Computational Research Progress in Applied Science & Engineering
©PEARL publication, 2017

ISSN 2423-4591

CRPASE Vol. 03(02), 81-84, June 2017

Thresholding Neural Network (TNN) Based Noise Reduction with a New Improved Thresholding Function

Noorbakhsh Amiri Golilarz*, Hasan Demirel

Department of Electrical and Electronic Engineering, Eastern Mediterranean University, Cyprus

Keywords

Thresholding function, Image de-noising, Wavelet domain, Thresholding neural network.

Abstract

In this paper, a new thresholding function is introduced for image de-noising in wavelet domain. In this technique we combined the new thresholding function with discrete wavelet transform (DWT). This thresholding function is continuous and nonlinear, so it is applicable on thresholding neural network (TNN) to act as its activation function. Experimental results have shown the superiority of the proposed technique over some alternative methods available in the literature. The proposed method achieves up to 2.90 dB improvement over the state-of-the-art for de-noising 'Lena' image.

1. Introduction

An Image can be influenced by noise during capturing and transmitting procedures. Analyzing the images required discarding or removing the noise from images properly. Noise discarding is kind of challenging aspects in image processing. Nowadays researchers are trying to reduce the presence of noise to enhance the quantitative and visual inspection of images. Then image analyzing will be possible. This noise reduction is very useful in medical image processing, satellite image processing, hyper-spectral image processing and signal processing.

Recently, researchers are focusing on de-noising based on wavelet transform and thresholding techniques. Demir and Erturk proposed a method to de-noise hyper-spectral images band by band [1]. Spectral domain noise reduction is introduced in a study conducted by Green et al., in 1988 [2]. Chen and Qian used principal component analysis and shrinkage technique for image de-noising [3]. Donoho and Johnstone in 1993 introduced an algorithm to de-noise images in spatial domain [4]. Lewen Dong proposed adaptive de-noising based on thresholding technique [5]. Anisimova et al., proposed efficiency of wavelet coefficients thresholding for multimedia and astronomical image de-noising [6]. Hyper-spectral denoising with cubic total variation (CTV) model was proposed by H. Zhang [7]. Sulochana et al., proposed de-noising and dimensionality reduction of Hyper-spectral images using framelet transform with different shrinkage functions [8]. X. P. Zhang proposed TNN for adaptive noise removing [9]. In addition, Sahraeian et al., in 2007 used improved thresholding neural network to remove noise from images and improve X. P. Zhang's de-noising results [10]. Chang et al., introduced adaptive wavelet thresholding for image de-noising and compression [11]. Adaptive to unknown smoothness via wavelet shrinkage is proposed by Donoho and Johnstone in 1995 [12] for image de-noising.

Wavelet based noise reduction can be combined with thresholding techniques. Then we need a suitable thresholding function to be applied on wavelet coefficients. This thresholding function controls wavelet coefficients. It allows large components to pass the threshold value and discard small noisy coefficients. Finally we can reconstruct the image through applying inverse discrete wavelet transform.

In this article, the authors proposed a unique technique for noise removing in wavelet domain combined with a thresholding function. We compared our technique with some state-of-the-art methods. Experimental results show the superiority of the proposed method over others.

2. Effect of Noise on Images and Wavelet Transform

According to the following formula noise can corrupt the image and decrease the resolution of image.

$$j(l,m) = i(l,m) + \eta(l,m) \tag{1}$$

where $i(l,m)$ is the original image, $\eta(l,m)$ is the noise which it can be additive white Gaussian noise with zero mean and standard deviation of σ and $j(l,m)$ is contaminated or corrupted image by noise.

