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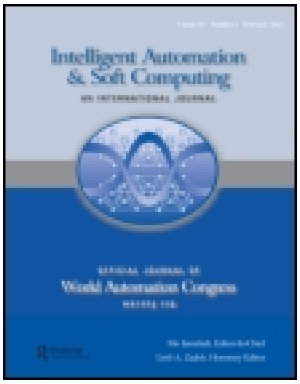

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DIRECTIONAL WEIGHT BASED CONTOURLET TRANSFORM DENOISING ALGORITHM FOR OCT IMAGE

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ABSTRACT—Optical Coherence Tomography (OCT) imaging system has been widely used in biomedical field. However, the speckle noise in the OCT image prevents the application of this technology. The validity of existing contourlet-based denoising methods has been demonstrated. In the contourlet transform, the directional information contained by spatial domain is reflected in the corresponding sub-bands, while the noise is evenly distributed to each sub-band, resulting in a big difference among the coefficients' distribution of sub-bands. The traditional algorithms do not take these features into account, and only use uniform threshold shrinkage function to each sub-band, which limits the denoising effect. In this paper, a novel direction statistics approach is proposed to build a directional weight model in the spatial domain based on image gradient information to represent the effective edge information of different sub-bands, and this weight is introduced into threshold function for denoising. The experiments prove the effectiveness of this method. The proposed denoising framework is applied in contourlet soft threshold and bivariate threshold denoising algorithms for a large number of OCT images, and the results of these experiments show that the proposed algorithm effectively reduces noise while preferably preserves edge information.

Key Words: Optical Coherence Tomography (OCT) Image; Image Denoising; Contourlet Transform; Directional Statistics of Image

1. INTRODUCTION

Optical coherence tomography (OCT) has played an important role in the biomedical field. However, the ubiquitous speckle noise prevents the further study of OCT image. Several algorithms have been proposed in some literatures to handle the speckle noise. The denoising effect of the spatial domain methods, such as Lee filter and RKT filter which blurs the edge easily while dealing with an image of OCT, is not satisfied [1,2]. In the frequency domain methods, Adler et al. first used the adaptive wavelet threshold denoising algorithm to realize the OCT retinal image denoising [3]. In the algorithm, for the horizontal structure of OCT retinal images, a more effective denoising is achieved by using an artificial setting parameter to control the threshold in vertical sub-band. The main idea of the algorithm is that the OCT retinal image contains less vertical direction information and the noise ratio in wavelet vertical sub-band is larger, so the vertical sub-and need a larger threshold to improve the denoising effect. However, the algorithm will be invalid while handling the images of multi-direction. The review of the OCT image denoising methods indicated that the wavelet-based threshold denoising algorithm does better in OCT image denoising while preserving edges [1][4].

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However, the wavelet transform is lack of directionality and can only characterize the horizontal, vertical and diagonal information of an image. This limits the denoising effect of wavelet-based algorithms, especially for the images with multi-direction. Do and Vetterli proposed the contourlet transform to realize the directionality and anisotropy in image representation [5]. Po and Do studied the inter-scale and intra-scale dependency of the contourlet coefficients and proposed the contourlet Hidden Markov Tree (HMT) to realize image denoising [6]. Guo et al. proposed bivariate shrinkage function based contourlet transform by considering the coefficient dependency between sub-bands to realize the OCT image denoising. Other contourlet-based image denoising algorithms are introduced in [8–11]. However, the state of the art contourlet-based image denoising algorithms are mainly an extension of the wavelet denoising algorithm and only use a unified shrinkage function for all of the directional sub-bands, without considering the coefficient distribution difference of each directional sub-band. This cannot take advantage of the directionality and anisotropy of the contourlet transform and limits the denoising effect of the contourlet-based denoising methods.

