International Journal of Multimedia and Ubiquitous Engineering
Vol.10, No.12 (2015), pp.27-36
http://dx.doi.org/10.14257/ijmue.2015.10.12.04

An Improved Recognition Algorithm for Retina Texture Based on Fusion Threshold Equalization

Zhongsheng Qiu

Naval Aeronautical and Astronautical University/Department of Traning, Yantai 264001, China
overflyq@yahoo.com

Abstract

To overcome the problem in recognition of retina texture with noise, an improved multi scale retina texture recognition algorithm is proposed based on fusion area threshold. Integrated with regional threshold filtering, it is useful to suppress the effect of non-uniform blocks for texture recognition. Also, the nonlinear multi-scale transform can analyze the geometric space coefficient of retinal vessels with multi direction invariant features. The maximum likelihood local mean standard deviation analysis is used for texture parameters estimation and recognition. Accurate identification of texture feature is obtained with the noise reduced greatly. The simulation results show that the algorithm can well characterize the retinal vascular texture, with good performance in different texture feature recognition. With good robustness, the recognition accuracy is improved also.

Keywords: *Threshold Equalization, Recognition, Contourlet Transform, Image Fusion, Retina*

1. Introduction

For some diseases, one of the basic diagnostic and monitoring tools is the recognition of texture feature of medical images [1]. Texture feature of medical images can be used to help clinical diagnosis, the medical image processing algorithms and technology are obtained more and more attention from people.

To improve the diagnosis reliability, quantitative image analysis is highly desirable. The medical images texture extraction method is becoming the trend in medical image processing [2]. The eye ground retinal blood vessel texture can predict various diseases in the human body in potential, using computer vision image processing technology, the clinical researchers and doctors can analyze the diseases and lesions trend of human body from the original multi hierarchy analysis process of texture data. The pathological phenomena and other interested regions can be analyzed in quantitative research [3]. But the eye ground texture is often influenced by noise and other non ideal imaging factors that influence the clinical diagnosis. Therefore, eye ground texture images processing has been the hot issue in the field of medical image processing [4].

Owing to the development of technology, retina texture images recognition is referred as a kind of special clinical effective means to diagnosis disease [5]. Due to noise and other non ideal imaging factors interference. The eye ground texture edge contour characteristics are basically concentrated in the high frequency image, the transform domain is susceptible to noise interference. Traditional texture noise recognition algorithm used the smoothing noise processing method, the eye ground texture information and important detail information are lost, the edge feature cannot be extracted effectively, it takes the difficulty for the subsequent image processing. In reference [6], a retinal texture recognition method is proposed based on mathematical morphology wavelet, the method adopts mathematic morphological processing method to process the

ISSN: 1975-0080 IJMUE
Copyright ⓒ 2015 SERSC

texture gradient segmented image, and then the image equalization filtering is taken, the texture recognition effect is improved to a certain degree, but the texture recognition is not clear. In reference [7], eye ground texture multi scale recognition algorithm is proposed based on global threshold ridgelet transform, different threshold values are used for binary processing of eye ground texture image. The blood vessel is recognized in the binary image. For parts of blood vessel textures, the recognition effect is good, but this method needs to divide the eye ground textures into different parts, the contour information features are taken with key segmentation, this method largely improves the texture recognition features, but the computing cost is big, and the high frequency suppression effect is poor, the computational complexity is high.

In this paper, the fusion threshold equilibrium and non sub-sampled multi-scale Contourlet transform are introduced in the eye ground texture recognition. Because eye ground texture is disturbed by non ideal imaging factor such as noise, it will affect the clinical diagnosis in practice, an improved multi scale retina eye ground texture recognition algorithm is proposed based on fusion area threshold [8]. Simulation results show that the new method has good robustness performance, and the recognition accuracy in improved greatly.

2. Basic Knowledge and Algorithm Principle

2.1. Non Sub-Sampled Contourlet Transform

The non-subsampled Contourlet transform a kind of special image multi-scale geometric space analysis method, Contourlet transform maps the image in the multi-scale and multi direction two-dimensional space, and the multi-scale analysis and multi direction analysis are used for two relatively independent process, the image pre-processing is obtained, this process is called Pyramidal Directional Filter Bank (PDFB).

