ORIGINAL RESEARCH PAPER

Engineering

LOCAL SPECTRAL DECOMPOSITION FOR RGB IMAGE DENOISING BY GRADIENT LEARNING METHOD

KEY WORDS: Gradient learning method, Tresholding neural network, local spectral component decomposition, spectral line, denoising.

Silpa B Krishna K Vedavyasa Institute of Technology, Malappuram, Kerala, India

C Periasami Vedavyasa Institute of Technology, Malappuram, Kerala, India

ABSTRACT

Images are containing a various type of noises during the transmission. The removing noise content from image is called as denoising. The objective of denoising is to remove the noise and to keeping the important features of images. Image denoising is a difficult problem in the field of image processing. This paper, discuss about a new method, called image denoising for multi channel image by using gradient learning method. Gradient based learning method is become possible by using a new thresholding method, called, thresholding neural network. TNN is used to find the optimum value of threshold in a mean square error(MSE) sense .first, local spectral component at each pixel is calculated, which called as spectral line. By spectral line vector, decompose the image in to three components: a single M channel image and two grey scale image. Noise is spread in to two components. The experiment result shows that, image denoising by using gradient based learning method improves the image quality and successfully achieves better PSNR value compares to other existing denoising method.

I. INTRODUCTION

Digital image processing has a wild range of applications such as remote sensing, image and data storage for transmission, medical imaging, acoustic imaging, Forensic sciences and industrial automation. These Images are containing a various type of noises during the transmission. The removing noise from any image is called as image denoising. The idea of denoising is to remove the noise and to keep the important features of images. In today world, many challenges have been prepared to minimize the noise from images by using wavelet transform as a multi-resolution image processing tool.

For removing small coefficients of detail sub-bands and preserving large coefficients, Wavelet domain based noise removal techniques prefers some threshold value. The term wavelet thresholding is defined as decomposition of the image into wavelet coefficients. In this process, detailed coefficients having a given threshold value, and compairing this coefficients with threshold value. Image is reconstructed from modified coefficients. This is also known as inverse discrete wavelet transform. In the case of thresholding, a wavelet coefficient is compared to the given threshold value and is put to zero if its magnitude is less than the threshold or else, it is retained or modified that based on the thresholding rule. Thresholding distinguishes between coefficients due to noise and the ones consisting of important signal information. The selection of a threshold and estimation of a threshold are an important point of interest. So, thresholding gives an important role in the removal of noise because de-noising most normally produces smoothed images, by reducing the sharpness of the image. A variety of methods are existing for wavelet thresholding, which rely on the choice of a threshold value. Soft thresholding and hard thresholding are the typically used methods for image noise removal techniques. In Soft thresholding is that the coefficients with greater than the threshold are close towards zero after comparing them to the threshold value. Soft method is giving much better and more visually lovely images.

From this framework, a new method such as local spectral component decomposition for multi channel image (RGB) denoising by using gradient learning method is proposed. In this work, first, local spectral component of RGB image at each pixel is calculated and defined the spectral line vector. By using this spectral line vector, we can decompose the noisy image in to three components: one will be mean spectral component, second will be spectral line component and third will be residual component. The basic purpose of the decomposition is to transfer the noise only to two components (spectral line component and residual component).so, here; algorithm is going to denoise these two components. After the decomposition, apply filtering to spectral line and residual component. In filtering, new method like TNN is introduced. By TNN, some gradient based algorithm become possible. Gradient based learning algorithm is about to find optimum value of threshold. Threshold value will be adjusted inlearning manner. Finally take the inverse wavelet transform to recover the original image.

Experimental result in this method shows that, our method gives the better result than the other existing denoising method in terms of PSNR and SSIM. Better PSNR value improves the image quality and noise reduction.

II. PROPOSED METHOD

Here, designing a new denoising method for RGB images based on the gradient learning algorithm over the line features of images. For denoising method, color line principle is introducing to reduce the discoloration of RGB image. Algorithm of proposed method consist of four steps that shown in fig 1.

