Is White Light the Best Illumination for Palmprint Recognition?

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Abstract. Palmprint as a new biometric has received great research attention in the past decades. It owns many merits, such as robustness, low cost, user friendliness, and high accuracy. Most of the current palmprint recognition systems use an active light to acquire clear palmprint images. Thus, light source is a key component in the system to capture enough of discriminant information for palmprint recognition. To the best of our knowledge, white light is the most widely used light source. However, little work has been done on investigating whether white light is the best illumination for palmprint recognition. In this study, we empirically compared palmprint recognition accuracy using white light and other six different color lights. The experiments on a large database show that white light is not the optimal illumination for palmprint recognition. This finding will be useful to future palmprint recognition system design.

Keywords: Biometrics, Palmprint recognition, $(2D)^2$PCA, Illumination.

1 Introduction

Automatic authentication using biometric characteristics, as a replacement or complement to traditional personal authentication, is becoming more and more popular in the current e-world. Biometrics is the study of methods for uniquely recognizing humans based on one or more intrinsic physical or behavioral traits [1]. As an important member of the biometric characteristics, palmprint has merits such as robustness, user-friendliness, high accuracy, and cost-effectiveness. Because of these good properties, palmprint recognition has received a lot of research attention and many systems have been proposed.

In the early stage, most of works focus on offline palmprint images [2-3]. With the development of digital image acquisition devices, many online palmprint systems have been proposed [4-12]. There are mainly three kinds of online palmprint image acquisition systems: desktop scanner [4-6], Charge Coupled Device (CCD) camera or Complementary Metal-Oxide-Semiconductor (CMOS) camera with passive illumination [7-8], and CCD or CMOS with active illumination [9-12].

Desktop scanner could provide high quality palmprint images [4-6] with different resolutions. However, it may suffer from the slow speed and requires the full touch with whole hand which may bring sanitary issues during data collection. Using CCD or CMOS with uncontrolled ambient lighting [7-8] does not have the above problems.

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However, the image quality may not be very good so that the recognition accuracy may not be high enough. Because CCD or CMOS camera mounted with active light could collect image data quickly with good image quality and does not require the full touch with the device, this kind of system have been attracting much attention [9-12]. Although all of these studies [9-12] used white light source to enhance the palmprint line and texture information, to the best of knowledge, no work has been done to systematically validate whether white light is the optimal light for palmprint recognition. This study focused on this problem through a series of experiments on a large multispectral palmprint database we established [17].

In general, there are mainly two kinds of approaches to pattern recognition and analysis: structural and statistical methods. Because the statistical methods are more computational effective and are straightforward to implement, many algorithms have been proposed, such as Principal Component Analysis (PCA) [5-6, 14], Locality Preserving Projection [7, 13]. In this study, we employ the $(2D)^2$PCA method [15-16] to extract palmprint features in order for feature extraction and matching. The $(2D)^2$PCA method can alleviate much the small sample size problem in subspace analysis and can better preserve the image local structural information than PCA.

The rest of this paper is organized as follows. Section 2 describes our data collection. Section 3 briefly introduces the $(2D)^2$PCA algorithm. Section 4 presents the experimental results and Section 5 concludes the paper.

2 Multispectral Palmprint Data Collection

It is known that Red, Green, and Blue are the three primary colors (refer to Fig. 1), the combination of which could result in many different colors in the visible spectrum. We designed a multispectral palmprint data collection device which includes the three primary color illumination sources (LED light sources). By using this device we can simulate different illumination conditions. For example, when the red and green LEDs are switched on simultaneously, the yellow like light could be generated. Totally our device could collect palmprint images under seven different color illuminations: red, green, blue, cyan, yellow, magenta and white.

The device is mainly composed of a monochrome CCD camera, a lens, an A/D converter, a light controller and multispectral light sources. To fairly study the illumination effect, the lens, A/D converter and CCD camera are selected according to

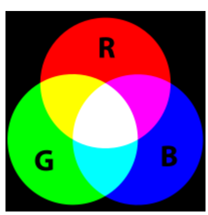
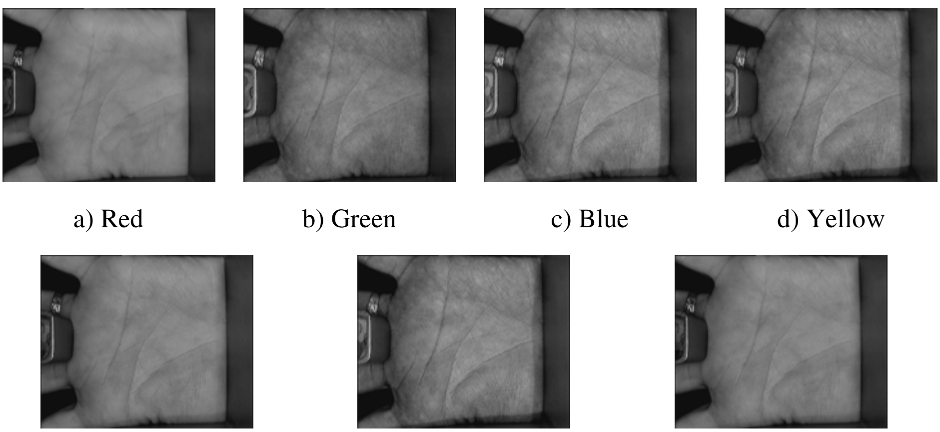