The inner product mathematical expression of subsampled Contourlet transform is shown as:

$$s_j = \langle x, \psi_j \rangle \quad (1)$$

Where, $\{\psi_j\}_{j=0}^{M-1}$ is the multi-scale pyramid directional filter banks, it is set in base space, the space coefficient can be determined by weighting computing, and x is the original image.

Tower direction filter has some limitations on the low-frequency part of the image processing, so before the tower direction conversion, the low frequency component of the filtered image is processed, and the tower direction filter interference is eliminated, the mathematical expressions after the transformation is shown as:

$$t_j = \langle x, \varphi_d \rangle \quad (2)$$

Where, $\{\varphi_d\}_{d=0}^{N-1}$ direction filter coefficient space, $R^N (N = 0, \cdots, 2^t - 1)$ is the base space, x is the original image input signal.

According to the formula as above, Contourlet transform mathematical expression is obtained as:

$$c_{j,d} = \langle s_j, \varphi_d \rangle = \langle \langle x, \varphi_j \rangle, \varphi_d \rangle \quad (3)$$

Furthermore, after the image process, the formula can be converted as:

 Copyright ⓒ 2015 SERSC

$$c_{j,d} = \left\langle x, \left\langle \psi_j, \varphi_d \right\rangle \right\rangle \tag{4}$$

Where, $\left\langle \psi_j, \varphi_d \right\rangle$ is the Contourlet transform coefficient of the original image space $R^{M \times N}$, x is the original image input signal.

In the transform domain, subsampled Contourlet transform and wavelet transform are used to suppress the noise effect, but the non-subsampled Contourlet transform has not sampling step in the direction of filter decomposition process, the transform is translation invariant. The sampling process is taken in the low-pass filter bandwidth restrictions. It helps to hold the image contour features, and it can produce the geometric data of multi scale space under the multi direction analysis. Therefore, this paper uses the non-subsampled Contourlet transform for image texture extraction and noise recognition.

2.2. High Order Cumulant Slice Texture Threshold Equalization Cancellation Algorithm

In this paper, the concept of higher order cumulant is proposed, for a single random variable x, the characteristic function is:

$$\Phi_x(\omega) = e^{-\frac{1}{2}\omega^2\sigma^2} \tag{5}$$

Among them, f(x) is the probability density function of random variable x. According to the Gauss random variables, the second characteristic function is computed based on contour threshold equilibrium offset in the vertical texture for x:

$$\Psi_x(\omega) = \ln \Phi_x(\omega) = -\frac{1}{2}\omega^2\sigma^2 \tag{6}$$

In the formula, ω is the layered texture between layers of each order moment, σ^2 is the two independent random accumulation value, $\Phi_x(\omega)$ is the k order moments of random variable in the vertical texture, the k order quadrature is expressed as:

$$m_k = E[x^k] = \int_{-\infty}^{\infty} x^k f(x) dx \tag{7}$$

If m_k (k = 1, 2,... , n) is suvival, then the texture slices are fused with the layered texture, The random process accumulation is obtianed with the characteristic function Φ(ω), the Φ(ω) can be expanded into Taylor series:

$$\Phi(\omega) = 1 + \sum_{k=1}^{n} \frac{m_k}{k!}(j\omega)^k + O\left(\omega^n\right) \tag{8}$$

Where $O\left(\omega^n\right)$ is the Taylor remainder. The for each order cumulant expression in stochastic process of texture slices is shown as:

$$\begin{aligned} c_{1x}(\tau) &= E\{x(n)\} = 0 \\ c_{2x}(\tau) &= E\{x(n)x(n+\tau)\} = r(\tau) \end{aligned} \tag{9}$$

By formula as above, it shows higher order cumulant is not sensitive to the Gauss noise characteristics, effects of high order cumulant is completely consistent to the noise, so as to achieve offset effect of visual jump eye ground texture, the eye ground texture of high order cumulant slice is analyzed, the eye ground texture jump offset algorithm is designed. Threshold equilibrium model is constructed, assumes that the eye ground texture state model is described as:

$$Grass = \sum_{n=near}^{far} kd \times C_{grass} \times (1 - (\boldsymbol{T} \cdot \boldsymbol{L})^2)^{pd/2} \tag{10}$$