According to the above problems, this paper proposes a novel contourlet threshold denoising framework for OCT image, which takes the difference of direction sub-bands into account through direction statistic information. In detail, a direction statistic approach based on image gradient information is proposed to get the direction weights which represent the difference between sub-bands. This method is discussed by experiments. Then, the direction statistic information in the form of weights will be introduced to threshold function so as to achieve more effective denoising effect. The paper does not propose a new threshold function but focuses on discussing a new threshold denoising framework, and it will be applied to a variety of threshold denoising methods to improve the algorithm widely.

The organization of this paper is as follows. Section 2 further describes the main idea of the paper by experiments. Section 3 introduces the proposed direction statistic approach and the direction weight model, and its performance is experimentally discussed. Section 4 presents a novel contourlet based framework and elaborates the implementation steps of the algorithm. Section 5 applies the proposed algorithm framework to contourlet soft and bivariate threshold denoising algorithm, and takes experiments of OCT retinal image and OCT chick embryo heart tube image respectively. The denoising effect and evaluation metrics prove that the algorithm greatly improves original contourlet threshold denoising algorithms and better preserves the edge information.

2. PROBLEMS ILLUSTRATING

This section demonstrates that the image direction information reflects the valid information of different direction sub-bands in the contourlet domain, and this feature has not been considered in the existing contourlet threshold algorithms, thus limiting the denoising effect. Add multiplicative noise to three images which contain different number of direction, as are shown in Figure 1. (a) - (c). Performing four scales and eight directions contourlet decomposition to the three images, the results of the third scale are shown in Figure 1. (d) - (f). According to the principle of contourlet transform, if one image only contains edge information in one direction as shown in Figure 1, image (a). Then edge information will be mainly distributed in the corresponding direction sub-band in contourlet domain. However, the noise does not have directivity and is distributed in all direction sub-bands as shown in Figure 1, image (d). If the image contains multi-direction information which can be reflected in the corresponding sub-bands, the process causes a big difference between different direction sub-bands. And the difference can be reflected by the direction information.

With each sub-band containing different amount of valid information, using a larger threshold value can achieve more effective denoising for the direction sub-band which contains much more noise. So parameters can be introduced to control the threshold value of sub-bands. The above experimental

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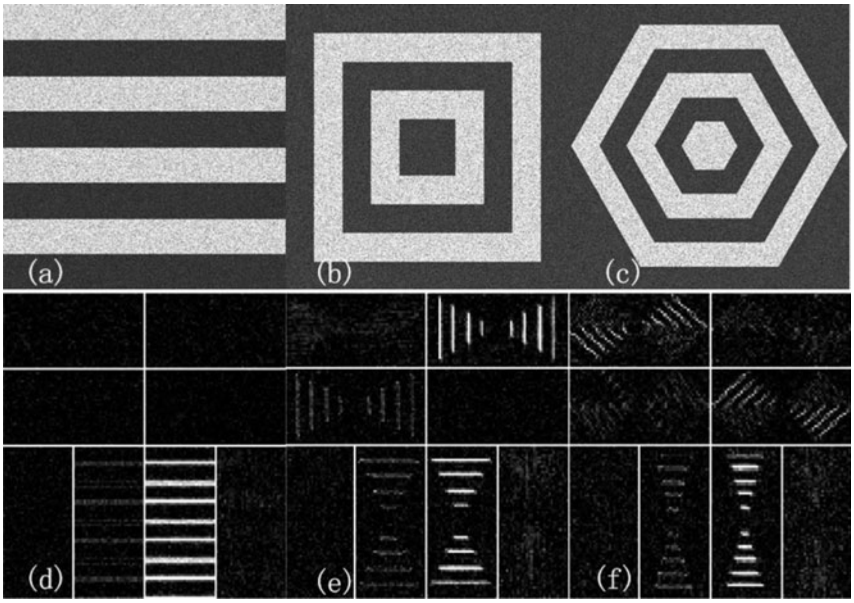

Figure 1. (a)-(c) three noisy images containing different number of direction, (d)-(f) the third scale contourlet decomposition results of (a)-(c) respectively.

