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Empirical Study of Image Compression for Palm Vein Recognition

***Zhenhua Guo*[1], *Qin Li*[2], *Yujiu Yang*[1], *Jane You*[3]**
[1]Graduate School at Shenzhen, Tsinghua University
[2]Shenzhen Institute of Information Technology
[3]the Hong Kong Polytechnic University

Abstract

Nowadays, cloud architecture is getting more and more popular, so biometrics with cloud computing is becoming a trend for many applications. As a relative new biometrics, palm vein recognition has many merits, such as user friendly, high accuracy and robust. It is very convenient to deploy palm vein recognition in cloud computing, for example, using a cell phone to capture a palm vein image and fulfilling comparison in cloud environment. Usually, to reduce computation burden in a cell phone and data transmission, a palm vein image is compressed before transmission. However, how image compression affect recognition accuracy is not well studied. This paper empirically studies JPG compression for three kinds of palm vein feature extraction methods. It is found that subspace method is robust, texture-based method is sensitive, while line-based method is moderate, to image compression.

Keywords: Palm Vein, Subspace Learning, Texture-based Coding, Line-based Detection

I. Introduction

Biometric characteristics are now widely used in security applications. Among various biometric techniques, hand-based recognition is getting popular in personal authentication because it provides robust features from a large hand area and the image can be captured with a cost-effective device. Although palmprint recognition has achieved great success, it has some intrinsic weaknesses. For example, some people may have similar palm lines, especially principal lines [1]; also it is not so difficult to forge a fake palmprint [2]. One way to improve the discriminativeness and anti-spoofing capability of palmprint systems is to use more features from the palm, such as the veins of the palm. The veins of the palm generally refer to the inner vessel structures beneath the skin and the palm vein images can be collected using both far infrared (FIR) and near-infrared (NIR) light [3]. Obviously, the palm vein is much harder to fake than the palmprint.

A number of studies have been conducted to study palm vein information for personal recognition [4-8]. For example, Hao et al. [4] evaluated various image level fusion schemes of palmprint and palm vein images. Wang et al. [5] developed a system to obtain palmprint and palm vein simultaneously. Zhang et al. [6] developed a personal verification system fusing palmprint and palm vein information, and obtained relatively good results on a large database. Lee [7] used palm vein features and designed a “VeinCode” to represent palm vein features. We [8] proposed to extract two kinds of features from a palm vein image and combined them at matching score level fusion.

Nowadays, it is a trend to apply recognition engine in cloud computing, for example, using a cell phone to capture a palm vein image and fulfilling comparison in cloud environment. Usually, to reduce computation burden in a cell phone and data transmission, a palm vein image is compressed before transmission. However, how image compression affect recognition accuracy is not well studied. To evaluate how image compression affect recognition accuracy, in this work, three mainstreams of palm vein feature extraction methods, subspace learning, texture-based coding and line-based detection, are studied.

The rest of the paper is organized as follows. Section II briefly describes the database. Section III introduces three kinds of feature extraction. Section IV reports the experimental results. Finally, section V makes the conclusions.

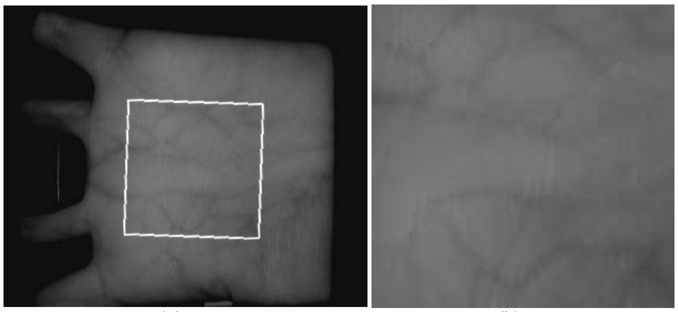
II. Palm vein database

In our previous work [8], we developed a palm vein image acquisition device. The developed image acquisition device is made up of a light source, a grey level CCD camera, lens, and an A/D (analogue-to-digital) converter connecting the CCD and the computer. The uniformly distributed 880nm LEDs (light emitting diode) are used for the NIR illumination as it has been shown that 880-930nm provides a good contrast of subcutaneous veins [9]. In order to acquire high quality palm vein feature, a near-infrared sensitive camera, is used in our system. Fig. 1 shows a photo of the acquisition device.

