Band Selection for Palmprint Recognition

Junwen Sun [1, 2], Waleed Abdulla [2], Weiming Wang[1 3], Qiong Wang [1, 3], and Hai Zhang [4]
[1]Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China
[2] University of Auckland, Auckland, New Zealand
[3] Department of Computer Science and Engineering, the Chinese University of Hong Kong, Hong Kong, China
[4] Department of Ultrasonography, Shenzhen People's Hospital, The Second Affiliated Hospital of Jinan University, Shenzhen, China
Email: {junwen.sun, w.abdulla}@auckland.ac.nz, {wm.wang, wangqiong}@siat.ac.cn, szzhhans@gmail.com

Abstract—**Biometrics based on palmprint has been developing fast in the past ten years. The newly proposed hyperspectral imaging can provide high accuracy and abundant information about the palms and the tissues, veins underneath. However, due to the limitations of computation speed and storage, we have to select the most representative bands for palmprint recognition. This paper proposes a band selection scheme for hyperspectral palmprint recognition. First, the images with high image entropies and Equal Error Rate (EER) are selected. Then a clustering method is introduced to choose the most representable bands. In our experiments on the HK-PolyU Hyperspectral Palmprint Database, three bands combination can generate the best EER 0.17325%. The proposed approach can also be used for band selection of other hyperspectral systems.**

Index Terms—**hyperspectral palmprint database, k-means, Gabor Filter**

I. Introduction

Palmprint recognition has been developing rapidly in the past ten years, not only due to the development of recognition algorithms, but also the help of cutting edge capturing devices. With depth camera and multispectral/hyperspectral camera being used in palmprint recognition technology, biometrics based on palm vein [1] [2], 2D and 3D palm print [3] [4], multispectral palmprint [5] [6], and hyperspectral palmprint [7][8] are made possible.

The human palm has abundant information both on the surface and underneath the skin. On the skin, the main lines, wrinkles and small creases are unique for each person. Underneath the skin, the pattern of the veins are special as well.

Combining different wavelength palmprint images can provide more distinctive information about the palm, and thus improve the performance of the palmprint recognition system. Ying Hao [5] used pixel-level fusion of multispectral images for the multispectral palmprint recognition and achieved best Equal Error Rate (EER) with two bands combination using Curvelet transform and shift-invariant digital wavelet transform. Dong Han [6] combined four bandwidth images, *i.e.* Red, Green, Blue and Infrared using wavelet transform to improve the performance. Since the hyperspectral imaging system is introduced to palmprint recognition, the amount of information can be more than enough. Zhenhua Guo [7] established a hyperspectral palmprint imaging system and used it to analyze the band selection for multispectral palmprint systems based on (2D) 2PCA method [9]. His team also implemented exhaustive search for the optimal combination [8].

As we can get information more easily and more accurately, the problem of information redundancy emerges, especially in hyperspectral imaging. In hyperspectral palmprint recognition systems, it's not convenient to use exhaustive search [8] for the optimal band selection and combination. Some researchers proposed information based band selection methods [10][11] as well.

In order to keep all the useful information about the palmprint and reduce the number of bands as many as possible, a selection of bands should be made prior to the palmprint recognition. In this paper, a band selection scheme for hyperspectral palmprint recognition is proposed. The scheme can be adjusted for other hyperspectral systems as well. First, the images captured in different wavelength illuminations are evaluated via image entropy and Equal Error Rate (EER). In the procedure, some bands containing low quality images are deleted. After that, the k-means clustering method is introduced to choose the most representable bands. In the end, a Gabor Filter based score level fusion method is proposed.

II. Band Pre-selection Based on Image Entropy and Equal Error Rate

A. The Hyperspectral Palmprint Database

The hyperspectral palmprint images consist of nearly a hundred equally spaced spectral images, thus provide much more information than regular multispectral images. However, apart from information about palm prints, redundant information and even noise due to different positions of the palms are introduced to the hyperspectral palmprint images as well.

