

ABSTRACT

Images are often corrupted as a result of various factors that can occur during acquisition and transmission processes. Image denoising is aimed at removing or reducing the noise so that a good-quality image can be obtained for various applications. This paper presents a neural network based denoising method implemented in the wavelet transform domain. In this method, a noisy image is first wavelet transformed into four subbands, then a trained layered neural network is applied to each subband to generate noise-removed wavelet coefficients from their noisy ones. 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.

1. INTRODUCTION

An image is often 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. Traditionally, linear processing methods such as Wiener filtering are employed for this purpose. Linear methods are simple and easy to implement, however, they tend to reduce the important image features such as edges in an image while removing the noise. To better preserve those features, non-linear methods have become the main stream approaches in the field of image denoising.

Wavelet transform provides excellent properties for signal and image processing. Non-linear denoising methods performed in the wavelet transform domain have received wide research attention. One of these methods is wavelet thresholding developed first by Donoho and Johnstone [1]. This method removes the noise in an image by removing the wavelet coefficients that are too noisy and preserving or shrinking the coefficients that contain important image signals. The success of the method depends heavily on the choice of the threshold parameters. As a result, various wavelet thresholding methods [2-7], which use different approaches to determine the threshold parameters, have

been reported. Among those methods are VisuShrink [1], SureShrink [2] and BayersShrink [5].

In this paper, a neural network based method performed in the wavelet transform domain is developed for image denoising. A layered neural network (LNN) [8] is properly designed and trained to explore the learning capability of the neural network to learn the correlation between the noise-free wavelet coefficients and their noisy observations. After a training process, the network is applied to the noisy coefficients to produce noise-reduced output values. Preliminary experimental results show that the proposed method generates better results than the Wiener, VisuShrink and BayersShrink methods. Unlike the wavelet thresholding methods which usually require three or more levels of wavelet decomposition and need the accurate estimate of the involved noise to obtain good denoising results, this method needs only one level of wavelet decomposition and can adapt itself to the various noise environments by learning.

2. METHODOLOGY

2.1 Noise analysis in the wavelet transform domain

Assuming additive noise, the corrupted signal, y , is modeled as

$$y = x + v \quad (1)$$

where x is the original uncorrupted signal and v is iid $N(0, \sigma^2)$ and independent of x , then in the wavelet transform domain, equation (1) can be expressed as

$$Y = Wy \quad (2)$$

where Y is the wavelet transformed version of y , and W is an orthogonal wavelet transform operator. Since W is orthogonal and v is independent of x , Y can be further expanded as

$$Y = Wx + Wv = X + V \quad (3)$$

where X is the contribution to the wavelet coefficients related to the original signal x , and V is the contribution to the wavelet coefficients related to the noise v .

The denoising problem in the wavelet transform domain is to obtain the estimate \hat{X} of X from Y . The denoised signal in spatial domain is simply the inverse transformed version \hat{x} of \hat{X} , i.e.,

$$\hat{x} = W^{-1} \hat{X} \quad (4)$$

where W^{-1} is the inverse wavelet transform operator. From equation (3), it can be seen that the contribution that the noise makes to Y is additive to the signal's contribution. In other words, the coefficients due to the signal are independent on the noise's contribution. It is reasonable to use LNN to learn the correlation of the coefficients corresponding to signal, and therefore to remove the contribution to the coefficients due to the noise. The design of the LNN is described in the next subsection.

2.2 The proposed LNN filter

The proposed LNN filter is a three-layer neural network with inputs derived from an $N \times N$ 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 $N \times N$ processing window, and $\Delta Y_k = Y_k - Y_p$ is the difference value between Y_p and the coefficient Y_k ($k=0,1,\dots,N^2-1$, $k \neq p$) of the other points in the $N \times N$ window. Figure 2 shows an example of a processing window with a size of 5×5 pixels. In this example, Y_{12} is the center of the window, and $\Delta Y_k = Y_k - Y_{12}$ ($k=0,1,\dots,24$, $k \neq 12$).

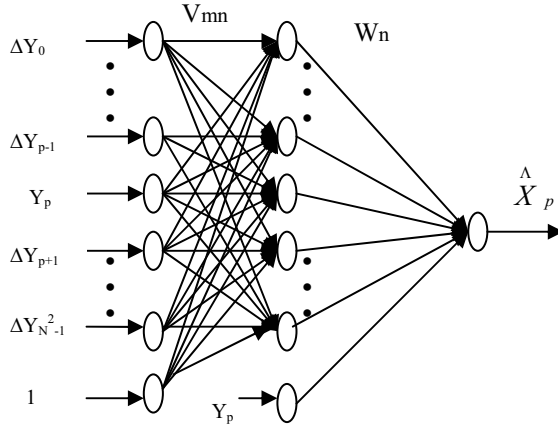


Fig. 1 Structure of the neural network

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}
Y_{20}	Y_{21}	Y_{22}	Y_{23}	Y_{24}