Fig.1. Photo of the image acquisition device.

We established a database which includes palm vein images from 500 different palms. In this database, 396 palms are from male and the age ranges are from 20 to 60. The images were captured by two separate sessions. The average time interval between two sessions was 9 days. On each session, the subject was asked to provide 6 samples from his/her palms. Finally, the database contains 6,000 NIR images of resolution 352*288.

Before feature extraction, it is necessary to extract Region of Interest (ROI) to remove the translation and rotation in the data collection process and to extract the most informative area in the images. In this study, we set up ROI coordinates using the algorithm proposed in [1] and then use the coordinates to crop the ROI (128*128) from the images. Fig. 2 shows an image sample and the extracted ROI.



(a) (b)

Fig.2. Sample image of (a) palm vein image, (b) ROI.

III. Feature extraction methods

In general, there are three kinds of popular approaches to palm vein recognition: structural methods, statistical methods and texture coding methods. Different approaches focus on different kinds of features. For example, structural methods pay attention to vein structure, statistical methods use holistic expression for palm vein recognition, and texture coding schemes assign a feature code for each pixel in the palm vein image. Thus, to study compression effect more comprehensively, this study employs three different kinds of feature extraction methods, i.e. Competitive Coding [10] (texture coding), wide line detection [11] (structural method), $(2D)^2$PCA [12] (statistical method), for palm vein recognition.

A. Competitive Coding(CompCode)

The orientation of palm vein is stable and can serve as distinctive features for personal identification. To extract the orientation features, six Gabor filters along different orientations ($\theta_j = j\pi/6$, where j={0,1,2,3,4,5}) are applied to the palm vein image. Here the real part of the Gabor filter is used and it is defined as:

$$\psi(x,y,\omega,\theta)=\frac{\omega}{\sqrt{2\pi}\kappa}e^{-\frac{\omega^2}{8\kappa^2}(4x'^2+y'^2)}\left(e^{i\omega x'}-e^{-\frac{\kappa^2}{2}}\right) \quad (1)$$

where $\begin{array}{l} x'=(x-x_0)\cos\theta+(y-y_0)\sin\theta, \\ y'=-(x-x_0)\sin\theta+(y-y_0)\cos\theta \end{array}$, (x_0, y_0) is the center of the function; ω is the radial frequency in radians per unit length and θ is the orientation of the Gabor functions in radians. κ is defined by $\kappa=\sqrt{2\ln 2}\left(\frac{2^\delta+1}{2^\delta-1}\right)$, where δ is the half-amplitude bandwidth of the frequency response. To reduce the influence of illumination, the direct current is removed from the filter.

By regarding palm vein as the negative lines, the orientation corresponding to the minimal Gabor filtering response (i.e. the negative response but with the highest magnitude) is taken as the feature for this pixel [10]. Because the contour of Gabor filters is similar to the cross-section profile of palm veins, the higher the magnitude of the response, the more likely there is a line. Since six filters are used to detect the orientation of each pixel, the detected orientation $\{0, \pi/6, \pi/3, \pi/2, 2\pi/3, 5\pi/6\}$ can then be coded by using 3 bits {000, 001, 011, 111, 110, 100} and the Hamming distance is used for comparison between two feature maps [10].