The HK-PolyU Hyperspectral Palmprint Database captured from 380 palms at 69 spectral bands with a step-width of 10nm over spectrum 420nm-1100nm is used for experiments [7]. The Region of Interest (ROI) is cropped

Manuscript received December 1, 2015; revised April 11, 2016.

doi: 10.12720/jait.7.4.287-290

from the original 1004*1002 pixels CCD images to 128*128 pixels using the algorithm proposed in [12]. However, due to the low transmission of Liquid Crystal Tunable Filter (LCTF) and low CCD response at long wavelength, the image quality is not consistent over the whole spectrum.

B. Spectral Band Image Entropy Method

Due to the device limitations mentioned above, the image quality varies in different spectrum. For low quality images, little information is involved and they can be discarded without affecting the recognition results.

Entropy is a measurement of the information that a grey-scale image carries by analyzing the distribution of the values of the pixels. It can also measure the distribution of the grey scales. It's defined as follows:

$$E = -\sum_k p_k * \log_2 p_k \qquad (1)$$

where

$$p_k = \frac{1}{m*n}\sum_{i,j}\{1|I_{i,j} = k\} \qquad (2)$$

$I_{i,j}$ is the pixel value in the 8-bit grey scale palmprint image, and m, n are the sizes of the image.

Fig. 1 shows the image entropy of each band with different wavelengths. The average entropy of the band images for 380 people are above 6 at the interval of 580nm-1030nm. While for the images captured in wavelength lower than 580nm or higher than 1030 nm, the images are unclear and only occupy a few grey scales due to the device limitations.

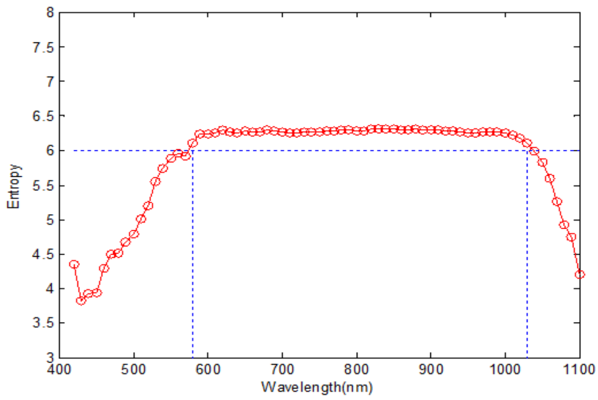

Figure 1. Image entropy vs. wavelength

C. EER for Each Spectral Band

Gabor Filter is a state-of-the-art palmprint recognition method [13]. A typical 2D Gabor Filter is defined as:

$$G(x, y, \theta, u, \sigma) = \frac{1}{2\pi\sigma^2} exp\left\{-\frac{x^2 + y^2}{2\sigma^2}\right\} * exp\{2\pi i(ux\cos\theta + uy\sin\theta)\} \qquad (3)$$

where $i = \sqrt{-1}$, x, y is the position of the filter, u is the frequency of the sinusoidal wave, θ is the orientation of the function and σ is the standard deviation of the Gaussian envelope.

The 2D Gabor Filter is applied to the palmprint images with six different orientations: $0, {}^{\pi}/_{6}, {}^{\pi}/_{3}, {}^{\pi}/_{2}, {}^{2\pi}/_{3}, {}^{5\pi}/_{6}$. Each pixel within the image will be represented with orientations, which are then coded into 3-bit. 2-D Gabor Filter can extract the comparatively stable orientation information of the palm vein image. An example of the original palmprint and Gabor Filter processed palmprint image is shown in Fig. 2. The different orientations at each pixel are represented with different colors.

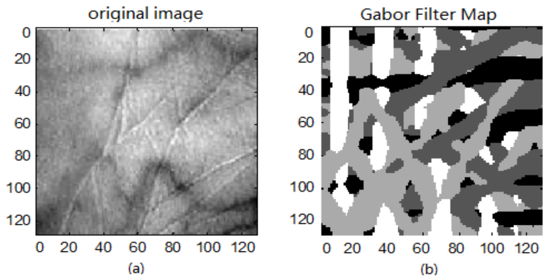

Figure 2. Original image and the gabor filter map

EER is stated as a percentage and represents the point at which the false rejection rate equals to the false acceptance rate. This value indicates that the proportion of false acceptances is equal to the proportion of false rejections. The lower the equal error rate value is, the higher the accuracy of the biometric system will be. The EER computed using the Gabor Filter method can be seen in Fig. 3.