Fig. 1. Additive Color Mixing: adding red to green yields yellow, adding all three primary colors together yields white

previous palmprint scanning [18] to remove the influence of scanner devices, and resolutions. The illuminator is a LED array, which is arranged in a circle to provide a uniform illumination. The peak spectrums of red, green, and blue LEDs are 660nm, 525nm, and 470 nm respectively. The LED array can switch to different light in about 100ms. The light controller is used to switch on or off the different color LEDs.

As shown in Fig. 2, in data collection the user is asked to put his/her palm on the device. The device could collect a multispectral palmprint cube, including seven different palmprint images, in less 2 seconds. Fig. 3 shows examples of the collected images by different illuminations.

Fig. 2. The prototype device



a) Red b) Green c) Blue d) Yellow

e) Magenta f) Cyan g) White

Fig. 3. A sample of collected image of one palm with different illuminations

3 Feature Extraction

In this study, we employ the $(2D)^2$PCA method [15-16] to extract palmprint features. 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 multispectral palmprint 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 the cumulant eigenvalues:

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

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 $\widetilde{T^b}$ by V_1^b and V_2^b. The distance of the projection result to the m^{th} individual is defined as:

$$d_{ms}^b = \left\| V_2^{bT} T^b V_1^b - \widetilde{X_{ms}^b} \right\| \tag{3}$$

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

$$c^b = \arg\min_m d_{ms}^b, m = 1,2,...,M, s = 1,2,...,S \tag{4}$$

4 Experiment Results

We collected multispectral palmprint images from 250 subjects using the developed data acquisition device. The subjects were mainly volunteers from our institute. In the database, 195 people are male and the age distribution is from 20 to 60 years old. We collected the multispectral palmprint images on two separate sessions. The average time interval between the two occasions is 9 days. On each session, the subject was asked to provide 6 samples of each of his/her left and right palms. So our database contains 6,000 images for each band from 500 different palms. For each shot, the device collected 7 images from different bands (Red, Green, Blue, Cyan, Yellow, Magenta, and White) in less than two seconds. In palmprint acquisition, the users are asked to keep their palms stable on the device. The resolution of the images is 352*288 (<100 DPI).

After obtaining the multispectral cube, a local coordinate of the palmprint image is established [9] from the blue band, 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. To remove the global intensity and contrast effect, all images are normalized to have a mean of 128 and standard deviation of 20.

The whole database is partitioned into two parts, training set and test set. The training set is used to estimate the projection matrix and is taken as gallery samples. The test samples are matched with the training samples, and Eq. 4 is used to decide the recognition output. 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. 4 shows the accuracies of different spectrum with different cumulant Eigenvalue threshosIds, C_u . Several findings could be found from Fig. 4.

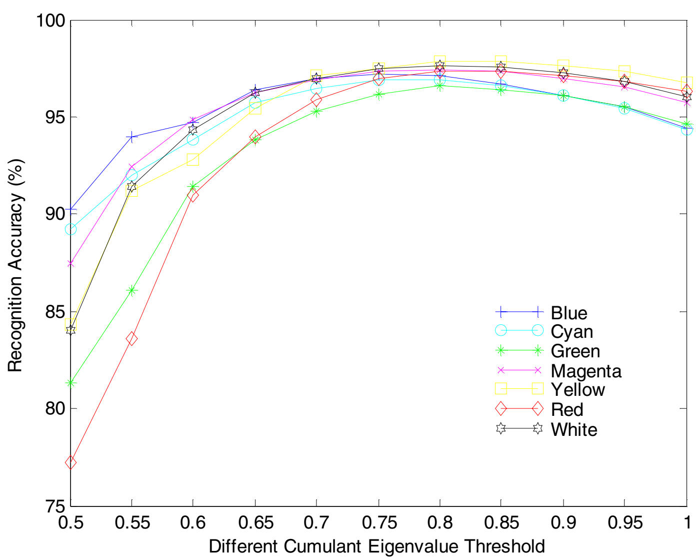


Fig. 4. Recognition Accuracy under different C_u

First, recognition accuracy is dependent with threshold. As threshold increases, the accuracy increases to a peak, then drops a little. The highest accuracy with the threshold for each color is listed in Table 1.

Table 1. The highest accuracy with threshold for each color

Color	Highest accuracy	Corresponding C_u
Blue	97.2000	0.75
Cyan	96.8777	0.75
Green	96.6334	0.80
Magenta	97.4333	0.80
Yellow	**97.8777**	0.80
Red	97.3555	0.80
White	97.6334	0.80

Second, no single spectrum could compete with all the others for all thresholds. This is mainly because different light could enhance different features of palms, while these different features have different intensity distributions which are in favor of different parameters.