B. Wide Line Detection(WLD)

A palm vein image contains many blood vessels and these vessels could be extracted by a wide line detector directly [11]. The thickness of the line is defined as:

$$\begin{aligned}
&L(x_0,y_0)=\begin{cases} g-m(x_0,y_0) & \text{if } m(x_0,y_0)<g \\ 0 & \text{otherwise}\end{cases}, \\
&m(x_0,y_0)=\sum_{x_0-r\le x\le x_0+r,\, y_0-r\le y\le y_0+r} c(x,y,x_0,y_0), \\
&c(x,y,x_0,y_0)=\omega_0 * \begin{cases} 0 \text{ if } I(x,y)>I(x_0,y_0) \\ 1 \text{ otherwise}\end{cases}, \\
&\omega_0=\frac{\omega}{\sum_{x_0-r\le x\le x_0+r,\, y_0-r\le y\le y_0+r}\omega(x,y,x_0,y_0,r)}, \\
&\omega(x,y,x_0,y_0,r)=\begin{cases} 1 \text{ if } (x-x_0)^2+(y-y_0)^2\le r^2 \\ 0 \text{ otherwise}\end{cases}
\end{aligned} \quad (2)$$

where g is the geometric threshold, r is radius of the circular mask, and m is the weighed mask having similar brightness. ω is a circular constant weighing mask and ω_0 is the normalization of the circular mask.

To remove noise, a Gaussian smoothing process is employed as a post-processing step. Then the response is binarized after thresholding:

$$\begin{aligned}
&\tilde{L}(x,y)=L(x,y)*g_\sigma(x,y) \\
&\text{where } g_\sigma(x,y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2})
\end{aligned} \quad (3)$$

$$B(x,y)=\begin{cases} 1 \text{ if } \tilde{L}(x,y)>t \\ 0 \text{ otherwise}\end{cases} \quad (4)$$

where σ is the scale of the Gaussian filter and t is a threshold. After binarization, the similarity between two palm veins is defined as the proportion of matched bits to the total bits of the two binary palm vein maps [11].

C. $(2D)^2$PCA

Principal component analysis (PCA) is a widely used statistical analysis method, and $(2D)^2$PCA [12] is an extension of it, which can alleviate much the small sample size problem and better 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 palm vein images were acquired at different times for each subject. Then, we denote by X_{ms} (the original image matrix) for the m^{th} individual in the s^{th} session. The covariance matrices along the row and column directions are computed as:

$$G_1 = \frac{1}{MS}\sum_{s=1}^{S}\sum_{m=1}^{M}(X_{ms} - \overline{X})^T(X_{ms} - \overline{X}),$$
$$G_2 = \frac{1}{MS}\sum_{s=1}^{S}\sum_{m=1}^{M}(X_{ms} - \overline{X})(X_{ms} - \overline{X})^T \quad (5)$$

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

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

$$\sum_{j_c=1}^{k_1}\lambda_{1j_c} / \sum_{j_c=1}^{I_c}\lambda_{1j_c} \geq C_u, \sum_{j_r=1}^{k_2}\lambda_{2j_c} / \sum_{j_r=1}^{I_r}\lambda_{2j_c} \geq C_u \quad (6)$$

where $\lambda_{11}, \lambda_{12}, ..., \lambda_{1k_1}$ are the first k_1 biggest eigenvalues of G_1 , $\lambda_{21}, \lambda_{22}, ..., \lambda_{2k_2}$ are the first k_2 biggest eigenvalues of G_2 , and C_u is a pre-set threshold. Given a test image T , it is projected to $\mathring{T}$ by V_1 and V_2 ($V_2^T \times T \times V_1$), then Euclidean distance is used to measure the dissimilarity [12].

IV. Experimental Results

A. JPG Image compression

Given a palm vein image, we first use Matlab to generate 21 JPG images with different quality index, from 0 to 100 with 5 as interval. Fig. 4 shows an example of a palm vein image with its compressed images. And Fig. 3 shows average compression rate for the whole database. As shown in Fig. 3 and Fig. 4, a JPG image with "50" quality looks similar to its original image while its file size is around 5% only, in other words, JPG compression could reduce image size significantly without losing much information.