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results show that the direction information in the spatial domain can reflect the amount of valid information of each direction sub-band, so the parameters can be gotten by direction information in the spatial domain. This paper is dedicated to finding a better statistic approach to reflect the direction information of the image, and introduce the results in the form of weight to different direction sub-bands in the contourlet domain so as to achieve better denoising result.

3. DIRECTION STATISTICAL APPROACH AND DIRECTION WEIGHT

To extract direction statistical information of an image, this section proposes and discusses a gradient information based direction statistical method. This method uses gradient direction to classify multi-directionally and perform gather statistics. Furthermore, two diagonal kernels are added into the process to reduce the effect of noise. Experimental results show that the method does well in extracting the direction information, and the statistical results accord with the actual feature of the image. Then, the statistical results are used to build the weight vector representing the difference between sub-bands in contourlet domain.

3.1 Image gradient information based direction statistical approach

Using the image gradient direction to classify gradient value and perform statistic has been widely applied to the target recognition and feature extraction in the detection domain, such as Edge Orientation Histogram (EOH) [12], gradient Histogram Orientation [13], *etc.* Levi and Weiss proposed Dominant Orientation Feature based on the EOH feature [14]. Inspired by their works, this section proposes the image gradient information based direction statistical method. The method is introduced as follows:

Step 1: do convolution to the image by using four directional kernels. The directional kernel can be described as Equation (1). After convolution, each pixel of the original image corresponds to four convolution values as shown in the Equation (2). In fact, $Grad_1$, $Grad_2$ are the gradient operators, and their convolution results with the original image are defined as the gradient.

$$Grad_1 = [-1, 0, 1], \quad Grad_2 = [1, 0, -1]^{\mathrm{T}}, \quad Grad_3 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Grad_4 = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix} \tag{1}$$

$$Conv_{\mathrm{k}} = Grad_k * I \quad k = 1, 2, 3, 4 \tag{2}$$

Step 2: calculate the variance of four convolution results of each pixel to get a variance matrix *Var*, and set a threshold value for the variance. If the variance of a pixel is greater than the threshold value, the pixel is labeled as edge point. Otherwise, the point is considered to be noise or the point in the flat region. Since the noise points and points of flat region have no directivity, the variance of those points is smaller. Actually, this process defines the edge of the image, which can be shown in Equation (3). T_{var} can be calculated by the optimal threshold method mentioned in [15] as

$$I_{edge}(x, y) = \begin{cases} 1 & if \quad Var(x, y) \geq T_{\mathrm{var}} \\ 0 & if \quad Var(x, y) < T_{\mathrm{var}} \end{cases} \tag{3}$$

Step 3: get the gradient magnitude $G\,(x, y)$ and the gradient direction $\theta\,(x, y)$ of each pixel (x, y), which are defined in Equation (4) and (5). The following equation omits location identifier (x, y)

$$G = \sqrt{Conv_1^2 + Conv_2^2} \tag{4}$$

$$\theta = \arctan(Conv_2 / Conv_1) \tag{5}$$

Step 4: for the unsigned direction range, segment the range uniformly into *Ndir* parts, namely $Bin_i(i = 1, \ldots, Ndir)$. For the pixel (x,y), if its gradient direction $\theta\,(x, y)$ is in the range of Bin_i, set the point (x, y) in *i*th matrix $SubI_i$ equal to the production of gradient magnitude $G\,(x, y)$ and $I_{edge}(x, y)$. And *Ndir* refers to the number of statistical directions. This process is presented as

$$SubI_i(x, y) = \begin{cases} I_{edge}(x, y) \cdot G(x, y) & \theta(x, y) \in Bin_i \\ 0 & \theta(x, y) \notin Bin_i \end{cases} \quad i \in 1, \ldots, Ndir \tag{6}$$

Step 5: sum up each matrix $SubI_i$ to obtain an *Ndir*-dimensional vector called **Val** including all directional statistics, and the gradient magnitude of each pixel is regarded as the statistical weights.

$$\boldsymbol{Val}(1, i) = \sum_{(x,y) \in SubI_i} SubI_i(x, y) \tag{7}$$

Use the above method to execute statistics to Figure 1, image (a) -(c), which contains different number of directions. Set $Ndir = 8$, and the results are showed in Figure 2, image (a) - (c); the edge detection results defined in (3) are showed in Figure 2, images (d) - (f). Experimental results indicate that this method can well express edge information of the noisy image. Also, the results of directional statistics accord with the actual image and direction sub-bands in the contourlet domain.