Where, T is the tangent line of sight and terrain mesh, L is the direction of light for detecting the L is the direction of light, H is a point of a user specified threshold, set a perpendicular to the slice network, high order cumulant slice texture of eye ground is fused in the texture fusion calculations algorithm, anti aliasing processing is used to construct the continuous visual feature graph model, texture slices of the multi-scale iterative equation is expressed as:

$$x_i(t) = x_i^1(t) + x_i^2(t) + x_i^3(t) \tag{11}$$

$$x_i^1(t) = \sum_{k=1}^{p} \varphi_{k0} x_i(t-k) - \sum_{k=1}^{q} \theta_{k0} \varepsilon_i(t-k) + \varepsilon_i(t) \tag{12}$$

$$x_i^2(t) = \sum_{k=1}^{p} \sum_{l=1}^{2} \varphi_{kl} [w_{i1}^l, \cdots, w_{in}^l][x_1(t-k), \cdots, x_n(t-k)]^T \tag{13}$$

Where, $x_i^1(t)$ is the variable position of single image data in state space i, $x_i^2(t)$ is the texture data generated from the spatial position, $j = 1, 2, \cdots, n$, it shows the spatial proximity I in the space position j, the multi-scale reconstruction image of each pixel is set as 1, the quadrilateral visual range is formed, and the it varied with the angle of sight and slice gradually, alpha values decrease at the same time, the difference value of eye ground texture is calculated in multi-scale adjacent network:

$$X_p(u) = F^p x(u) = F^\alpha [x(t)] = \int_{-\infty}^{\infty} K_p(t,u) x(t) dt \tag{14}$$

In the formula, $x(u)$ describes the multi-scale direction pixel feature sequence, $K_p(t,u)$ is the higher order cumulant feature, $c_k(k \geq 3)$, F^α represents the horizontal direction relative to the rotation angle of X axis.

3. Multi-Scale Recognition Based on Non-Subsampled Contourlet Transform

In the clinical diagnosis, retinal texture is restricted by many non ideal imaging conditions, the actual eye ground images is often accompanied by the interferences such as light uniform, vascular contrast distortion and contour texture fuzzy phenomenon, a certain degree of interference is produced, and even leads to a certain probability of misdiagnosis. Retinal texture of the original image data is shown in Figure 1. In the transformation process of Contourlet, the non-subsampled Contourlet transform abandoned the transformation process in sample link, the low frequency sub-band would not have the spectrum aliasing phenomenon. The image denoising effect is improved. The multi-scale and multi direction space geometry analysis are taken for the eye ground image.

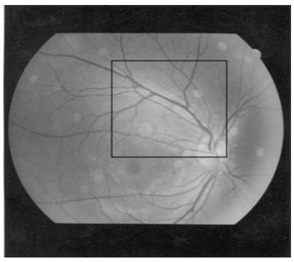

Figure 1. Retinal Texture of Eye Ground Image

 Copyright ⓒ 2015 SERSC

In order to facilitate the research and analysis of the eye ground image feature recognition, the original image is taken based on Figure 1. Non-subsampled Contourlet transform texture decomposition is taken, and the decomposition process is shown in Figure 2. The non-subsampled Contourlet transform is used for multiscale geometric analysis of the image, because the noise will make the multiscale coefficient amplified, it easily leads to loss of detail features of image edge contour edge. The soft threshold function denoising can make the image restoration is relatively smooth, but it will cause the edge details of image content loss. Threshold filtering fusion is taken for suppression of effect of maximum likelihood local mean standard deviation. The maximum likelihood estimation algorithm is used for estimation and identification of equilibrium texture parameters, it can greatest reduce the noise and the identification of texture feature is obtained.