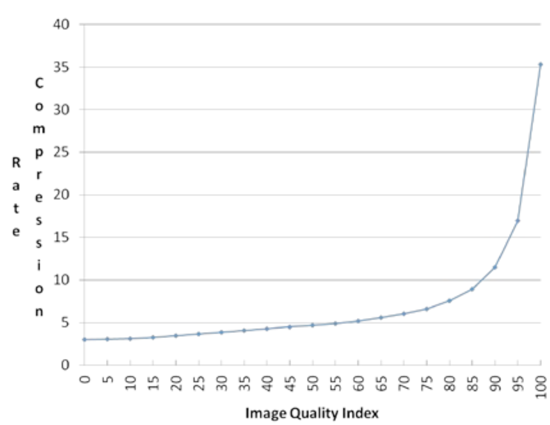


Fig.4. JPG image quality index vs. compression rate.

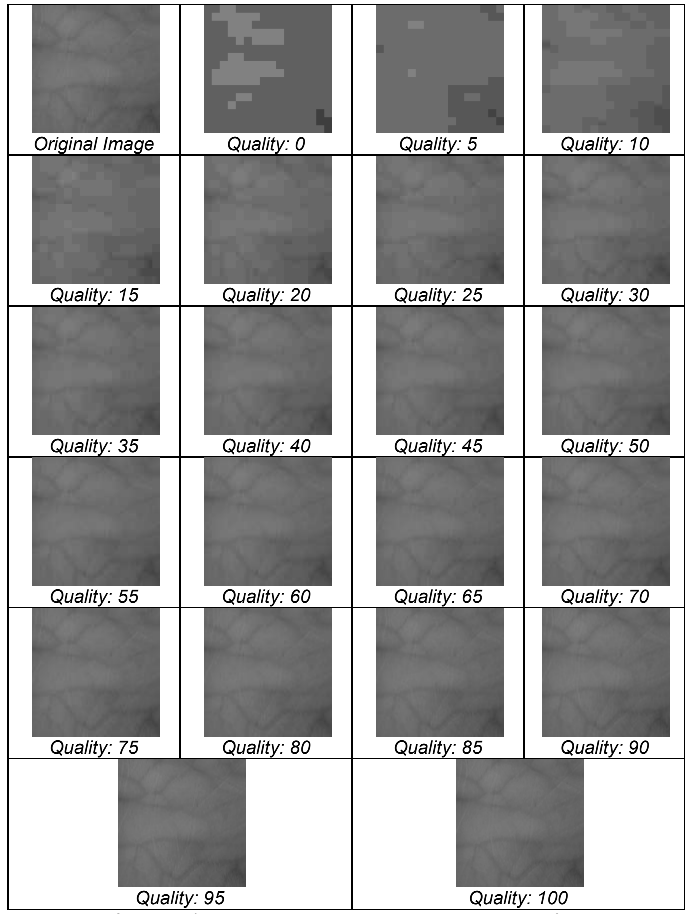


Fig.3. Sample of a palm vein image with its compressed JPG images.

B. Verification test for CompCode and WLD

Table 1 Verification accuracy for CompCode and WLD.

Quality Index\EER(%)	CompCode	WLD
0	33.3228	37.9124
5	26.0109	33.9872
10	13.4238	16.7956
15	5.5384	6.3809
20	2.6253	3.2052
25	1.1874	1.7226
30	0.6473	1.1460
35	0.3879	0.8247
40	0.2950	0.7034
45	0.1968	0.6485
50	0.1755	0.5424
55	0.1491	0.5238
60	0.1332	0.5238
65	0.1061	0.5005
70	0.1090	0.4605
75	0.1002	0.4273
80	0.0933	0.4329
85	0.0819	0.4272
90	0.0788	0.4368
95	0.0759	0.4208
100	0.0728	0.4000
Original Image	0.0757	0.4177

In this sub-section, we do verification test. To compute the verification accuracy, each palm vein image is matched with all the other palm vein images in the database. A match is counted as a genuine if the two palm vein images are from the same palm;

otherwise, it is counted as an impostor. The total number of matches is 17,997,000 and the number of genuine is 33,000. The Equal Error Rate (EER) (the point when False Accept Rate (FAR) is equal to False Reject Rate (FRR)) is used to evaluate the accuracy.