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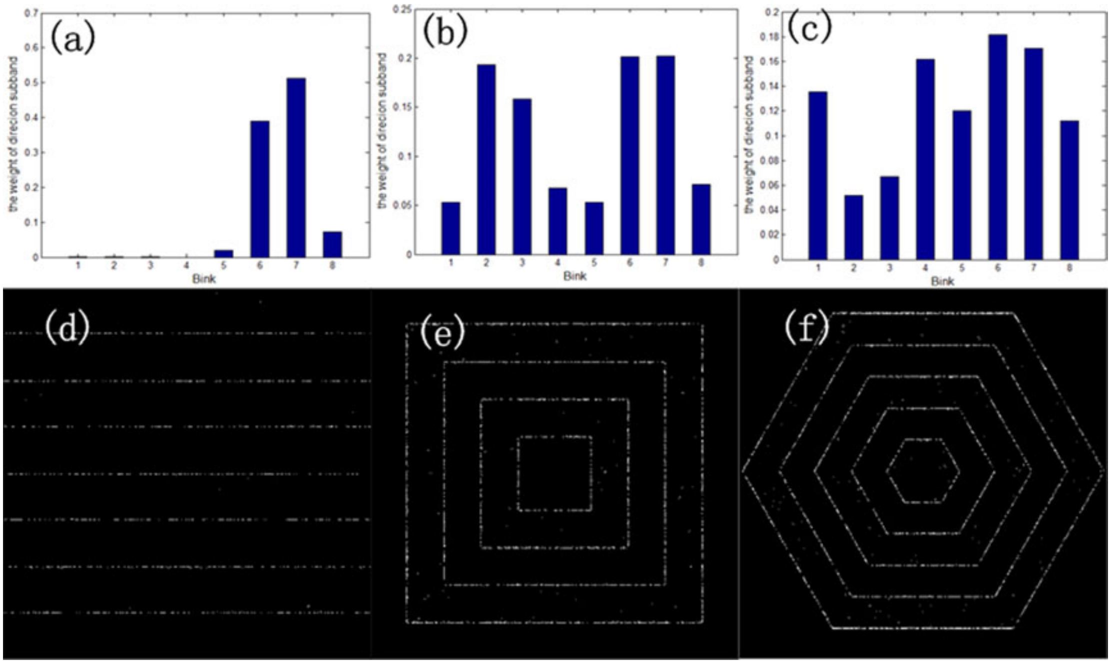

Figure 2. (a)-(c) statistic results of Figure 1, image (a)-(c). (d)-(f) edge detection results of Figure 1, image (a)-(c).

3.2 Direction weight model

The statistic vector **Val** of *Ndir* directions can be obtained from above method. The vector represents the directional distribution of the whole image. As is showed in Figure 2, image (a), the results show that the direction of the whole image mainly distributed in the horizontal direction represented by $Bin_{6,7}$. This is in accord with the results of actual Figure 1 image (a) and the distribution of directional sub-band information in contourlet domain, Figure 1 image (d). Other statistical results have similar conclusions. Section 2 describes that the direction information of the image can reflect different sub-bands' valid information in contourlet domain, so the obtained directional statistic vector **Val** can be used to reflect the difference among directional sub-bands. The weight vector is known as $\mathbf{w_v}$ and defined in Equation (8).

$$\mathbf{w_v}(1, vi) = \frac{Val(1, vi)}{\sum_i^{Ndir} Val(1, i)} \quad vi = 1, \ldots, Ndir \tag{8}$$

Equation (8) illustrates that the larger the frequency of one direction is, the larger the weight it has, and the more the effective edge information this directional sub-band contains. So it's reasonable to use the weight vector $\mathbf{w_v}$ to control the threshold of each direction sub-band.

