Feature Band Selection for Multispectral Palmprint Recognition

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Abstract—**Palmprint is a unique and reliable biometric characteristic with high usability. Many palmprint recognition algorithms and systems have been successfully developed in the past decades. Most of the previous works use the white light sources for illumination. Recently, it has been attracting much research attention on developing new biometric systems with both high accuracy and high anti-spoof capability. Multispectral palmprint imaging and recognition can be a potential solution to such systems because it can acquire more discriminative information for personal identity recognition. One crucial step in developing such systems is how to determine the minimal number of spectral bands and select the most representative bands to build the multispectral imaging system. This paper presents preliminary studies on feature band selection by analyzing hyperspectral palmprint data (420nm~1100nm). Our experiments showed that 2 spectral bands at 700nm and 960nm could provide most discriminate information of palmprint. This finding could be used as the guidance for designing multispectral palmprint systems in the future.**

Biometrics; Palmprint recognition; Multispectral; (2D)^{2}PCA

I. INTRODUCTION

Biometric authentication is the study of methods for recognizing humans based on one or more physical or behavioral traits [1]. Palmprint is a unique biometric characteristic and palmprint recognition has been attracting much attention in the past decade [2-5] because of its attributes such as high accuracy, high speed, high user-friendliness and low cost, etc. However, there is much room to improve the palmprint systems, e.g. in the aspects of both accuracy and its vulnerability to spoof attacks [6].

One potential solution to such improvement may be multispectral imaging. By multispectral imaging, a series of palmprint images at various spectral bands can be captured simultaneously. The spectral signature of the palm can not only provide more discriminative information to improve the accuracy [7-10], but also improve the anti-spoof capability of palmprint systems because it is very difficult to make a fake palm which can have the same spectral signatures with a real palm.

Some pioneering works have been made on multispectral palmprint recognition [7-10]. Hao et al. [7] applied image fusion schemes to multispectral palm images. Rowe et al. [8] developed a multispectral high resolution whole-hand biometric system, which could collect palmprint images with clear fingerprint features. Recently, Han et al. [9] developed an online multispectral palmprint system by multispectral image fusion. Hao et al. [10] designed a contact-less multispectral palmprint device and used image fusion method to integrate multispectral palmprint information.

The above works show the superiority of multispectral palmprint systems to single band systems. However, the multispectral bands were empirically selected. There lacks a solid analysis on how to choose the bands in multispectral palmprint systems. Feature band selection plays a key role in designing multispectral palmprint systems. Optimized band selection could not only reduce the cost of illumination sources, reduce the data storage amount and save the computational time, but also reduce the redundant features and improve the recognition accuracy.

In this paper, we will establish a hyperspectral palmprint imaging system and use it to analyze the band selection for multispectral palmprint systems. First, statistical feature is extracted and compared for each single band, after that, score-level fusion is evaluated to find the best combination from all candidates. Our experiments showed that 2 spectral bands could provide most of the discriminate information of palmprint. The findings in this paper could be used as the guidance for future multispectral palmprint system design.

The rest of the paper is organized as follows. Section 2 briefly introduces the hyperspectral palmprint imaging system and data collection. Section 3 describes the feature extraction. Section 4 presents the experiments for feature band selection and Section 5 gives the conclusion.

II. HYPERSPECTRAL PALMPRINT DATA COLLECTION

To study the multispectral band selection of palmprint images, we established a hyperspectral imaging system to collect the palmprint images in consecutive spectral bands. The imaging system consists of a Liquid Crystal Tunable Filter (LCTF) made by Meadowlark Inc., a Charged Coupled Device (CCD) made by Cooke Corporation and two Osram halogen lights. The full width at Half Max of the filter is 5nm when the center wavelength is 550nm. The object (i.e. palm) will be imaged at 69 spectral bands with a step-length of 10nm over spectrum 420nm-1100nm. The resolution of CCD is 1004*1002 pixels and its response spectral range is 290nm~1100nm. For a uniform and strong enough illumination, two 500W halogen lights are placed at the two sides of the CCD. Fig. 1 illustrates the palmprint imaging system.