* Corresponding Author:
E-mail address: noorbakhsh.amiri@students.emu.edu.tr

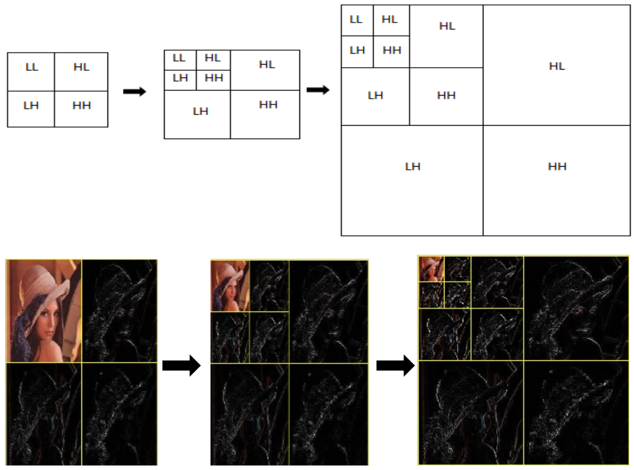
Received: 01 April 2017; Accepted: 28 May 2017

Here our objective is estimating $\hat{\imath}(l,m)$which leads to minimizing the error function as follows [5]

$$MSE=\frac{1}{N^2}\sum_{l,m=1}^{N}(\hat{\imath}(l,m)-i(l,m))^2 \quad (2)$$

where N^2 is the number of pixels.

Applying discrete wavelet transform (DWT) on noisy image ($j(l,m)$) provides us with wavelet noisy coefficients. As we see in Figure 1(a) applying two dimensional discrete wavelet transform (2D-DWT) on input noisy image is followed by four sub images HH, HL, LH and LL which H represents the high frequency and L represents the low frequency [14]. Figure 1(b) and Figure 1(c) show 2D-DWT for 2 and 3 levels of decomposition, respectively. Higher level of decomposition will take place in low frequency sub bands (LL sub-band).



(a) (b) (c)

Figure. 1. 2D-DWT for One, Two and Three Levels of Decomposition

3. Thresholding Techniques

Hard and soft thresholding are the most common thresholding techniques in wavelet based noise reduction. These function are given in Eqs. (3) and (4), respectively [5].

$$H_h\,(x)=\begin{cases} x\,, & |x|>th \\ 0\,, & otherwise \end{cases} \quad (3)$$

$$H_s\,(x)=\begin{cases} sgn(x).(|x|-th)\,, & |\omega|\geq th \\ 0\,, & otherwise \end{cases} \quad (4)$$

where $H_h\,(x)$ is hard thresholding function, $H_s\,(x)$ is soft thresholding function, x is wavelet coefficients and *th* is universal threshold [4] which can be obtained by Eq. (5).

$$th=\sigma_n\sqrt{2log(b)} \quad (5)$$

where $b=N^2$ *and* σ_n is standard deviation of noise in highest *HH* sub band in diagonal direction [5] which it is defined in Eq. (6).

$$\sigma_n=Median\,(|HH|)/0.6745 \quad (6)$$

In hard thresholding function wavelet components which are greater than the th will be remained un-changed, otherwise they become zero while in soft thresholding technique, wavelet components which are greater than th will be shrunk, otherwise they become zero [5]. Figure 2 illustrates hard and soft thresholding functions.

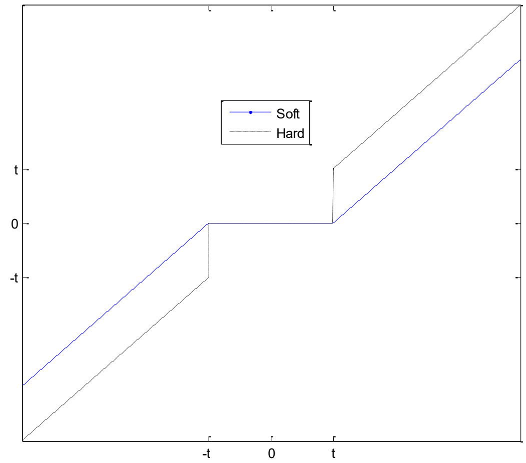


Figure 2. Hard and Soft Thresholding Functions.

In wavelet thresholding first we apply DWT on input signal to get wavelet coefficients. These coefficients can be categorized in two groups: one is very important having the crucial characteristic of image and other is non- important or noisy coefficients which should be removed or reduced by applying different de-noising algorithms. We can apply thresholding techniques (hard or soft thresholding) to obtain thresholded wavelet coefficients. Last step is applying inverse discrete wavelet transform (IDWT) on thresholded wavelet components to get final reconstructed or de-noised image. The general block diagram for obtaining de-noised image is shown in Figure 3.

