman image when noise level is 20 dB.

Figure 4 shows that output images obtained for parrots image when the noise level is 25 dB.

Simulations demonstrate that the proposed method can remove the noise efficiently, and improve the visual quality of the degraded image.

5. CONCLUSION AND FUTURE WORK

In this paper, a neural network based non linear filter in wavelet domain is constructed for the removal of noises in digital images. In this method LNN learn the correlation of the wavelet coefficients and generate the noise–removed values from their noisy versions. Simulation demonstrates that it can efficiently remove the noise, and improve the visual quality of the degraded image. The LNN filter method requires no priori knowledge about the noise and needs only one level of signal decomposition to obtain very good denoising result. In terms of PSNR, this method outperforms the standard denoising methods. This work can be extended by using functional link neural network to reduce the computation complexity and time.

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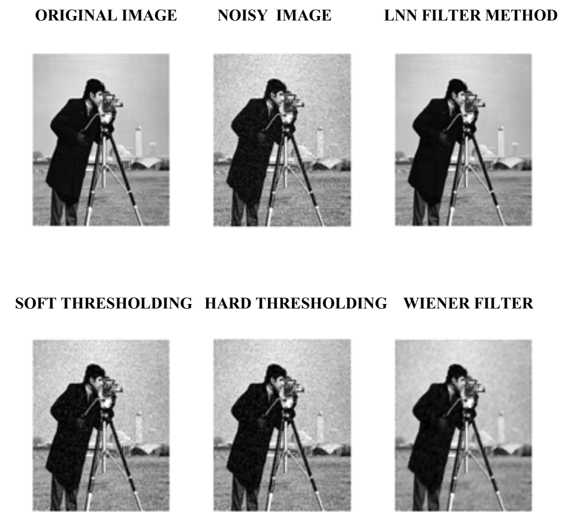

Figure 3.Output images obtained for cameraman image when the noisy level is 20 dB

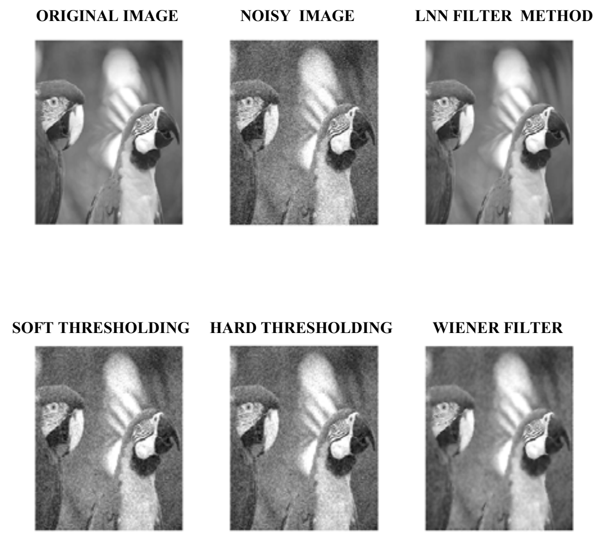

Figure 4 Output images obtained for parrot image when the noisy level is 25 dB

TABLE 1 PSNR VALUES OF THE NOISY IMAGE OF CAMERAMAN AND PARROTS BY THE LNN FILTER METHOD AND STANDARD METHODS

INPUT IMAGE AT VARIOUS NOISE LEVELS(dB)	NOISY IMAGE (PSNR)	NOISE REDUCED PSNR(dB)			
		LNN FILTER METHOD	SOFT THRESHOLDING	HARD THRESHOLDING	WIENER FILTER
Cameraman $\sigma = 10$	28.0358	**49.2130**	27.0826	28.2188	29.0423
$\sigma = 15$	24.5421	**49.1069**	25.6131	26.1911	28.1453
$\sigma = 20$	22.0035	**49.0588**	24.4724	24.7728	27.1147
$\sigma = 25$	20.1172	**48.9956**	23.4326	23.5968	26.2004
Parrots $\sigma = 10$	28.1397	**49.9619**	29.2103	30.2771	32.3015
$\sigma = 15$	24.6220	**50.8412**	27.2710	27.7628	30.7722
$\sigma = 20$	22.1618	**50.7787**	25.8742	26.1187	29.4985
$\sigma = 25$	20.1807	**46.6144**	24.5230	24.6293	28.2893