Vein Texture Extraction using the Multiscale Second-Order Differential Model

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Abstract

In order to analyze the back of hand vein pattern rapidly and effectively, a novel approach based on multi-scale second-order differential model is proposed to extract the vein texture from vein samples directly, which is made up of two section: one is the foundation of local second-order differential model of vein texture (VLSDM), the other is texture extraction based on the multi-scale VLSDM. This paper analyzes the vein extraction using the multi-scale VLSDM and handles the filter response using the method of multi-scale analyzed noise filtered. This new algorithm has achieved good results for the vein texture, which is fuzzy, uneven distributed and cross-adhesion. Additionally this method keeps the original form of local shape and achieves orientation and scale information of the vein texture. The experiment result getting from this new method has also compared with another method and shown its outstanding performance.

Keywords*: back of hand vein pattern, vein pattern texture, multi-scale VLSDM, filter response*

1. Introduction

Biological characteristics which are used for authentication and identification can be divided into two categories: physiological characteristic and the behavior characteristic. After years of development, physiological characteristic and the behavior characteristic respectively contain specific types become more and more abundant. For the physiological characteristic, such as fingerprint, face, vein [1-3]; for the behavior characteristic, such as gait, handwritten signature [4, 5].

This paper mainly has researched on the back of hand vein pattern as the object and key technology of extraction of vein texture. At present, there are two main kinds of methods of the extraction of vein texture: 1. the statistical properties method based on pixel gray value distribution of the vein texture [6]; 2. the point tracking method of minimum gray value based on vein texture cross section [7, 8]. The above two methods have a common defect: they can only obtained the region information of vein texture, but they lost the local curved surface distribution morphological information and scale information of vein texture. This paper put forward a new method which has used the second-order differential structure characteristic of the vein texture.

The method proposed by this paper has complied like this: firstly, according to the difference of constraint index value of local curved surface shape. Combining the sampling theorem and weighted fusion method to obtain a calculation model of constraint index value of fusion shape (SICM); secondly, selecting curved surface of maximum main curvature as significant second-order differential structure characteristics of vein texture in VLSDM; finally, adopting improved combination based on maximum likelihood estimation model to fuse SICM and significant second-order differential structure characteristics. From the above three steps, the VLSDM has been formatted. Then according to this model, the paper has apposed a method of vein texture based on multi-scale.

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2. Foundation of Multiscale VLSDM

2.1. Foundation of SICM

Firstly, sampling the Shape Index value by using sampling function- Shannon, forming similarity formula between curved surface of pixel neighborhood and curved surface shape index value of sampling target texture; secondly, adopting the method of weighted fusion, similarity fusion between cross vein texture and dark-ridged vein texture can form the final constraint model of vein shape. Mathematical formula of similarity calculation is expressed as below.

$$\text{shapeness} = \begin{cases} 0 & , \ \text{SapeIndex} \le 0 \\ \dfrac{\sin(\alpha(\text{SapeIndex} - \text{shape}_D))}{\alpha(\text{SapeIndex} - \text{shape}_D)} & , \ \text{SapeIndex} > 0 \end{cases}$$

Where ShapeIndex is shape index value, Shape_D is ideal shape index of sampling texture shape, α is attenuation coefficient of Shannon function, Shapeness is shape similarity of curved surface of pixel neighborhood and Shape_D. The reason for Shapeness>0 is the two type textures, cross vein texture and dark-ridged vein texture whose ideal SapeIndex are 0.5 and 1, both of them are more than 0.

Attenuation coefficient α of the Shannon function has relations with ideal value Shape_D of neighborhood interval length. Calculation rules is to ensure the Shapeness corresponding to the neighborhood SapeIndex in [0.9,1]. α is estimated from equation below.

$$\sin(\alpha \times r)/(\alpha \times r) = 0.9$$

Where r is radius of the neighborhood range. α is approximately 4 in vein texture regions, α is approximately 10 in cross vein texture regions.Mathematical formula of weighted fusion is expressed as below.

$$\text{vein\_shape} = \beta \times \text{ridge} + (1 - \beta) \times \text{concavity}$$

Where vein_shape is the final shape constraint value, ridge is sampling value of dark-ridge area in vein samples, concavity is sampling value of concave shape area in vein samples, β is combination coefficients. Figure 1 is the vein_shape response images with differential scale being 3 and various values of the parameter β .