4. DIRECTION WEIGHT BASED CONTOURLET TRANSFORM THRESHOLD DENOISING FRAMEWORK

The key of basic contourlet threshold denoising method is to derive an effective threshold function. The existing functions were put forward based on considering the contourlet domain coefficients' characteristics.

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The commonly used threshold denoising methods at present are: hard-threshold function, soft threshold function, bivariate threshold function *etc*. The commonly process for OCT image denoising is: (1) perform logarithm transform to the original OCT image to transform the multiplicative noise into additive noise; (2) make contourlet transform on the image; (3) Substitute the coefficients within the contourlet into the threshold function and estimate the noise-free coefficients; (4) make contourlet and logarithmic inverse transform to get the denoised image.

However, in the method described above, the threshold function is built by considering the characteristics of coefficients in the contourlet domain. For example, [6] discusses the correlation of the general neighbour coefficients in the contourlet domain, but it doesn't consider the threshold function from the global image features, for example the distribution of the direction information. The experiment in section 2 indicates that the distribution of information on the direction of the image affects the amount of valid information of each sub-band. Thus, this paper proposes a contourlet threshold denoising algorithm based on direction weights, which introduces the direction weight into the threshold function to improve the denoising effect. The direction weight is deduced from the method introduced in section 3. Figure 3 shows the overall framework. Y, X, N respectively means the original image, the ideal noiseless signal and noise; y, w, ϵ, respectively corresponds to the noisy, ideal noiseless and noise coefficient in the contourlet domain; T() is the threshold function, $\hat{w}$ is the estimated noiseless coefficient, and $\hat{X}$ is the final denoised image. Details are as follows:

Step 1: Perform logarithm and contourlet transform to the noisy image I. I can be defined as Equation (9). The result after transformation can be described as Equation (10).

$$\mathrm{Y} = \mathrm{XN} \tag{9}$$

$$y_{ij} = w_{ij} + \varepsilon_{ij} \tag{10}$$

where i and j are the decomposition level and the direction sub-band.

Step 2: In the ith decomposition level, the number of direction sub-bands is $Ndir_i$. Use the method proposed in section 3 to get the direction weight $\mathbf{W_{v,i}}$ of the image in spatial domain with the input $Ndir_i$.

Step 3: Build the threshold function according to methods proposed in [6,7].

Step 4: use Equation (11) to handle each coefficient in the decomposition level i and direction sub-band j, and do the same to other sub-bands and decomposition levels.

$$\hat{\omega}_{i,j} = \left(\frac{\mathrm{c}}{\boldsymbol{w}_{\mathbf{v},\mathbf{i}}(1,j)+1}\right)\cdot T(y_{i,j}) \tag{11}$$

where c is a constant to control the extent of the weight.

Step 5: perform contourlet and logarithm inverse transform to the denoised contourlet coefficients and get the denoised image.

5. EXPERIMENTS AND EVALUATION

In order to verify the effectiveness of the proposed method, apply the above framework to the contourlet soft threshold denoising algorithm and bivariate threshold denoising algorithm separately. Use a large number of OCT images as the experimental images, including the OCT heart tube images [16], retinal images [18] and so on. Contrast experiments are performed among the following denoising algorithms: wavelet threshold bivariate denoising (WTB) [17], contourlet soft thresholding (CTSoft) [5], contourlet threshold bivariate denoising algorithm (CTB) [7], contourlet soft thresholding based on the direction weight (CTSoftDW) and contourlet threshold bivariate denoising based on the direction weight (CTBDW).