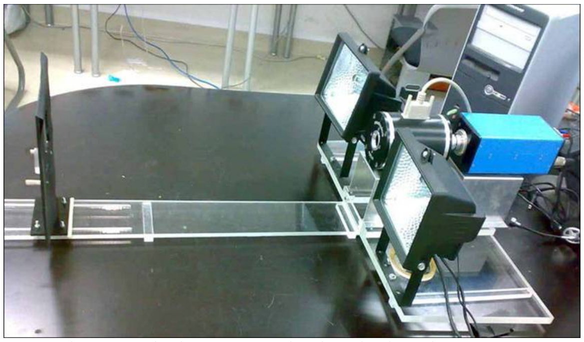

Figure 1. The hyperspectral palmprint imaging system.

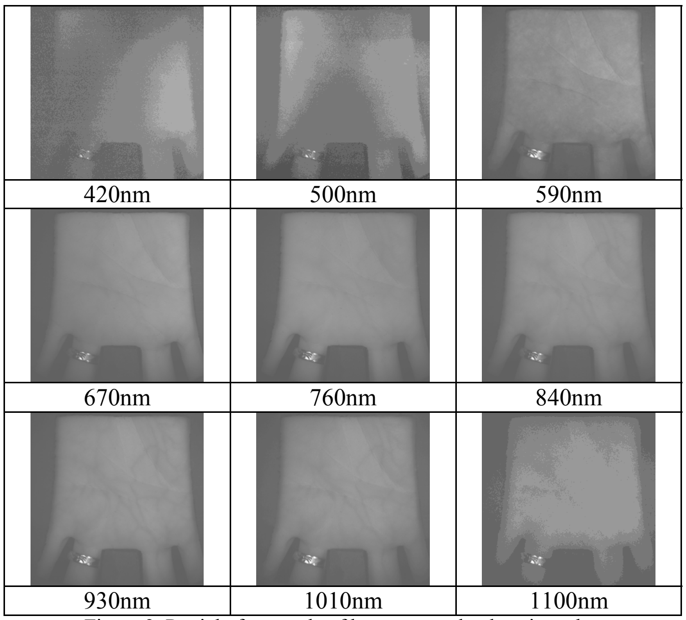

Figure 2. Partial of a sample of hyperspectral palmprint cube.

In data collection, the users are asked to put their palms on the panel in front of the LCTF with the halogen lights power on. Several pads are used to reduce the degree of freedom of the palm. A hyperspectral image cube (with dimension 1004*1002*69) of the palm can be collected in a short time. Fig. 2 shows partial of the hyperspectral palmprint cube. After obtaining the hyperspectral cube, a local coordinate of the palmprint image is established [5] in the center band (760nm), and then a Region of Interest (ROI) is cropped from each band based on the local coordinate. For the convenience of analysis, we normalized these ROIs to a size of 128*128. Because of the low transmission of LCTF at short wavelength, the image quality of the first several bands are not good. Meanwhile, since the CCD's response is not high enough at long wavelength, the image quality at the last several bands are not good either.

III. FEATURE EXTRACTION

From the viewpoint of application, a good band selection should preserve only the most informative bands while removing bands that convey little discriminatory information. Thus, a subset of the original spectral bands but conveys the most distinctive information of the object should be selected. On the other hand, reduction in dimensionality for each spectral could greatly facilitate the transmission, computation, storage and improve the analysis performance. Thus, reducing dimension in each spectral and investigating score-level fusion for band selection will be used in this study.

Here, we employ the $(2D)^2$PCA method [11] to extract palmprint features in order for feature band determination. The $(2D)^2$PCA method can much alleviate the small sample size problem in subspace analysis and can well preserve the image local structural information.

Suppose we have M subjects and each subject has S sessions in the training data set, i.e. S hyperspectral cube were acquired at different times for each subject. Then, we denote by X_{ms}^{b} the b^{th} band image for the m^{th} individual in the s^{th} session. X_{ms}^{b} is an $I_r * I_c$ matrix, where I_r and I_c represent the numbers of rows and columns of the image. The covariance matrices along the row and column directions are computed as:

$$\begin{aligned} G_1^b &= \frac{1}{MS}\sum_{s=1}^{S}\sum_{m=1}^{M}(X_{ms}^b-\overline{X^b})^T(X_{ms}^b-\overline{X^b}) \\ G_2^b &= \frac{1}{MS}\sum_{s=1}^{S}\sum_{m=1}^{M}(X_{ms}^b-\overline{X^b})(X_{ms}^b-\overline{X^b})^T \end{aligned} \tag{1}$$

where $\overline{X^b} = \frac{1}{MS}\sum_{s=1}^{S}\sum_{m=1}^{M}X_{ms}^b$.