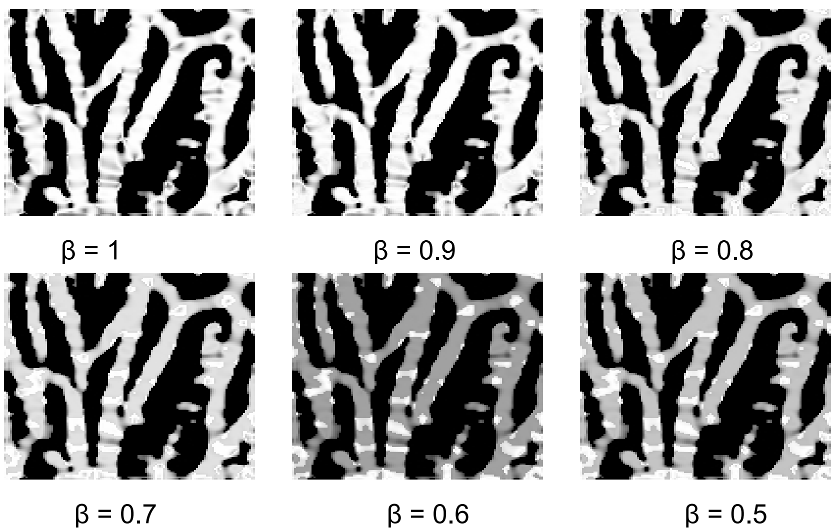


Figure 1. The vein_shape Greyscale Response with Various Values of the Parameter β

Figure 1 illustrates that with the β growing, the small dark spot area of vein_shape greyscale response become less. When β is 0.8, the effect is best, at the same time, the number of the dark spot area is very small and shape constraint values are consistent. When β <0.8, it has led the dark spots area become bright spots area and affect the model effect. In this paper β is selected as 0.8.

2.2. Multiscale VLSDM

In this paper, model of maximum likelihood estimation has improved from the method introduced in literature [9]. VLSDM is adopting improved combination based on maximum likelihood estimation model to fuse SICM and significant second-order differential structure characteristics. The improved combination of the model of maximum likelihood estimation mathematical formula is expressed as below.

$$\text{vein\_ness} = (1-\exp(-\frac{\text{vein\_shape}^2}{\sigma_1}))(1-\exp(-\frac{\text{vein\_feature}^2}{\sigma_2}))$$

$$\sigma_1 = \frac{{T_{shape}}^2}{\text{mln}^{10}}$$

$$\sigma_2 = \frac{\lambda_{max}^2}{\text{mln}10}$$

Where, vein_feature is structure characteristics. If vein_feature<0, let the vein_feature be equal to 0. α_1 is sensitive parameter of shape constraint model, α_2 is sensitive parameter of vein_feature, m is the value of the shape constraint term, iThe value of threshold T_{sape}, is equal to 0.5, λ_{max} is maximum value of vein_feature in the samples of vein region.

This paper has referred the concept of blood vessels degree [9]. The response of VLSDM is called venous degree. In order to ensure the maximum main curvature can make a good description of vein texture the shapes, the paper has put forward a new method that conducts further improvement for the improved combination based on maximum likelihood estimation model, calculation formula of the further improved venous degree is expressed as below.

$$\text{vein\_ness}' = \sqrt{\sigma_2 \times \ln(\frac{1}{1-\text{vein\_ness}})}$$

Where $\text{vein\_ness}'$ is the further improved venous degree.