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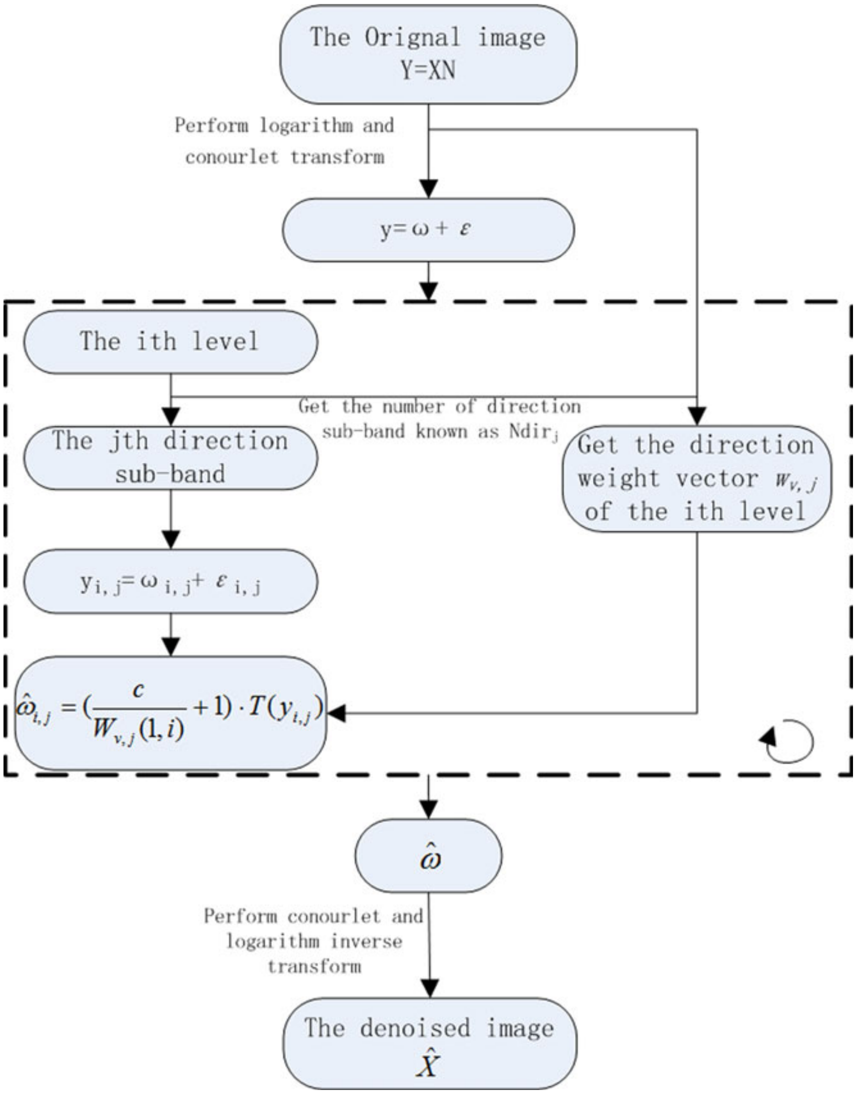

Figure 3. Proposed threshold denoising framework.

The following three metrics are used to evaluate the experimental results.

$$SNR = 20\lg\frac{\mu_m}{\sigma_b} \tag{12}$$

$$CNR_m = 10\lg\frac{\mu_m - \mu_b}{\sqrt{\sigma_m^2 + \sigma_b^2}} \tag{13}$$

$$ENL_m = \frac{\mu_m^2}{\sigma_m^2} \tag{14}$$

where u_m and σ_m are the mean and standard deviation of the m-th target region, and u_b and σ_b are the mean and standard deviation of the background. CNR measures the contrast between an image feature region and