The project matrix $V_1^b = [v_{11}^b, v_{12}^b, ..., v_{1k_1^b}^b]$ is composed of the orthogonal eigenvectors of G_1^b corresponding to the k_1^b largest eigenvalues, and the projection matrix $V_2^b = [v_{21}^b, v_{22}^b, ..., v_{2k_2^b}^b]$ consists of the orthogonal eigenvectors of G_2^b corresponding to the largest k_2^b eigenvalues. k_1^b and k_2^b can be determined by setting a threshold to cumulant eigenvalues:

$$\sum_{j_c=1}^{k_1^b}\lambda_{1j_c}^b / \sum_{j_c=1}^{I_c}\lambda_{1j_c}^b \geq C_u, \sum_{j_r=1}^{k_2^b}\lambda_{2j_c}^b / \sum_{j_r=1}^{I_r}\lambda_{2j_c}^b \geq C_u \tag{2}$$

where $\lambda_{11}^b, \lambda_{12}^b, ..., \lambda_{1I_c}^b$ are the first I_c biggest eigenvalues of G_1^b , $\lambda_{21}^b, \lambda_{22}^b, ..., \lambda_{2I_r}^b$ are the first I_r biggest eigenvalues of G_2^b , and C_u is a pre-set threshold.

For each given band b^{th}, the test image T^b is projected to $\hat{T}^b$ by V_1^b and V_2^b . The distance of the projection result to the m^{th} individual is defined as:

$$d_{ms}^b = \left\| V_2^{bT} T^b V_1^b - \hat{X}_{ms}^b \right\| \tag{3}$$

where $\hat{X}^b_{ms} = V_2^{bT} X^b_{ms} V_1^b$ is the projection data from the training set. Then the classification decision of a test band image is made as:

$$c^b = \arg\min_m d^b_{ms}, m = 1,2,...,M, s = 1,2,...,S \qquad (4)$$

The information presented by multiple traits can be fused at various levels: image level, feature level, matching score level or decision level [12]. Because the match scores contain richer information about the input pattern than decision level and it is relatively easy to combine the scores generated by different matchers, we adopt it in this study and use the SUM rule for score level fusion:

$$f_{ms} = \sum_{b=1}^{B} \tilde{d}^b_{ms} \qquad (5)$$

where B is the number of bands in the fusion and $\tilde{d}^b_{ms}$ is the normalized distance [12]:

$$\tilde{d}^b_{ms} = \frac{d^b_{ms} - \mu^b}{\sigma^b} \qquad (6)$$

where σ^b and μ^b are computed from the training sets. Finally, the nearest neighborhood classifier is used for classifying the input palmprint:

$$c = \arg\min_m f_{ms}, m = 1,2,...,M, s = 1,2,...,S \qquad (7)$$

IV. FEATURE BAND SELECTION

With the $(2D)^2$PCA feature extraction method, to evaluate which wavelengths and what combination of them perform the best for palmprint authentication, a large hyperspectral palmprint database was collected. The database includes hyperspectral palmprint cubes of 390 different palms from volunteers. The cubes were captured by 2 separate sessions with around 1 month interval. For each session, the user was asked to provide around 7 palmprint cubes. There are totally 5246 cubes in the database.

The whole database is partitioned into two parts, training set and test samples. The training set is used to estimate the projection matrix and is taken as gallery samples. The test samples are compared with the training samples, and Eq. 4 is used to decide the recognition output. When the output class is the same as that of test sample, it is counted as a correct match. The ratio of the number of correct matches to the number of test samples, i.e. the recognition accuracy, is used as the evaluation criteria. To reduce the dependency of experimental results on training sample selection, we designed the experiments as follows. Firstly, the first three samples in the first session are chosen as training set and the remaining samples are used as test set. Secondly, the first three samples in the second session are chosen as training set, and the remaining samples are used as test set. Finally, the average accuracy is computed. Fig. 3 shows the recognition accuracy of each band with different cumulant eigenvalue thresholds.