1) First take the noisy input image, and find the local spectral distribution for spectral line by using PCA. For the alignment of spectral line, we adopt the Jacobi relaxation method to specify the sign.
2) After find the spectral line, we decompose the image in to three component a mean spectral component, spectral line component Di and residual component. The aim of the decomposition method is to noise components is transferred to two components (spectral line and residual components).Mean spectral component have a little noise. In spite of of the number of channels, here, only need to denoise the two components.
3) Apply filtering to the spectral line and residual components. In filtering, new types of soft thresholding and hard thresholding functions are created to provide the activation function of the TNN. By using this new thresholding functions, some gradient based learning algorithms is promising or more efficient. Gradient based learning algorithms is about to find the optimal value of threshold in a sense of MSE for noise reduction. In each steps the threshold value is adjusted along with gradient descent of the MSE risk based on soft thresholding.
4) Finally, by applying inverse wavelet transform on modified coefficients, the reconstructed image is obtained.

Block diagram of proposed method is illustrated below.fig 2 block diagram consist of three operations, that are describe below.

1) DWT
2) Tuning threshold vale using TNN
3) Inverse DWT

First take the input image and noises is added to this image and calculates the local spectral distribution at each pixel and find the principal component for each pixel by PCA. Then define the spectral line. Using the spectral line vector, decompose each pixel into the three components: a mean spectral component, spectral line component and residual component. After performing PCA applying DWT to noisy image and get the noisy wavelet coefficient.

The second step known as thersholding value by using TNN. Its s a simple non-linear technique,which operates on one wavelet coefficients at a time. After decomposition, each coefficient is threshold by comparing threshold, if the coefficient is smaller than threshold, that set to zero, if not it kept. as a result threshold value can be adjusted in learning phase. Optimization threshold value is obtained during learning process. TNN uses proposed thresholding function. In test phase, computed threshold value in learning phase is used by proposed thresholding function to denoise wavelet coefficients of test images.

The final step is recomposition of the resulting image from its constituent components. In these steps, taking the wavelet coefficients of the noisy image and outputs are thresholded wavelet coefficients. After applying the inverse wavelet transform, denoised image is available.

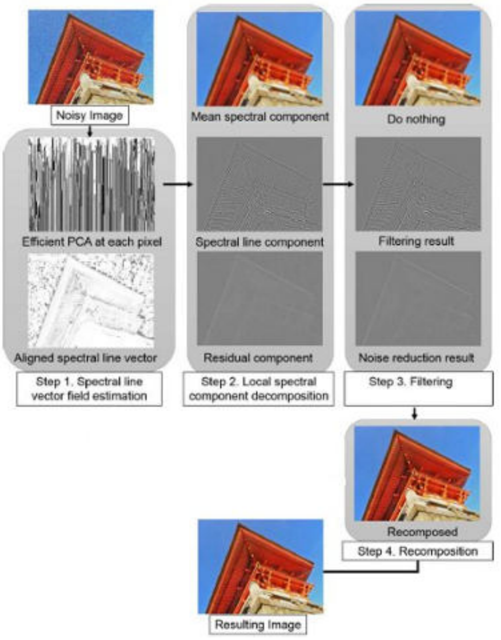


Fig 1:Flow chart of proposed algorithm

The proposed thesholding function is presented as follow:

$$n(x,t) = x + \frac{1}{2}\left\{\left|x - \frac{t}{\exp(|x|-t)/\lambda)}\right) - |x + \frac{t}{\exp((|x|-t)/\lambda)}\right\}|$$

Where t is the threshold and $\lambda > 0$ is a user-defined (fixed) function parameter. Obviously, the soft-thresholding functions $\eta\ (x,t)$ have all higher order derivatives for $\lambda > 0$. Note that when $\lambda \to \infty$, $\eta\ (x,t)$ is just the standard soft-thresholding function $\eta s\ (x,t)\ s$; when $\lambda \to 0$, is just the standard hard-thresholding function $\eta h(x,t)$. The new thresholding functions perform the operations similar to the standard soft-thresholding function. Therefore, similar thresholding effects of the estimate using the new thresholding functions can be expected

Assume that, x is an image with a noise n.so, y is represented the noise image given by

$$y = x + n$$

MSE (mean square error) can be written as,

$$MSE = \frac{1}{N*N}\sum_{i=0}^{1-N}\sum_{j=0}^{1-N}(Y_{i,}j - Y\hat{}_{i,}j)\hat{}2$$

j is learning step, threshold value is adjusted by using

$thr(j+1) = thr(j) + \Delta thr(j)$
Where $\Delta thr(j)$ is calculated by

$$\Delta thr(j) = -\alpha \frac{\partial MSE}{\partial thr}\bigg|_{thr=thr(j)}$$

α is the learning rate.