3. Texture Extraction based on Multiscale VLSDM

The information in the near-infrared back of hand vein patterns can be roughly divided into the following categories: thick vein texture, thin veins texture, noise texture in the background, cross vein texture and noise texture at the edge of vein. This section has discussed the noise filtering method of the above various kinds of vein information, it is based on the multi-scale VLSDM and according to the performance of the above vein information in different differential scales.

3.1. Differential Scales Effect of the Response of VLSDM

In Figure 2, the number of each picture is differential scale, in the paper, s is presented as differential scale. It can be analyzed from Figure 2 that the thick vein texture is not sensitive to the s which is narrowed than its width, so the s which is narrowed than its width could be selected; thin veins texture is sensitive to s, too big may lead to the shape of vein texture irregular, too small may lead to the vein texture crack; noise texture in the background may disappear with the s becoming bigger; noise texture at the edge of vein generally appears the response of s which is similar to the thin veins texture, with the s becoming lager, this kind of noise may becoming less and less. For the cross vein texture, two kinds of situations may appear: one is this kind of vein may disappear and this situation mainly appears in the area which is crossed with thin veins texture; the other is adhesion of cross vein texture, this situation mainly appears in the area which is crossed with thick vein texture, this can be seen from Figure 2(d) and Figure 2(e), Figure 2(f), Figure 2(g) and Figure 2(h).

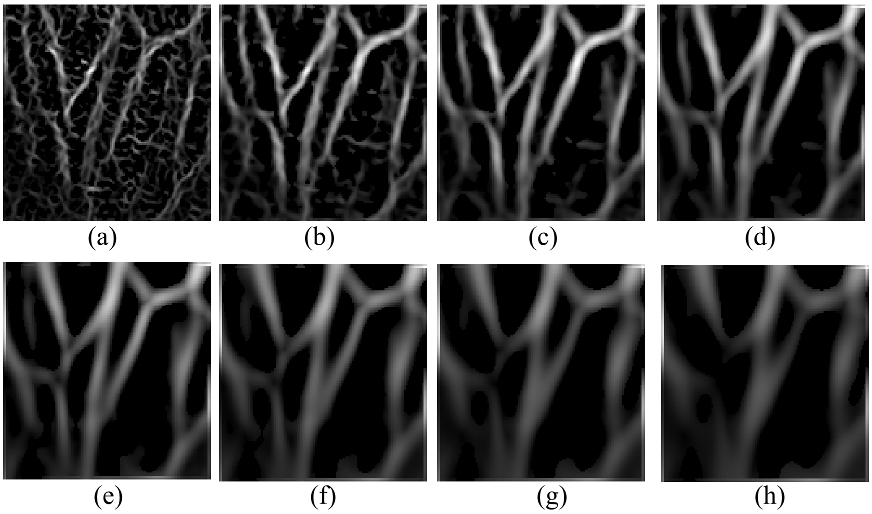


Figure 2. The Grayscale Response of the Improved Combination with Different Differential Scales: (a) s=1; (b) s=2; (c) s=3; (d) s=4; (e) s=5; (f) s=6; (g) s=7; (h) s=8

The vein pattern is processed by VLSDM, s can reach its maximum value when it gradually becomes bigger. Selecting the maximum as the final venous degree through comparing the venous degree from Pixel points of different s. Mathematical expression of multiscale VLSDM is expressed as below.

$$\mathrm{vein}(i,j) = \max_{s_{min} \le s \le s_{max}} \mathrm{vein\_ness}(s,i,j)$$

Where vein(i, j) is venous degree obtained through multiscale VLSDM in the pixel (i,j). The value of scale can be determine by equation as below.

$$s = (n/2 - 1) \times 0.3 + 0.8$$

Where n is the width of filter window, s is the value of scale.