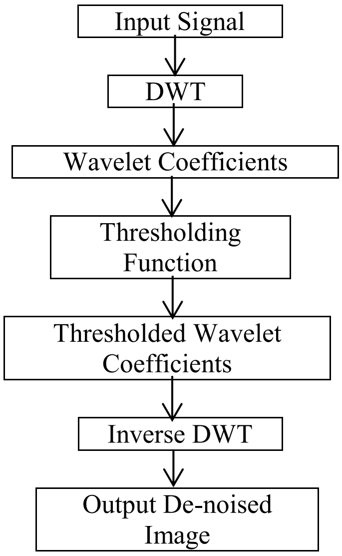


Figure 3. General Block Diagram of De-noising Technique

4. Thresholding Neural Network (TNN) Based Noise Reduction

Zhang in 2001 [9] proposed TNN based noise removing. As it is clear, in multilayer neural network we have activation function and weights of the linear transform of the input signal samples. Similarly in TNN we have linear transform and activation function. In neural network (NN) the linear transform is adaptive and activation function is fixed while in thresholding neural network (TNN) the activation function is adaptive and linear transform is fixed [9]. Figure 4 shows the structure of TNN.

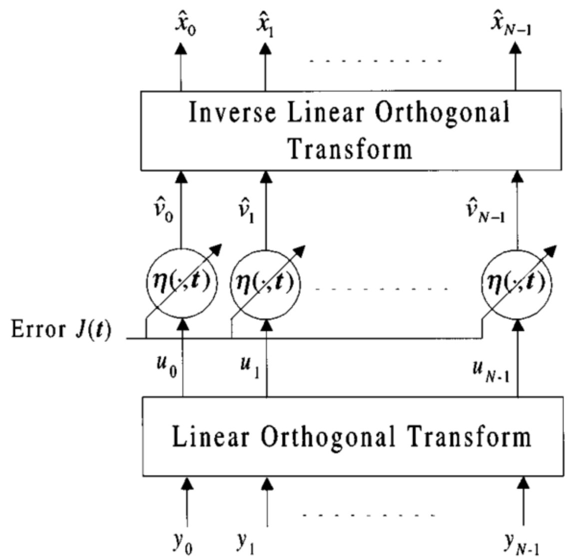


Figure 4. The structure of TNN [9]

As we see in Figure 4, y is input signal corrupted by noise. By applying orthogonal wavelet transform we will get noisy coefficients u. Then thresholding function η is used as activation function to threshold the noisy components to get thresholded wavelet coefficients $\hat{v}$. Then applying inverse linear orthogonal transform provides us with de-noised or desired signal $\hat{x}$ [13].

Here the activation function or thresholding function should be the smooth or nonlinear version of soft and hard thresholding functions. Due to this nonlinearity, we will get more components to be determined in comparison with soft thresholding function or even discontinuous hard thresholding function.

Zhang [9] proposed two continuous nonlinear improved soft and hard thresholding functions which out performs standard hard and soft thresholding in terms of obtaining higher Peak Signal to Noise Ratio (PSNR) and resolution. Eq. (7) and Eq. (8) denote improved hard and improved soft thresholding functions proposed by Zhang [9].

$$\tau_{ht}t(x,th)=\left(\frac{1}{1+\exp\{\frac{-x+th}{\mu}\}}-\frac{1}{1+\exp\{\frac{-x-th}{\mu}\}}+1\right)x \quad (7)$$

where x is the wavelet coefficients, th is the threshold and $\mu > 0$ is a user-defined (fixed) function parameter.

$$\tau_{st}(x,th)=x+\frac{1}{2}\left(\sqrt{(x-th)^2+\lambda}-\sqrt{(x+th)^2-\lambda}\right) \quad (8)$$

where x is the threshold and $\lambda > 0$ is a user-defined (fixed) function parameter.

These functions can be shaped based on changing different μ values for improved hard and λ values for improved soft thresholding functions. Here it is better to use SURE shrink [12] because of its performance in acquiring higher PSNR results and better visual quality.