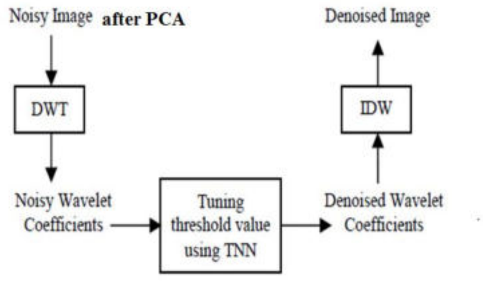


Fig 2: Block diagram of proposed method method

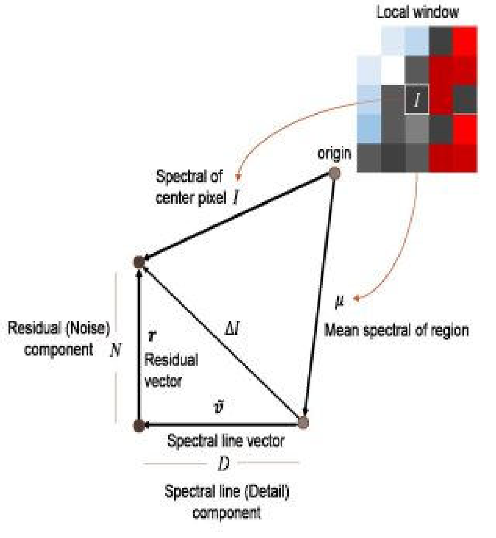


Fig. 3: Spectral decomposition: In local spectral component decomposition, each pixel is decomposed into a spectral line vector, a spectral line component, and a residual component.

III. EXPERIMENTAL CRITERIA

Parameters used in this paper are peak signal to noise ratio (PSNR) and structural similarity index (SSIM) to measure the quality of image.

1) Peak Signal To Noise Ratio

PSNR is the peak signal to noise ratio measured in decibels (DB) and in terms of bits per sample or bits per pixel. The greater PSNR value gives, the better the image quality and noise suppression.

Peak signal to ratio can be calculated as

$$PSNR = 10X\log_{10}\left(\frac{peak^2}{MSE}\right)$$

MSE is the mean square error. That, can be calculated as,

$$MSE = \frac{1}{M*N}\sum_{i=0}^{1-N}\sum_{j=0}^{1-M}(A(i,j) - B(i,j))\hat{}2$$

Here A - Perfect image

B - Denoised image
I – Pixel row index
j – Pixel column index

2) Structural similarity index measure (SSIM)
The structural similarity index is measuring the similarity between two images. SSIM is designed to improve the image quality and can be calculated as,

$$\mathrm{SSIM} = \frac{(2\mu_A\mu_B + C_1)(2\sigma_{AB} + C_2)}{(\mu_A^2 + \mu_B^2 + C_1)(\sigma_A^2 + \sigma_B^2 + C_2)}$$

Where μ_A and μ_B are the estimated mean intensity along A, B directions.
σ_A and σ_B are the standard deviation respectively.

$$\sigma_{AB} = \frac{1}{(N-1)}\sum_{i=1}^{N}(A_i - \mu_A)(B_i - \mu_B)$$

C1 and C2 are the constants and values are given as

$$C_1 = (K_1L)^2$$
$$C_2 = (K_2L)^2$$

Where K1,K2 <<1 is a small constant and value of L is 255.The maximum value of SSIM is 1.

IV. RESULTS AND DISCUSSIONS

Experiments are conducted in MATLAB 2009b as simulation software. Test images used this are Lena (512X512), Baboon (512X512), peppers (512x512), airplane (512x512) and sailboat on lake. Test images are corrupted by additive Gaussian noise of different standard deviation 0.03, 0.05, 0.08 and 0.1. here, Proposed method is compared with existing method in terms of PSNR and SSIM value basis.

In this experiment, here, choose PSNR and SSIM as evaluated standard. The greater PSNR and SSIM value shows that our proposed method gives better noise suppression without artifacts.

Below tables evaluates the performance of different test images with standard deviations 0.03, 0.05, 0.08 and 0.1

Table 1: PSNR and SSIM for existing and proposed method of Lena image.