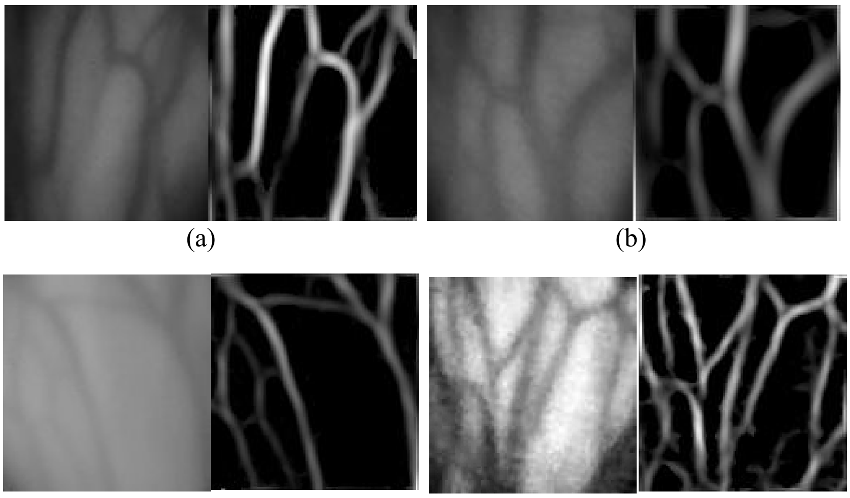
3.2. Noise Filtering Method based on Multi-scale Analysis

The key for filtering of multiscale VLSDM response is distinguishing thin vein region from noise region. According to s which is corresponded to maximum venous degree in the differential scale-space, noise vein region and thin vein region can be divided into many different connected regions. Venous degree is generally small in noise connected region, while it is big in noise connected region and small in boundary region, much smaller especially in the region which is crossed with other vein texture. The response values of multiscale VLSDM, which are corresponded to some pixel point in thin vein connected region and noise connected region, are equal. But the differences of the maximum response values of multi-scale VLSDM between the two connected regions are big. A threshold can keep them apart. Noise vein connected region can be filtered out. The threshold of maximum gray value of multi-scale VLSDM response has relations with the gray value corresponded to extreme value of histogram. For convenience of description, T_{max} represents the threshold of maximum gray value of multi-scale VLSDM response and $G_{k\text{-}max}$ represents gray value of multiscale VLSDM response, the value is corresponded to maximum point of Histogram. Through analyzing the back of hand vein patterns, after 256 gray-scaled normalizing the response of multiscale

VLSDM, the response gray values of dark noise connected region are mainly near to $G_{k\text{-}max}$, the response gray values of Light noise connected region are generally bigger than $G_{k\text{-}max}$ two to three times. The response gray values of thin connected region are generally bigger than $G_{k\text{-}max}$ six to eight times. In order to ensure the noise be filtered off and have no effect on the thin vein texture. In this paper T_{max} is equal to 4 times of $G_{k\text{-}max}$.

4. Expreiment Analysis

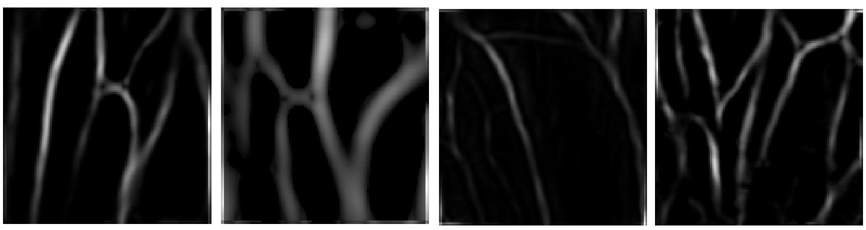
In order to examine the effectiveness of the vein texture method approved in this paper. In his section, respectively extracting vein texture of different types patterns. Figure 3 are gray patterns of different types patterns response after handling multi-scale VLSDM.