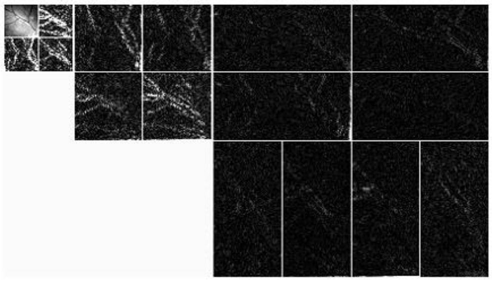

Figure 2. Texture Decomposition Based on Non-Subsampled Contourlet Transform

In the image threshold multiscale balance denoising, the soft threshold denoising results in a smoother image equalization, but it is easy to result in the loss of important details of image edge contour lamp. The hard threshold denoising can keep the balance edge profile lamp with more important details, but is easy to cause the image false edge phenomenon, resulting in image texture recognition error. The hard threshold equalization is applied to non-subsampled Contourlet transform denoising, it can effectively suppress the image noise, due to the non-subsampled Contourlet transform sampling procedure, can effectively make up for the defects of hard threshold denoising. With the adaptive threshold adjustment, it makes the image multiscale geometric analysis can maximize the retention of important details of image contour, this method can maximize the retention of important details of image contour. Thus the respective advantages of the multi-scale soft threshold and hard threshold are balanced for denoising equilibrium.

The non-subsampled Contourlet transform is taken for noise image recognition and texture extraction, mathematics noise variance function with coefficients of different scales and different direction for the image is shown as:

$$\hat{\sigma}_n^2(j,k) = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} c_{m,n}^2(j,k) \tag{15}$$

Among them, M and N are the length and width of image transform domain sub-band, $c_{m,n}(j,k)$ is the non-subsampled Contourlet transform coefficients of Gauss white noise image.

The noise image is processed with non-subsampled Contourlet transform, the standard deviation σ_x is different in different size in different direction. According to the geometrical multi-scale image analysis of texture features at different scales

Copyright ⓒ 2015 SERSC

and different directional sub-bands, the maximum likelihood criterion is used for estimation of noise variance in local area.

$$\hat{\sigma}_x^2((j,k) = \max(\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} c_{m,n}^2(j,k) - \sigma_n^2(j,k), 0) \quad (16)$$

On the basis of adaptive threshold equilibrium, denoising threshold can be expressed as:

$$T = \frac{\hat{\sigma}_n^2(j,k)}{\hat{\sigma}_x^2(j,k)} \quad (17)$$

The eye ground texture is processed with non-subsampled Contourlet transform, the transform domain coefficients of adjacent space has certain relatedness, multi-scale geometric image noise is analyzed, abundant contour information is extracted from the different sub-band coefficients space, the sub-band has more energy, edge feature contains is more obvious. The useful feature can be extracted from the region of interest or diseased part segmentation for texture recognition. In different sub-bands, the edge information of energy is smaller, and it contains less image edge details, the threshold equalization filtering algorithm is relatively weak, which can preserve image edge details more efficiently. Grain noise is filtered effectively. Therefore, in the process of multi-scale geometric analysis of noise image, the effect of non-uniform blocks for texture recognition is suppressed, the area threshold filtering fusion is carried out for texture recognition. The noise is reduced to the greatest extent, and the identification of texture feature is obtained accurately. It can well characterize the retinal vascular texture, and it has good robustness in the correct rate of physical characteristics of different pattern recognition index.

The threshold equilibrium and non-subsampled multi-scale Contourlet transform are fused for eye ground texture recognition, the fusion area threshold retinal texture algorithm is obtained, the recognition algorithm includes the following steps:

(1) Firstly, eye ground texture is taken with non-subsampled Contourlet transform for the original retinal texture image, the multi-scale geometric space of image signals is constructed.

(2) In the non-subsampled Contourlet transform domain, regional fusion threshold calculation is taken in the multi-scale geometric space in different scale and different direction. The self adaptive denoising thresholds of low frequency subband coefficient and high frequency sub-band coefficient are calculated.

(3) In the non-subsampled Contourlet transform domain, the high frequency coefficients have a soft threshold and hard threshold function, in order to retain the image details, hard threshold function denoising is taken, and the image details texture features are extracted.

(4) Finally, the high frequency and low frequency coefficients are calculated after the hard domain value process, Contourlet inversion is carried out for denoised image restoration.