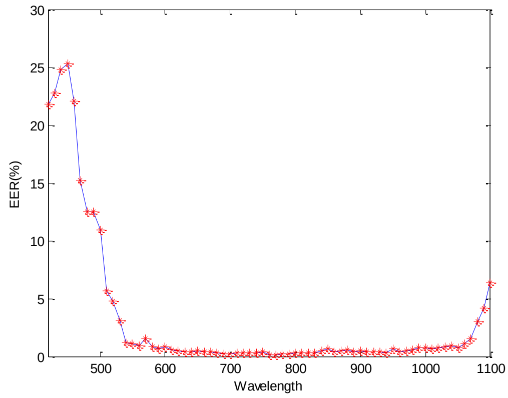

Figure 3. EER vs wavelength

The images of a single wavelength in the wavelength interval 580nm to 1080nm can contain enough information to obtain a satisfactory EER using Gabor Filter. However, for the images in the wavelength in other intervals, the EER can go up to 26% and thus introduce lots of noises or inaccuracy to the recognition system.

According to the image entropy and EER measure, it's clear that a number of bands in the middle should be selected for subsequent process. In order to select the images containing enough information and discard low quality images, the wavelength interval 580nm to 1020nm are selected for further analysis.

III. Spectral Band Selection Based on K-Means Clustering

A. EER for Each Spectral Band

The palmprint images do not only carry information about the palmprint and palm vein, but also contain the reflection of the flash, stains on the surface and noises introduced by the capturing device. Due to different positions of the hands, the ROI images are not exactly the same, but with small rotation or offset. The Gabor filter is useful to preserve the main features of palmprint images, *i.e.* the main orientation in each pixel.

B. Band Selection Based on Clustering

The K-means clustering method is an unsupervised learning algorithm that can be used to reveal the relationships within the spectral bands.

The k-means method classifies a given dataset through a certain number of clusters (for example k clusters). The main idea is to define k centroids, one for each cluster. These centroids are first randomly selected from the spectral bands. The next step is to take each point belonging to a given cluster and associate it to the nearest centroid. The Hamming Distance is used instead of the commonly used Euclidean distance. Because the images are represented with orientations at each pixel, *i.e.* Gabor Filter values. Then the k new centroids are calculated as the center of each cluster. As a result of this procedure the k centroids change their locations step by step until the change is significantly small. Then the spectral bands are divided into k groups.

IV. Experiments and Results

The wavelength interval 580nm to 1020nm from the Hyperspectral Palmprint Database is selected according to the image entropy and EER measure described in Section 2.

In order to evaluate the performance of the clustering method, the sum of Hamming distance between the points within the cluster and the cluster centroid is adopted. The sum is defined as

$$S = \sum_{j=1}^{k} \sum_{i=1}^{n} d\left(x_i^{(j)}, c_j\right) \tag{4}$$

where $d\left(x_i^{(j)}, c_j\right)$ is the Hamming Distance between the point $x_i^{(j)}$ and the cluster center c_j. (j) indicates that the ith data point $x_i^{(j)}$ that belongs to jth cluster.

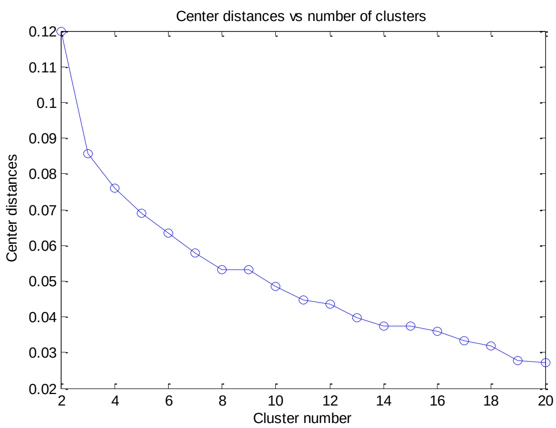

Figure 4. Cluster distances vs cluster number.

The sum decreases as the number of clusters increases as shown in Fig. 4. In other words, the more samples selected, the better we approximate the images over the spectrum.