Fig. 2. 5×5 processing window

The output of the neural network can be formulated as

$$\hat{X}_p = f_o \left(\sum_{n=0}^M w_n f_h \left(\sum_{m=0}^{N^2} Y_m v_{mn} \right) \right) \quad (5)$$

where \hat{X}_p is the output of the LNN corresponding to the central point in the processing window, Y_m is the m -th input in the input layer and its value is taken from the set $(\Delta Y_0, \Delta Y_1, \dots, \Delta Y_{p-1}, Y_p, \Delta Y_{p+1}, \dots, \Delta Y_{N^2-1}, 1)$, M is the number of the neurons in the hidden layer, w_n is the connecting weight between the n -th neuron in the hidden layer and the neuron in the output layer, v_{mn} is the weight of the connection between the m -th neuron in the input layer and the n -th neuron in the hidden layer. The activation functions of the neurons in hidden and output layers are

$$f_h(x) = x e^{-\gamma x^2} \quad (6)$$

and

$$f_o(x) = 2 / (1 + e^{-\lambda x}) - 1 \quad (7),$$

respectively, where $\gamma > 0$ and $\lambda > 0$ are the function coefficients. The selection of $f_h(x)$ shown in equation (6) as the activation function of the hidden layer provides the network with a good ability to learn the correlation of the wavelet coefficients. Figure 3 shows the shape of the function.

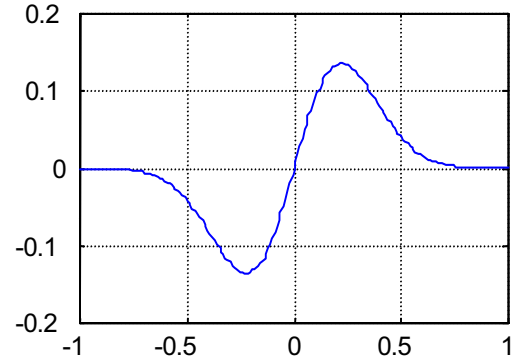


Fig. 3 The curve of the function $f_h(x)$ with $\gamma = 10$

The proposed denoising method uses four LNNs, each having the same structure as shown in Figure 1. A noisy image is decomposed into four subbands using a wavelet transform. Each of the LNNs is trained using one of the four subbands of the decomposed image. After the training process, the four LNNs are applied to the corresponding subband of the wavelet transformed noisy image. The outputs of the networks are noise-removed coefficients and the denoised image is obtained by performing an inverse wavelet transform on the coefficients.

3. PRELIMINARY EXPERIMENTAL RESULTS

The proposed denoising method is evaluated using experiments, and the simulation results are presented in this section. The 512 x 512 8-bit “lenna” image was used to train the proposed LNNs at different noise levels. After training the networks, they were applied to the “lenna” image and another image “model” for denoising purposes. Figures 4(a) and 5(a), 4(b) and 5(b), 4(c) and 5(c) show the original, noisy ($\sigma=20$) and denoised “lenna” and “model” images, respectively.

To quantitatively evaluate the method, the PSNRs of the images were calculated and the results were compared with those obtained by using Wiener filter, VisuShrink and BayersShrink methods. Table 1 shows that the PSNRs of the images are significantly improved at all of the noise levels. The table also shows that the proposed method outperforms all of the three comparable methods in terms of the merit PSNR. This is more evident when the noise level is high.

4. DISCUSSION AND CONCLUSION

We have presented a neural network based denoising method. This method takes use of the learning capability of LNNs to learn the correlation of the significant wavelet coefficients and generates the noise-removed values from their noisy versions. Simulations demonstrate that it can efficiently remove the noise, and thus, significantly improve the visual quality of the degraded image. The proposed method requires no a priori knowledge about the noise and needs only one level of signal decomposition to obtain very good denoising result. In terms of PSNR, it

outperforms the comparable methods considered in our simulations.

5. REFERENCES

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Table 1. PSNRs in dB of the noisy images, and the denoised images by the proposed, Wiener, VisuShrink and BayersShrink methods, respectively

Input image at various noise levels	Noisy (PSNR)	Noise Reduced PSNR (dB)			
		Proposed Method	Wiener Filter	VisuShrink	BayersShrink
Lenna $\sigma=10$	28.12	34.49	32.66	32.56	33.49
	$\sigma=15$	24.63	32.78	31.27	29.35
	$\sigma=20$	22.13	31.73	30.02	26.74
	$\sigma=25$	20.23	30.58	28.85	24.53
Model $\sigma=10$	28.13	36.28	36.15	34.05	36.18
	$\sigma=15$	24.64	34.63	33.96	30.16
	$\sigma=20$	22.15	33.92	32.06	27.16
	$\sigma=25$	20.24	32.47	30.43	24.84



Fig. 4 “lenna” images: (a) Original (b) Noisy ($\sigma=20$) (c) Denoised by the proposed method

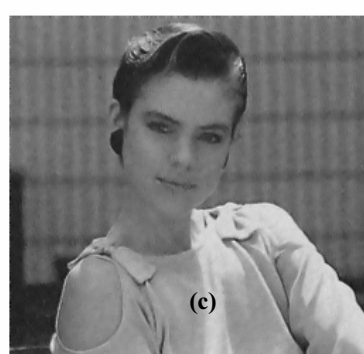
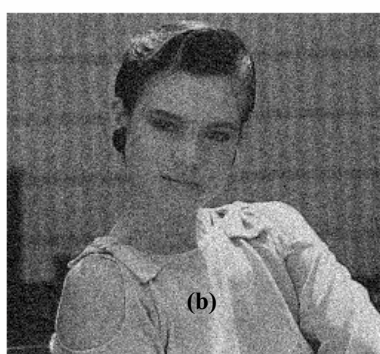


Fig. 5 “Model” images: (a) Original (b) Noisy ($\sigma=20$) (c) Denoised by the proposed method