Test .image	variance	Existing method		Proposed method	
		PSNR	SSIM	PSNR	SSIM
Lena	0.03	33.5611	0.4652	44.2586	0.6853
	0.05	30.9681	0.4712	42.0370	0.6842
	0.08	27.7278	0.4731	40.0048	0.6807
	0.1	26.0188	0.4768	39.0586	0.6756

Table 2: PSNR and SSIM for existing and proposed method of Baboon image.

Test image	variance	Existing method		Proposed method	
		PSNR	SSIM	PSNR	SSIM
Baboon	0.03	29.2095	0.1544	44.2631	0.7486
	0.05	28.0506	0.1561	42.0210	0.7451
	0.08	26.0773	0.1573	39.9852	0.7433
	0.1	24.0773	0.1580	39.0338	0.7426

Table 3: PSNR and SSIM for existing and proposed method of Peppers image.

Test image	variance	Existing method		Proposed method	
		PSNR	SSIM	PSNR	SSIM
Peppers	0.03	32.9109	0.4778	43.8130	0.6883
	0.05	30.4738	0.4803	41.7674	0.6862
	0.08	27.3702	0.4867	39.8215	0.6825
	0.1	25.7139	0.4872	38.8897	0.6775

Table 4: PSNR and SSIM for existing and proposed method of Airplane image.

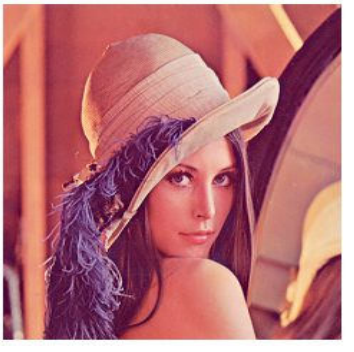
Test image	variance	Existing method		Proposed method	
		PSNR	SSIM	PSNR	SSIM
Airplane	0.03	33.6049	0.5696	44.3375	0.6862
	0.05	31.1041	0.5930	42.1044	0.6868
	0.08	28.0030	0.6097	40.1127	0.6854
	0.1	26.3992	0.6168	39.1950	0.6827

Table 5: PSNR and SSIM for existing and proposed method of Saiboat on Lake Image.

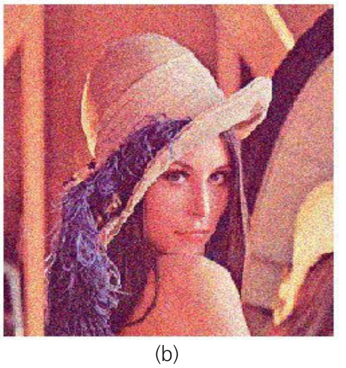
Test image	variance	Existing method		Proposed method	
		PSNR	SSIM	PSNR	SSIM
Saiboat on lake	0.03	32.0133	0.3263	44.0824	0.7259
	0.05	29.9978	0.3300	41.9268	0.7246
	0.08	27.2130	0.3314	39.9322	0.7193
	0.1	25.6650	0.3316	38.9948	0.7149

From these tables, we can show that, PSNR and SSIM values of proposed method successfully performed better result than compared to existing method. Greater the PSNR value will give better image quality.

Fig 3 illustrated the comparison result of existing and proposed method is given to this paper are shown below.

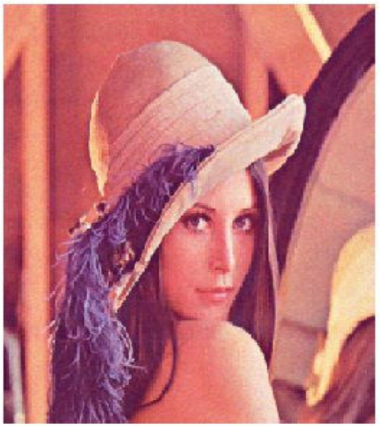


(a)



(b)

(c)



(d)

Fig 3:Denoising of test image Lena.

Here,

a) Original Image.
b) Image corrupted with Gaussian noise with std. deviation = 0.03
c) method using local spectral component decomposition for RGB image.
d) method using local spectral component decomposition by using gradient learning method.