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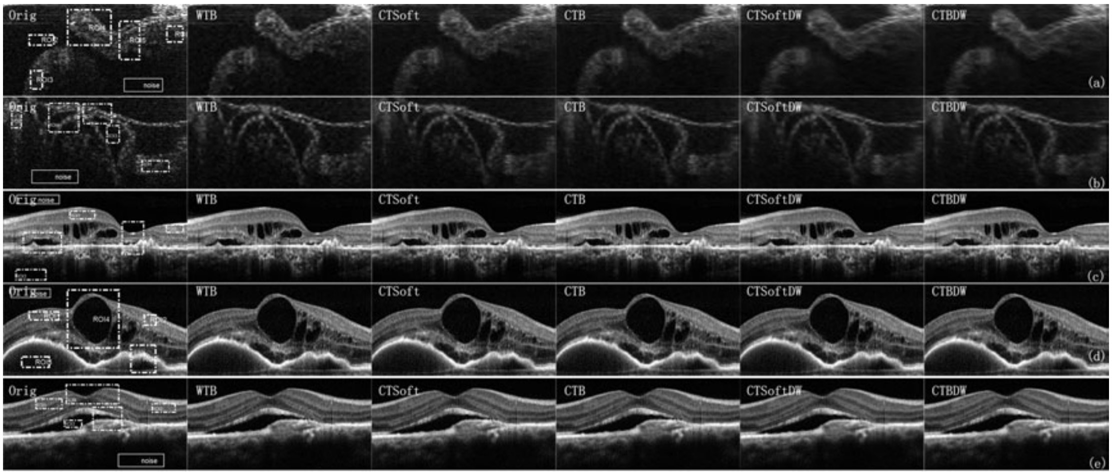

Figure 4. (a)-(e) results of five OCT images after handling with five kinds of denoising algorithms. The first column is the original image, in which the broken line is the ROI for evaluation, and the solid box represents the background noise. Column 2–6 shows the results of various denoising algorithms, and each algorithm appears in the upper left corner.

Table I. The SNR, CNR and ENL values of five OCT images through five kinds of denoising algorithms.

		Orig	WTB	CTSoft	CTB	CTSoftDW	CTBDW
OCT1	SNR	15.89	20.54	20.19	20.97	22.24	22.13
	CNR	3.68	4.78	4.75	4.96	5.13	5.12
	ENL	6.60	15.43	18.37	20.84	23.57	23.75
OCT2	SNR	16.15	19.50	20.30	20.90	22.12	22.07
	CNR	3.95	4.84	4.98	5.15	5.42	5.42
	ENL	6.55	15.24	23.41	25.99	32.21	32.21
OCT3	SNR	24.11	25.06	25.54	25.78	26.33	26.27
	CNR	6.45	6.64	6.68	6.77	6.86	6.83
	ENL	43.18	74.61	71.76	73.04	82.34	81.24
OCT4	SNR	18.44	19.28	19.80	20.09	20.51	20.41
	CNR	6.46	6.75	6.87	6.94	7.01	7.02
	ENL	26.51	44.98	41.19	42.47	46.23	45.74
OCT5	SNR	20.93	21.87	22.36	22.52	23.28	23.21
	CNR	5.99	6.21	6.32	6.34	6.47	6.45
	ENL	18.59	25.12	26.43	26.88	29.63	29.30

the background noise; ENL measures the smoothness of a homogeneous region. The denoising results of five images of the experimental images are showed in Figure 4 and Table I. The three values corresponding to each image are the mean values of selected ROI metrics, while the ENL values are the mean values of homogeneous regions. Experimental results indicate that the proposed method greatly improves the denoising effect compared with existing contourlet denoising algorithms.

6. CONCLUSIONS

This paper proposes a direction weight based contourlet transform denoising framework for OCT image, aiming to take the sub-band diversity in contourlet domain into account, which is not considered in present algorithms. In detail: (1) a directional statistic method based on the gradient information of the image is proposed. This method has good anti-noise performance, which can effectively extract the directional information from noisy OCT images; (2) the paper realizes a new framework to enhance the contourlet soft and bivariate threshold denoising algorithms by introducing the directional information in the form of weight into contourlet domain threshold function. The result of experiment shows that the proposed algorithm can effectively improve the traditional contourlet threshold denoising algorithms, and performs better in denoising OCT images.

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REFERENCES

[1] Pižurica, A., Jovanov, L., Huysmans, B., Zlokolica, V., De Keyser, P., Dhaenens, F. & Philips, W. (2010). Multiresolution denoising for optical coherence tomography: A review and evaluation. *Current Medical Imaging Reviews*, *4*, 270–284.