In step k, the threshold value can be obtained by Eq. (9) [13]

$$t(k+1)=t(k)-\Delta t(k+1) \quad (9)$$

where $\Delta t(k)$ is calculated by Eq. (10) [13].

$$\Delta t(k)=\alpha(k)\frac{\partial J(t)}{\partial},t=t(k) \quad (10)$$

where α is learning rate.

Zhang's research was followed by some other techniques proposed by Sahraeian et al., [10] and Norouzzadeh and Rashidi [13] to improve the PSNR results and visual quality.

5. Proposed Improved Thresholding Function

In this part a new type of thresholding function is proposed. Being nonlinear and continuous are advantageous of using this thresholding function over hard and soft thresholding. Eq. (11) indicates the proposed improved thresholding function. Figure 5 shows hard, soft and proposed thresholding functions. This proposed function is data dependent function due to its dependency to the threshold value and wavelet coefficients.

$$f=xe^{-(\frac{th}{x})^2} \quad (11)$$

where x is wavelet coefficients and th is threshold value.

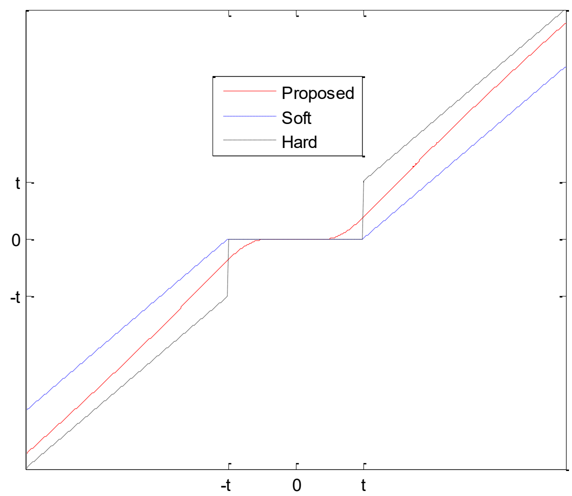


Figure 5. Alternative Thresholding Functions

6. Experimental Results

To show the superiority of the proposed thresholding function two experiments were used. Here 'sym4' wavelet with four levels of decomposition to implement DWT was used. In the first experiment, 'Lena', 'Barbara' and 'Zelda' images (256×256) corrupted by additive white Gaussian noise (AWGN) with zero mean and standard deviation of 15 were utilized. Figure 6 shows performance analysis of the proposed method in comparison with Zhang's method [9].

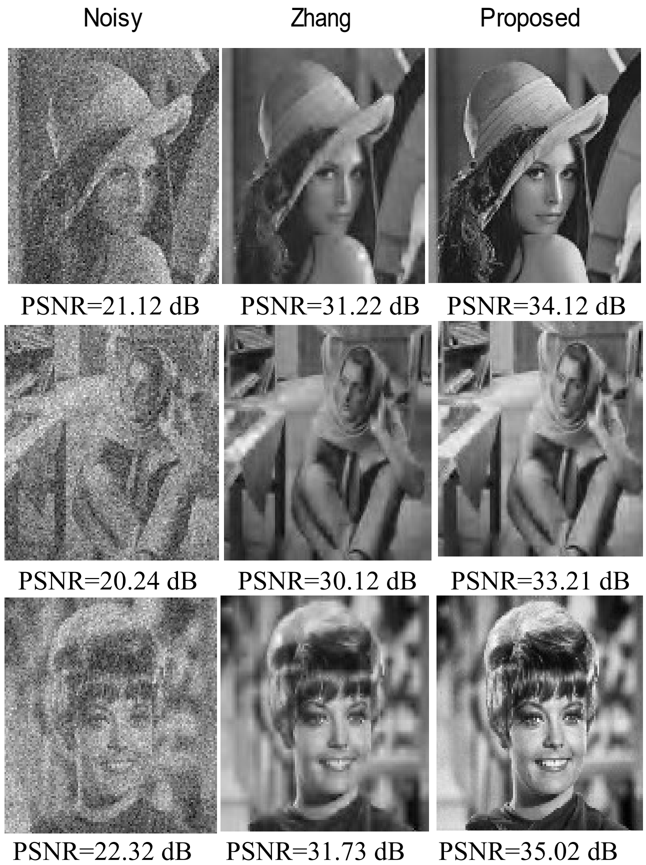


Figure 6. Comparison of Visual Inspection and PSNR Results for Noisy Image, Zhang's De-noising Method [9] and Proposed Technique

In the second experiment, a camparison between the proposed method with some other available techniques for image de-noising was conducted .Table 1 shows de-noising results based on PSNR values for varying different amounts of σ. For this correspondence, we used 256×256 'Peppers' image.