An example of band selection with cluster number k=4 is shown in Fig. 5. The wavelength interval from 580nm to 1020nm, which consists of 45 spectral bands, is divided into 4 clusters with centroids 600, 770,850 and 1000. These centroids will be selected as the representative bands for the whole spectral bands in the palmprint recognition system.

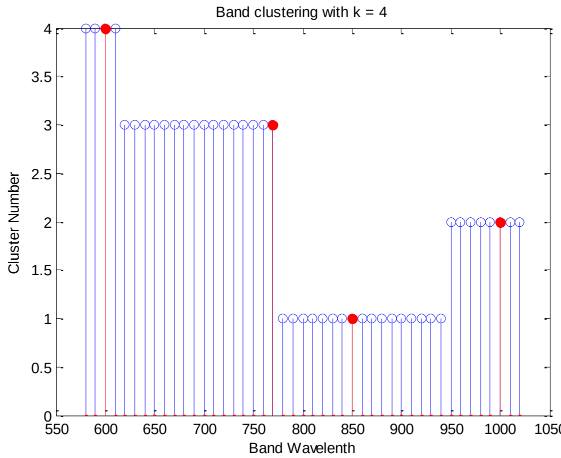

Figure 5. Clustering based band selection with k=4

In order to evaluate the performance of the selected bands, the score level fusion is used. A score level fusion based on Gabor Filter image is employed to evaluate the performance of the band selection and cluster fusion.

$$\mathrm{TS} = \frac{1}{k} \sum_{i=1}^{k} CS_i \tag{5}$$

where CS_i is the Hamming distance for the ith selected spectral band.

The EER of the palmprint recognition system is evaluated based on the fusion score TS for different number of band selection.

The best combination according to Table I is three bands combination with EER 0.17325%. While combining more bands, not only the information adds up, but the noises will be introduced as well. The EER for 4 bands selection even drops 0.00657% compared with 3 bands selection.

TABLE I. Bands Selection

Number of Bands	Optimal Selection	EER
2	600, 1000	0.22149%
3	600,770,1000	0.17325%
4	600,770,850,1000	0.17982%

V. Conclusion

In this paper, a band selection scheme for hyperspectral palmprint recognition is proposed. By using image entropy and EER measure, low quality bands are deleted directly. A clustering method is further used to select the optimal band combination and the clustering method is validated by the band fusion method in the end.

Moreover, the biometrics system should not only have high recognition rate, but also be robust against spoof attacks. The hyperspectral images can provide abundant information to identify a real human hand, not just a printed palmprint paper or a rubber hand. In the future research, spoof attacks will be considered as well in the design of a hyperspectral palmprint recognition system.

ACKNOWLEDGMENT

The work described in this paper was partially supported by a grant from Ministry of Science and Technology of the People's Republic of China under the Singapore-China 9th Joint Research Programme (Project No. 2013DFG12900), a grant from the Natural Science Foundation of Guangdong Province (Project No. 2014A030310381), and grants from the National Natural Science Foundation of China (Project No. 61233012 and 61305097).

We would like to acknowledge the Hyperspectral Palmprint Database developed by the Biometric Research Centre (UGC/CRC) at the Hong Kong Polytechnic University. We also want to thank Chinese Scholarship Committee for the financial support for Mr. Sun's PhD study in University of Auckland as well.

REFERENCES

[1] F. A. I. Sarkar, T. Kim, and D. Bhattacharyya, "Palm vein authentication system: A review," *Int. J. Control Autom.*, vol. 3, no. 1, 2010.

[2] L. Chih-Lung and F. Kuo-Chin, "Biometric verification using thermal images of palm-dorsa vein patterns," *Circuits Syst. Video Technol. IEEE Trans.*, vol. 14, no. 2, pp. 199–213, 2004.

[3] V. Kanhangad, A. Kumar, and D. Zhang, "Combining 2D and 3D hand geometry features for biometric verification," in *Proc IEEE Computer Society Conference on*. *Computer Vision and Pattern Recognition Workshops,* 2009, pp. 39–44.

[4] L. Z. W Li, D. Zhang, G. M. Lu, and J. Q. Yan, "Efficient joint 2D and 3D palmprint matching with alignment refinement," in *Proc. CVPR 2010*, 2010.