(a) (b) (c) (d)

Figure 3. The Texture Images of the Multiscale VLSDM by Extracting Different Types of Vein Samples: (a) uneven thickness of the pattern; (b) thick vein pattern; (c) fuzzy vein pattern; (d) noise vein pattern

In Figure 3(a), the VLSDM response values of thick vein texture region are bigger than venous degree of thin vein texture region, as a result, it is leading to the pixel gray values of thick vein texture region in response gray pattern are bigger the values of thin vein texture region. In Figure 3(b), the vein texture pattern is much thicker, it also can be seen that the width value of the response of VLSDM in thick vein region is much bigger. In Figure 3(c), the vein texture pattern is fuzzy. The local contrast is low, but the second-order differential pattern can also test the variation of the local pixel gray value. In Figure 3(d), it is the result of the vein texture pattern with noise, the method which is proposed by the paper can still extract the structure of the vein texture, it can be seen that multi-scale VLSDM have strong ability of resistance to noise. It is convenient for response of the multi-scale VLSDM to filter off noise using the method proposed in the paper.



(a) (b) (c) (d)

Figure 4. The texture images of the vascular degree model by extracting different types of vein samples :(a) uneven thickness of the pattern; (b) thick vein pattern; (c) fuzzy vein pattern; (d) noise vein pattern

In order to compare the effect of vein texture between multi-scale VLSDM and vascular model proposed by literature [9, 10]. Figure 4 is the pattern of vein texture extracted by using the vascular model. The four patterns are corresponded to the pattern in Figure 3.

Comparing the pattern in Figure 3 with the corresponded pattern in Figure 4, it can be seen that the effect of the model proposed in the paper is better than vascular model, especially for the thin vein pattern and cross vein pattern. Vascular model has adopted structure degree as characteristic quantity to describe the curved surface information of vein texture, in this paper, it has adopted the maximum main curvature to describe the curved surface information of vein texture. It can be seen from comparison that for the description ability of curved surface information, maximum main curvature do much better than structure degree. What's more, adopting the improved combination based on maximum likelihood estimation model can make further contribution to enhance the vein texture; the reason why the cross vein texture clearer, less breakage in Figure 3 than in Figure 4 is that the method proposed in the paper take the cross vein textures form factor into consideration when the shape control model is built, but the vascular model has ignored it. So the VLSDM is more suitable to extract the vein texture.

5. Conclusion

According to intrinsic multi-scale characteristics, a method to extract the vein texture is proposed. The method based on VLSDM can not only distinguish the vein texture from background area, but also keeps the vein texture original form of the local curved surface. At the same time, it can get the direction and scale information of vein texture. In addition, according to the character that the scales correspond to maximum venous degree and response value are small in differential scale space which is correspond to noise region.

References

[1] D Maltoni, D Maio, A Jain, S Prabhakar. Handbook of fingerprint recognition. New York: Springer-Verlag Inc. 2009.

[2] Stan Z Li, Anil K Jain. Handbook of face recognition. New York: Springer-Verlag Inc. 2011.

[3] Ding yuhang. Research of back of hand vein recognition. PhD Thesis. Harbin: Harbin Engineering Univerisity. 2006.

[4] Wang kejun, Hou benbo. Survey of gait recognition. *China Journal of Image and Graphics*. 2007; 12(7): 1152-1160.

[5] P Deng, H Liao, C Ho, H Tyan. Wavelet-based off-line handwritten signature verification, *Computer Vision and Image Understanding*. 1999; 76(3): 173-190.

[6] N Miura, A Nagasaka, T Miyatake. Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification. *Machine Vision and Applications*. 2004; 15(4): 194-203.

[7] Liu Q. An Adaptive Blind Watermarking Algorithm for Color Image. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(1): 302-309.

[8] Y Ding, D Zhuang, K Wang. A *study of hand vein recognition method*. IEEE International Conference on Mechatronics and Automation. Luoyan. 2006; 4: 2106-2110.

[9] A Frangi, W Niessen, K Vincken, M Viergever. *Multiscale vessel enhancement filtering*, Medical Image Computing and Computer-Assisted Interventation. 1998: 130-137.

[10] Deng Y, Zhou Q, Fang W. Research on Train Visualization of Different Resolution in TCS Simulation. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(1): 383-391.