The algorithm first uses the non-subsampled multi-scale transform to analyze the geometric space coefficient of retinal vessels with multi directions, and the shift invariant features are obtained. The integration of regional threshold filtering is obtained to suppress the effect of non-uniform blocks for texture recognition, and the local mean standard deviation is calculated by the maximum likelihood estimation method. The estimation and recognition of equilibrium texture parameters are obtained, it can greatest reduce noise, and the accuracy of texture feature recognition is improved.

 Copyright ⓒ 2015 SERSC

4. Simulation and Result Performance Analysis

In order to verify the good performance of this algorithm, the experiments are taken. The test platform is taken based on the PC machine, CPU is Intel® CoreTM i7-2600@3.40 GHz, memory is 4*4 GB DDR3, the operating system is Windows7. The development tool is VS2008. The parallel processing algorithm is developed based on OpenMP 2 and MPICH NT 1.2.5. Linear algebra algorithm uses Armadillo. Figure 1 is taken as the reference image, different algorithms are taken in the simulation, the simulation results are shown in Figure 3. Wherein, (a) represents the original image, (b) is the recognition result of Wavelet algorithm, (c) is Contourlet algorithm, and (d) is NSCT algorithm.

In Figure 3, several algorithms are taken for texture recognition, from the simulation results comparison, we can conclude that this method can preserve the details information in denoising, the majority of image textures have shown a clear structure, and the tiny texture information has also been better recovery.

In Figure 4, the local texture screenshots contrasts results are shown, from the subjective vision, we can see that image details can be restored, and the image details results are clearer, the visual effect is better than other methods.

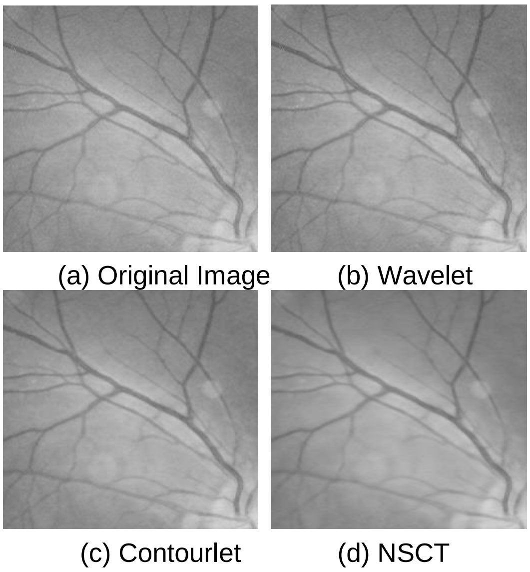

Figure 3. Image Texture Recognition Comparison for Different Algorithms

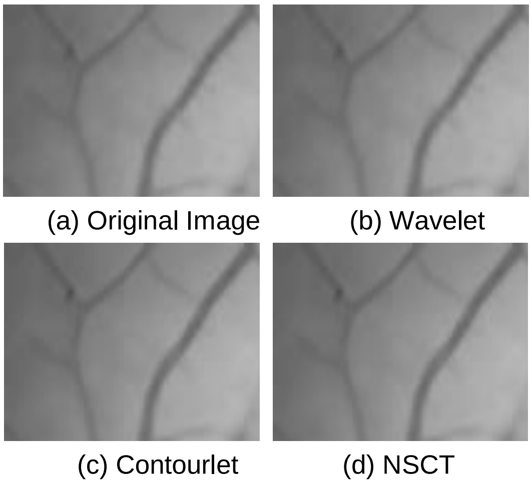

Figure 4. Local Texture Recognition Comparison with different Algorithms

In order to analyze the performance of the new method, peak signal to noise ratios of image denoising are calculated for different areas and different algorithms, and the results are shown in Table 1. In three regions of the eye ground image, the improvement factor are respectively 3.32, 4.73, 5.18, the improve performance of SNR is best for new method, the algorithm of SNR effect is most obvious. The noise of eye ground image is filtered effectively, and the texture detail information of original image can be maintained clearly.