[5] H. Ying, S. Zhenan, T. Tieniu, and R. Chao, "Multispectral palm image fusion for accurate contact-free palmprint recognition," in *Proc*. *15th IEEE International Conference on Image Processing,* 2008, pp. 281–284.

[6] D. Han, Z. Guo, D. Zhang, H. Dong, G. Zhenhua, and D. Zhang, "Multispectral palmprint recognition using wavelet-based image fusion," in *Proc*. *9th International Conference on Signal Processing,* 2008, pp. 2074–2077.

[7] Z. Z. Guo, D. Zhang, L. Zhang, and D. Zhang, "Feature band selection for multispectral palmprint recognition," in *Proc. Pattern Recognition,* 2010, pp. 1136–1139.

[8] Z. Guo, D. Zhang, L. Zhang, and W. Liu, "Feature band selection for online multispectral palmprint recognition," *IEEE Trans. Inf. Forensics Secur.*, vol. 7, no. 3, pp. 1094–1099, June 2012.

[9] W. Zuo, D. Zhang, and K. Wang, "Bidirectional PCA with assembled matrix distance metric for image recognition," *IEEE Trans. Syst. Man. Cybern. B. Cybern.*, vol. 36, no. 4, pp. 863–872, Aug. 2006.

[10] A. Koschan, B. Abidi, and M. Abidi, "Improving face recognition via narrowband spectral range selection using Jeffrey divergence," *IEEE Trans. Inf. Forensics Secur.*, vol. 4, no. 1, pp. 111–122, Mar. 2009.

[11] E. Sarhrouni, A. Hammouch, and D. Aboutajdine, "Band selection and classification of hyperspectral images using Mutual Information: An algorithm based on minimizing the error probability using the inequality of Fano," in *Proc*. *2012 International Conference on Multimedia Computing and Systems*, 2012, pp. 155–159.

[12] D. Zhang, J. You, M. Wong, and W. K. Kong, "Online palmprint identification," *IEEE Trans. PATTERN Anal. Mach. Intell.*, vol. 25, no. 9, 2003.

[13] A. W. K. Kong and D. Zhang, "Competitive coding scheme for palmprint verification," in *Proc*. *17th International Conference on Pattern Recognition,* vol. 1, 2004, pp. 520–523.

Junwen Sun received the Bachelor and Master Degree in School of Electrical Engineering and Automation, Tianjin University, China, in 2007 and 2009, respectively. He is currently doing his PhD research in Electrical and Computer Engineering in University of Auckland, New Zealand. His research interests are biometrics, computer vision and pattern recognition.

Waleed H. Abdulla holds a PhD Degree from the University of Otago, New Zealand. He is an Associate Professor in the University of Auckland. He was the Vice President- Member Relations and Development (APSIPA) for two terms. He has been a Visiting Researcher/Collaborator with Tsinghua University, Siena University (Italy), Essex University (UK), IDIAP (Switzerland), TIT (Japan), ETRI (Korea), HKPU (Hong Kong). He has published more than 150 refereed publications. He is member of Editorial Boards of six journals. He supervised over 25 postgraduate students. He is a recipient of many awards and funded projects exceeding $1M and was awarded JSPS, ETRI, and Tsinghua fellowships. He received Excellent Teaching Awards for 2005 and 2012. He is a Member of APSIPA and Senior Member of IEEE.

Weiming Wang received the PhD Degree from the Department of Computer Science and Engineering at the Chinese University of Hong Kong in 2014. He is an assistant researcher in the Center for Human Computer Interaction, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. His research interests include medical image processing, visualization and rendering, GPU parallel computing, human computer interaction and virtual/augmented reality.

Qiong Wang received the PhD Degree from the Department of Computer Science and Engineering at the Chinese University of Hong Kong in 2013. She is an assistant researcher in the Center for Human Computer Interaction, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. Her research interests include human computer interaction, haptics, virtual reality and computer-assisted surgery.

Hai Zhang received the Master Degree from Tongji Medical Institute at Huazhong University of Science and Technology in 1992. He is an associate professor in the Department of Ultrasonography, Shenzhen People's Hospital, The Second Affiliated Hospital of Jinan University. His research interests include ultrasonography, nanophase and particulate materials and molecular imaging.