Third, among the three primary colors, Red has a little higher accuracy than Blue and Green. This is mainly because Red could not only capture most of the palm line information, but also capture some palm vein structures as shown in Fig. 3. This additional palm vein information helps classify those palms with similar palm lines. It could also explain why those composite colors Magenta, Yellow, White get better accuracy than Cyan.

Finally, White color could not get higher accuracy than Yellow color. This is probably because Blue and Green collect redundant information for palm skin. As shown in Fig. 3, the palmprint images under Blue and Green illumination are more similar to each other than to the image under Red illumination. The redundancy makes White color fail to capture more information than the Yellow color, and sometimes the accuracy drops a little.

5 Conclusion

Palmprint recognition has been attracting lots of research attention in the past decade and many novel data collection devices have been proposed. Because the good image quality and capture speed, CCD or CMOS camera mounted with active lighting source is the most popular device configuration. All these devices use white light as the illumination source but there was no systematic analysis on whether the White light is the optimal light source for palmprint recognition. This paper made a good effort on this problem by establishing a large multispectral palmprint database using our developed device. With the database we empirically evaluated the recognition accuracies of palmprint images under seven different colors. Our experimental results showed that the White color is not the optimal color for palmprint recognition and the Yellow color could achieve higher accuracy than the White color. In the future, other feature extraction methods, such as structural and texture coding methods will be used to further investigate the best illumination conditions of palmprint recognition.

Acknowledgments

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References

1. Jain, A., Bolle, R., Pankanti, S.: Biometrics: Personal Identification in Network Society. Kluwer Academic Publishers, Boston (1999)
2. Duta, N., Jain, A.K., Mardia, K.V.: Matching of palmprint. Pattern Recognition Letter 23, 477–485 (2002)
3. Zhang, D., Shu, W.: Two novel characteristics in palmprint verification: datum point invariance and line feature matching. Pattern Recognition 32, 691–702 (1999)
4. Lin, C., Chuang, T., Fan, K.: Palmprint verification using hierarchical decomposition. Pattern Recognition 38, 2639–2652 (2005)
5. Ribaric, S., Fratric, I.: A biometric identification system based on Eigenpalm and Eigenfinger features. IEEE Trans. on Pattern Analysis and Machine Intelligence 27, 1698–1709 (2005)
6. Connie, T., Jin, A.T.B., Ong, M.G.K., Ling, D.N.C.: An automated palmprint recognition system. Image and Vision Computing 23, 501–515 (2005)
7. Wang, J.-G., Yau, W.-Y., Suwandy, A., Sung, E.: Person recognition by fusing palmprint and palm vein images based on "Laplacianpalm" representation. Pattern Recognition 41, 1514–1527 (2008)
8. Han, Y., Sun, Z., Wang, F., Tan, T.: Palmprint recognition under unconstrained scenes. In: Yagi, Y., Kang, S.B., Kweon, I.S., Zha, H. (eds.) ACCV 2007, Part II. LNCS, vol. 4844, pp. 1–11. Springer, Heidelberg (2007)
9. Zhang, D., Kong, W., You, J., Wong, M.: Online Palmprint Identification. IEEE Trans. Pattern Analysis and Machine Intelligence 25, 1041–1050 (2003)
10. Han, C.: A hand-based personal authentication using a coarse-to-fine strategy. Image and Vision Computing 22, 909–918 (2004)
11. Michael, G.K.O., Connie, T., Teoh, A.B.J.: Touch-less palm print biometrics: novel design and implementation. Image and Vision Computing 26, 1551–1560 (2008)
12. Wu, J., Qiu, Z., Sun, D.: A hierarchical identification method based on improved hand geometry and regional content feature for low-resolution hand images. Signal Processing 88, 1447–1460 (2008)
13. Hu, D., Feng, G., Zhou, Z.: Two-dimensional locality preserving projections (2DLPP) with its application to palmprint recognition. Pattern Recognition 40, 339–342 (2007)
14. Kumar, A., Zhang, D.: Personal authentication using multiple palmprint representation. Pattern Recognition 38, 1695–1704 (2005)

15. Zuo, W., Zhang, D., Wang, K.: Bidirectional PCA With Assembled Matrix Distance Metric for Image Recognition. IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics 36, 863–872 (2006)
16. Zhang, D., Zhou, Z.: (2D)2PCA: 2-Directional 2-Dimensional PCA for Efficient Face Representation and Recognition. Neurocomputing 69, 224–231 (2005)
17. Han, D., Guo, Z., Zhang, D.: Multispectral palmprint recognition using wavelet-based image fusion. In: International conference on signal processing, pp. 2074–2077 (2008)
18. Wong, M., Zhang, D., Kong, W.-K., Lu, G.: Real-time palmprint acquisition system design. IEE Proc.-Vis. Image Signal Process. 152, 527–534 (2005)