V. CONCLUSION

Image denoising has been a classical problem in image processing.for image denoising, threshold selection is a big problem in the field of image processing. In this paper a new thresholding function is proposed which utilize TNN for tuning threshold value in learning phase. This function is continues and have higher order derivation and which make it suitable for gradient decent learning algorithms like TNN. In this frame work, proposed thresholding function doesn't need to additional parameters. new thresholding function is used that it is possible to search for optimal thresholds using gradient based learning algorithms. The numerical results show that the proposed method performed better result than the existing method in terms of PSNR and SSIM value for improving imagre quality and noise reduction.

REFERENCES

[1] M. Johnstone and B.W. Silverman, "Wavelet threshold estimators for data with correlated noise," J. Roy. Statist. Soc. B, vol. 59, pp. 319–351, 1997.
[2] Mar. 1998. P. Blomgren and T. F. Chan, "Color TV: Total variation methods for restoration of vector-valued images," IEEE Trans. Image Process, vol. 7, no. 3, pp. 304–309.
[3] S. Chang, B. Yu, M. Vetterli, "Adaptive wavelet thresholding for image enoising and compression"n, IEEE Trans. Image Process. 9, 2000, 1532–1546.
[4] May 2001 Xiao-Ping Zhang, Member, IEEE," Thresholding Neural Network for Adaptive Noise Reduction", IEEE transactions on neural networks, Vol. 12, No. 3.
[5] Dec. 2001 T. F. Chan, S. H. Kang, and J. Shen, "Total variation de noising and enhancement of color images based on the CB and HSV color models," J. Vis. Commun. Image Represent., vol. 12, no. 4, pp. 422–435.
[6] Jul.2003 I. Atkinson, F. Kamalabadi, and D. L. Jones, "Wavelet-based hyper spectral image estimation," in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), vol. 2, pp. 743–745.
[7] Jun.2004 I. Omer and M. Werman, "Color lines: Image specific color representation," in Proc. IEEE Conf. Comput. Vis. Pattern. Recognit. (CVPR), vol. 2, pp. II-946–II-953.
[8] Omer and M. Werman, "Using natural image properties as demosaicing hints," in Proc. IEEE Int. Conf. Image Process. (ICIP), vol. 3. Oct. 2004, pp. 1665–1670.
[9] M. Eftekhari, Y. Norouzzadeh and S.D. Katebi, "Wavelet denoising using genetic programming". 7th Conference of Intelligence Systems K.N.T. University of Technology, Tehran, Iran, 2005, (In Persian).
[10] December 2008, G. Sambasiva Rao*,C. Naga Raju, Dr. L.S.S. Reddy, Dr .E.V. Prasad," A Novel Thresholding Technique for Adaptive Noise Reduction using Neural Networks", IJCSNS International Journal of Computer Science and Network Security, VOL.8 No.12.
[11] March 2011, Yaser Norouzzadeh, Masoud Rashidi," Image Denoising in Wavelet Domain Using a New Thresholding function", International Conference on Information Science and Technology.
[12] W C. Tu, C L. Tsai, and S Y. Chien, "Collaborative noise reduction using color line model," in Proc. IEEE Int. Conf. Acoust. Speech Signal Process. (ICASSP), May 2014, pp. 2465–2469.
[13] March 2011, Yaser Norouzzadeh, Masoud Rashidi," Image Denoising in Wavelet Domain Using a New Thresholding function", International Conference on Information Science and Technology.
[14] January 2014, Rajni and Anutam, "Image denoising techniques-an overview",International Journal of Compute Applications (0975 – 8887) Volume 86 – No 16
[15] June 2014, Sandeep Kaur1, Navdeep Singh," Image Denoising Techniques: A Review", international Journal of Innovative Research in Computer and Communication Engineering, Vol. 2, Issue 6.
[16] 2014, Arun Dixit, Poonam Sharma,"A Comparative Study of Wavelet Thresholding for Image Denoising" I.J. Image, Graphics and Signal Processing, 12, 39-46.
[17] Y. Q. Zhao and J. Yang, "Hyper spectral image denoising via sparse representation and low-rank constraint," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 1, pp. 296–308, Jan. 2015.
[18] Mia Rizkinia, Tatsuya Baba, Keiichiro Shirai and Masahiro Okuda, "Local Spectral Component Decomposition for Multi-Channel Image Denoising," IEEE Transactions on image processing, vol. 25, no. 7, july 2016.