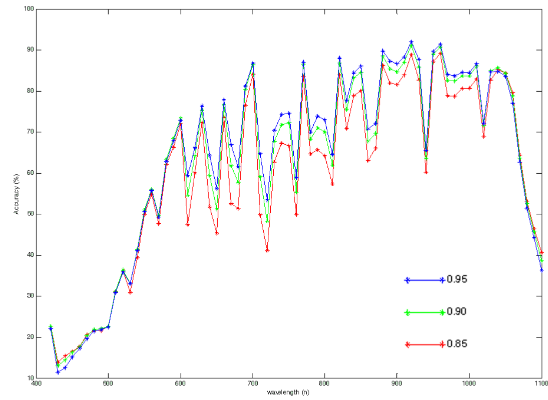

Figure 3. Recognition Accuracy vs. wavelength C_u.

There are some observations that could be found from Fig.3. First, the first and last several bands have low recognition accuracy. This is because of the poor image quality of them, as discussed in Section 2. Second, the accuracy curves with different C_u are similar in shape. Third, the best band in visible spectrum (380-750nm) is at 700nm. It achieves an accuracy of 84.02%, 86.43%, and 86.77% when C_u is 0.85, 0.90 and 0.95 respectively. While the best band in Near Infrared (NIR, 760-1100nm) wavelength is at 920nm. It achieves an accuracy of 88.83%, 91.17% and 91.42% with different C_u. The second best NIR wavelength is 960nm, and it could achieve 89.19%, 90.78% and 91.42% correspondingly.

To find the best band combination, the exhaustive search from the combination space is implemented and Eq.7 is used to determine the output label. For example, by three band fusion, the highest accuracy from 52394 (69*68*67/3/2) combinations is computed and shown in Table 1.

From Table 1, we see that 700nm and 960nm are the best bands for two-band combination. Although 700nm itself has not very high accuracy, by coupling with 960nm it could improve the accuracy significantly. It can also be found that although using three bands could improve the accuracy, the improvement is very little (less than 0.5%), which implies that using two bands, one from visible spectrum (700nm) and the other from NIR (960nm) could convey most of the palmprint information for recognition.

To better explain these findings, the correlation map between different bands is plotted in Fig. 4. For better visualization, the correlation map is normalized into 0~255. The whiter the pixel is, the higher the correlation is. As can be seen in Fig. 4, there are roughly two white blocks, i.e. highly correlated regions. One lies in the visible spectrum, centered at about 700nm. The other one lies in NIR bands, centered at about 960nm. This is identical to our band selection results. It can also be seen that the correlation in NIR bands is higher than that in visible spectrum, which may be used to explain why NIR bands work better than visible bands in palmprint recognition.

TABLE I. BEST EXPERIMENT RESULTS BY USING TWO/THREE BANDS.

C_u	Best two bands		Best three bands	
	Bands (nm)	*Accuracy (%)*	*Bands (nm)*	*Accuracy (%)*
0.85	700, 960	90.7331	700, 920, 960	90.9279
0.90	700, 960	92.4257	700, 920, 960	92.6449
0.95	700, 920	92.8032	700, 880, 960	93.2538

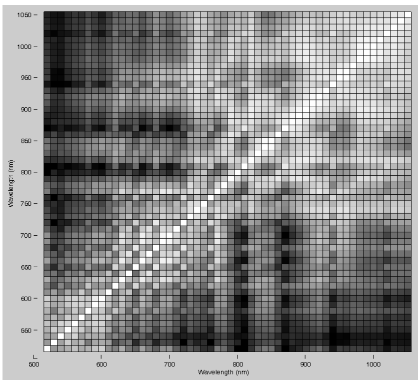

Figure 4. Correlation map.

V. CONCLUSION

There has been a growing demand for high accuracy and robust biometric systems in recent years. Although multispectral palmprint system could be a good solution to such demands, little work has been done on analyzing how to select the multiple bands and how many bands should be used. This paper made a good effort on this problem. A hyperspectral palmprint imaging system was built and a hyperspectral palmprint database was established, including 5460 hyperspectral palmprint cubes from 390 palms. Based on our experiments using (2D)2PCA, some findings can be concluded. First, two bands could convey most of discriminative information of palmprint; second, 700nm and 960nm are the best bands for two-band combination. In the future, other palmprint feature representation methods will be used to further validate these findings, and the corresponding multispectral palmprint system will be developed.

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