Table 1. PSNR results for different de-noising methods for average of 10 experiments

Methods	Standard Deviation			
	$\sigma = 10$	$\sigma = 15$	$\sigma = 20$	$\sigma = 25$
Visu[4]	32.45	30.05	29.10	27.94
Bayes[11]	34.15	32.63	30.75	29.02
Sahraeian[10]	35.10	33.69	31.35	30.52
Proposed	36.23	34.85	32.68	31.79

7. Conclusion

In this paper, we have proposed a new technique for wavelet based noise reduction. In this technique, a unique thresholding function is used for image de-noising with wavelet transform. This thresholding function is suitable to be applied on thresholding neural network (TNN) algorithm due to its continuity and nonlinearity. Experimental results show that de-noising using proposed technique provides us with higher PSNR values and better visual inspection in comparison with other state-of-the-art techniques available in the literature.

References

[1] B. Demir, S. Erturk, Improved Hyper-spectral Image Classification with Noise Reduction Pre-process. In: Proceedings of European Signal Processing Conference (EUSIPCO), (2008).

[2] A.A. Green, M. Berman, P. Switzer M.D. Craig, A Transformation for Ordering Multispectral Data in Terms of Image Quality with Implications for Noise Removal, IEEE Trans Geoscience and Remote Sensing 26 (1988) 65–74.

[3] G. Chen, S. Qian, De-noising of Hyper-spectral Imagery Using Principal Component Analysis and Wavelet Shrinkage, IEEE Transactions Geoscience and Remote Sensing 49 (2011) 973–980.

[4] D.L. Donoho, I.M. Johnstone, Ideal Spatial Adaptation by Wavelet Shrinkage, Biometrika 81 (1993) 425–455.

[5] L. Dong, Adaptive Image De-noising Using Wavelet Thresholding. In: Proceeding of IEEE International Conference on Information Science and Technology, (2013).

[6] E. Anisimova, J. Bednář P. Páta, Efficiency of Wavelet Coefficients Thresholding Techniques Used for Multimedia and Astronomical Image De-noising. In: Proceeding of IEEE International Conference On Applied Electronics (AE), (2013).

[7] H. Zhang, Hyper-spectral Image De-noising with Cubic Total Variation Model. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Science 1 (2012) 95–98.

[8] S. Sulochana, R.Vidhya, D.Vijayasekaran, K. Mohanraj, De-noising and Dimensionality Reduction of Hyper-spectral Images Using Framelet Transform with Different Shrinkage Functions, Indian Journal of Geo-Marine Science 45 (2016) 978–986.

[9] X.P. Zhang, Thresholding Neural Network for Adaptive Noise Reduction, IEEE Transactions on Neural Networks 12 (2001) 567–584.

[10] S.M.E. Sahraeian, F. Marvasti and N. Sadati, Wavelet Image De-noising Based on Improved Thresholding Neural Network and Cycle Spinning. In: Proceeding of IEEE International Conference on Acoustics, Speech and Signal Processing, (2007).

[11] S. Chang, B. Yu and M. Vetterli, Adaptive Wavelet Thresholding for Image De-noising and Compression, IEEE Transactions Image Processing 9 (2000) 1532–1546.

[12] D.L. Donoho I.M. Johnstone, Adaptive to Unknown Smoothness via Wavelet Shrinkage, (1995) 1200–1224.

[13] Y. Norouzzadeh and M. Rashidi, Image De-noising in Wavelet Domain Using a New Thresholding Function, In: Proceedings of the IEEE International Conference on Information Science and Technology, (2011).

[14] B. Rasti, J.R. Sveinsson, M.O. Ulfarsson, J.A. Benediktsson, Hyper-spectral Image De-noising Using 3D Wavelets. In: Proceedings of the IEEE International Conference on Geoscience and Remote Sensing Symposium (IGARSS), (2012).