[2] Rogowska, J., & Brezinski, M. (2000). Evaluation of the adaptive speckle suppression filter for coronary optical coherence tomography imaging. *IEEE Transactions on Medical Imaging*, *19*(12), 1261–1266.

[3] Adler, D. C., Ko, T. H., & Fujimoto, J. G. (2004). Speckle reduction in optical coherence tomography images by use of a spatially adaptive wavelet filter. *Optics Letters*, *29*, 2878–2880.

[4] Ozcan, A., Bilenca, A., Desjardins, A. E., Bouma, B. E., & Tearney, G. J. (2007). Speckle reduction in optical coherence tomography images using digital filtering. *Journal of the Optical Society of America A-optics Image Science and Vision*, *24*(7), 1901–1910.

[5] Do, M. N., & Vetterli, M. (2005). The contourlet transform: An efficient directional multiresolution image representation. *IEEE Transactions on Image Processing*, *14*, 2091–2106.

[6] Po, D. D.-Y., & Do, M. N. (2006). Directional multiscale modeling of images using the contourlet transform. *IEEE Transactions on Image processing*, *15*(6), 1610–1620.

[7] Guo, Q., Sun, S., Dong, F., Gao, Z., & Wang, R. (2012). Optical coherence tomography heart tube image denoising based on contourlet transform. *Proc. of 2012 International Conference on Machine Learning and Cybernetics* (pp. 1139–1144).

[8] Zhou, Z. F., & Shui, P. L. (2007). Contourlet-based image denoising algorithm using directional windows. *Electronics Letters*, *43*, 92–93.

[9] Hiremath, P. S., Akkasaligar, P. T., & Badiger, S. (2011). Performance comparison of wavelet transform and contourlet transform based methods for despeckling medical ultrasound images. *International Journal of Computer Applications*, *26*, 34–41.

[10] Satheesh, S., & Prasad, K. (2011). Medical image denoising using adaptive threshold based on contourlet transform. *Advanced Computing: an International Journal*, *2*, 52–58.

[11] Eslami, R., & Radha, H. (2003). The contourlet transform for image de-noising using cycle spinning. *Conference Record of the Thirty-Seventh Asilomar Conference on Signals, Systems and Computers* (pp. 1982–1986).

[12] Freeman, W., & Roth, M. (1995). Orientation histogram for hand gesture recognition. *International workshop on automatic face- and gesture-recognition*.

[13] Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. *Proc. of international conference on computer vision and pattern recognition* (pp. 886–893).

[14] Levi, K., & Weiss, Y. (2004). Learning object detection from a small number of examples: The importance of good features. *Proc. of International conference on computer vision and pattern recognition* (pp. 53–60).

[15] Huang, L., & Wang, M. J. (1995). Image thresholding by minimizing the measures of fuzziness. *Pattern Recognition*, *28*, 41–51.

[16] Wang, R., Yun, J. X., Yuan, X. C., Goodwin, R., Markwald, R., & Gao, B. (2011). An approach for megahertz OCT: Streak mode Fourier domain optical coherence tomography. *Proc. of SPIE 7889* (pp. 788920–788925).

[17] Sendur, L., & Selesnick, I. W. (2002). Bivariate shrinkage functions for wavelet-based denoising exploiting inter-scale dependency. *IEEE Transactions on Signal Processing*, *50*, 2744–2756.

[18] http://www.optos.com/en/Professionals/Image-library/Spectral-OCTSLO-images/

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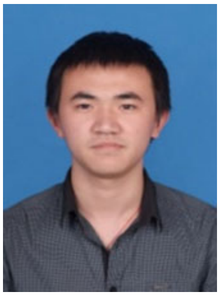

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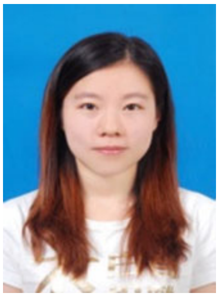

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