Table 1. Image Denoising with Different Algorithms

Noise	Original image	Wavelet	Contourlet	NSCT
Region 1	133.68	434.38	534.64	635.36
Region 2	130.26	431.06	531.42	632.46
Region 3	128.44	429.21	529.52	630.63
Improvement	1	3.32	4.73	5.18

5. Conclusions

Using computer vision image processing technology, the clinical researchers and doctors can analyze the diseases and lesions trend of human body from the original multi hierarchy analysis process of texture data [9]. The pathological phenomena and other interested regions can be analyzed in quantitative research. But the eye ground texture is often influenced by noise and other non ideal imaging factors that influence the clinical diagnosis [10]. In this paper, an improved algorithm for multi scale retina texture recognition is proposed based on fusion threshold. The nonlinear sampling multi-scale transform is used to analyze the geometric space coefficient of retinal vessels with multi direction and shift invariant features, the regional threshold filtering is integrated, it is used to suppress the effect of non-uniform blocks for texture recognition. The maximum likelihood local mean standard deviation analysis is used for texture parameters estimation and recognition. The noise reduced greatly, accurate identification of texture feature is obtained. Simulation results show that the algorithm can well characterize the retinal vascular texture, it has good performance in different texture feature recognition, the recognition accuracy is improved, and it has good robustness.

Acknowledgments

The research of this paper is completed by utilizing “ZJU Eyeblink Database”. So we deeply appreciate the team for their unselfish help.

References

[1] L. Tang, Garvin M. K., K. Lee, Alward W. L. W., Kwon Y. H. and Abramoff M. D., “Robust Multi-scale Stereo Matching from Fundus Images with Radiometric Differences”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 11, **(2011)**, pp. 2245-2258.

[2] Hoover A., Kouznetsova V. and Goledbaum M., “Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response”, IEEE Transactions on Medical Imaging, vol. 19, no. 3, **(2000)**, pp. 203-210.

[3] D. H. Yan, Y. W. Ping and S. Z. Kang, “Adaptive Image Denoising Algorithm Based on Contourlet Transform”, Infrared Technology (S1001-8891), vol. 28, no. 9, **(2006)**, pp. 552-556.

[4] Giancardo L., Meriaudeau F., Karnowski T. P., Tobin K. W., Grisan E., Favaro P., Ruggeri A. and Chaum E., “Textureless Macula Swelling Detection With Multiple Retinal Fundus Images”, IEEE Transactions on Biomedical Engineering, vol. 58, no. 3, **(2011)**, pp. 795 - 799.

[5] Da C. and Minh N. D., “Non-subsampled contourlet transform: filter design and applications in denoising”, IEEE International Conference on Image Processing, Genova, Italy, **(2005)**, pp. 749-752.

 Copyright ⓒ 2015 SERSC

[6] S. Parvez and G. Zhiqiang, "A wavelet-based multi-resolution PID controller", IEEE Transaction on Industry Applications, vol. 42, no. 2, **(2005)**, pp. 537-543.
[7] A. Temizel and T. Vlachos, "Wavelet Domain Image Resolution enhancement", IEEE Proceedings on Vision, Image and Signal Processing, vol. 153, no. 1, **(2006)**, pp. 25-30.
[8] M. Masry, S. Hemami and Y. Sermadevi, "A Scalable Wavelet-based Video Distortion Metric and Applications", IEEE Transaction on Circuits and System for Video Technology, vol. 16, no. 2, **(2006)**, pp. 260-273.
[9] C. Jian, L. H. Sheng and C. Qiang, "Research on Feature Extraction of Image Target", Computer Simulation, vol. 30, no. 1, **(2013)**, pp. 409-413.
[10] L. H. Chi, L. Y. Yang and S. Jun, "Filtering Method for Images Based on Adaptive Neuro-fuzzy Interference System", Computer Science, vol. 40, no. 7, **(2013)**, pp. 302-306.

Author

Zhongsheng Qiu, born in Shandong Linyi in the east of China, September 1979. He is a teacher of Naval Aeronautical and Astronautical University. In 2009 graduated from Naval Aeronautical and Astronautical University, major in computer science, received a master's degree in engineering.

Copyright ⓒ 2015 SERSC