Table 1 reports EER under different quality index for CompCode and WLD. From Table 1, we could have the following findings. First, CompCode is sensitive to image compression, better image quality, and better accuracy. We can get sound results as long as image quality is no less than 90. Second, WLD is not so sensitive to image compression, lower image quality may get better result some time. We can get sound results as long as image quality is no less than 75. Third, with “100” JPG quality, both CompCode and WLD could get better result than original image. This is probably because JPG compression could remove some noise. This finding is useful for some applications because we can save data communication while get better performance.

C. Identification test for $(2D)^2$PCA

In this sub-section, identification instead of verification is implemented. 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 the nearest neighborhood classification is employed. 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. Table 2 shows identification accuracy for $(2D)^2$PCA.

Table 2 Recognition accuracy for $(2D)^2$PCA.

Quality Index	Accuracy(%)	Quality Index	Accuracy(%)
0	42.0667	55	94.0778
5	62.2111	60	94.0778
10	88.5555	65	94.1556
15	92.0000	70	94.1334
20	93.0667	75	94.2000
25	93.4333	80	94.1667
30	93.5888	85	94.1778
35	93.6778	90	94.2445
40	94.0333	95	94.2666
45	94.0667	100	94.2555
50	94.0444	Original Image	94.2445

From Table 2, we can get several findings. First, as $(2D)^2$PCA extracts global features, it is robust to image compression. For example, it can get sound results as long as image quality is no less than 40. Second, JPG compression may remove some noise, so compression may improve accuracy a little (for example, “95” and “100” JPG quality) which is similar as above sub-section.

V. Conclusion

In this paper, we empirically studied JPG compression for palm vein feature extraction by three kinds of feature extraction methods. It may be useful for people who are going to apply palm vein recognition in cloud environment. It is found that subspace method is robust, texture-based method is sensitive, while line-based method is moderate, to image compression. Our possible future works include studying deep learning based feature extraction, exploring JPG robust feature extraction and designing palm vein specific compression scheme.

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Authors Biography

Zhenhua Guo received the M.S. and Ph.D degree in computer science from Harbin Institute of Technology and the Hong Kong Polytechnic University in 2004 and 2010 respectively. Since April 2010, he has been worked in Graduate School at Shenzhen, Tsinghua University. His research interests include texture classification, biometrics, computer vision, deep learning, etc.

Qin Li received his B.Eng. degree in computer science from the China University of Geoscience, Wuhan, China, in 2001,his M.Sc. degree (with distinction) in computing from the University of Northumbria at Newcastle, Newcastle, U.K., in 2003, and his Ph.D. degree in computing from the Hong Kong Polytechnic University, Hong Kong, in 2010.From 2011 to 2012, he was a post-doctoral researcher in the Medical Device Testing Center, Shenzhen Academy of Metrology and Qualify Investigation, and Shenzhen University. Now, he is an associate professor at the Department

of Software, Shenzhen Institute of Information Technology, Shenzhen, China. His current research interests include medical image analysis, biometrics, image processing, and pattern recognition.

Yujiu Yang received the Ph.D. degree in pattern recognition from the Institute of Automation, Chinese Academy of Sciences, in 2008. He is currently an associate professor with the Graduate School at Shenzhen, Tsinghua University. His current research interests include statistical learning theory, web data mining, big data analytics, and machine learning. He has served as a member of the IEEE Computer Society and the Association for Computing Machinery from 2008.

Jane You obtained her B.Eng. in Electronic Engineering from the Xi'an Jiaotong Universityin1986 and herPh.D. in Computer Science from LaTrobe University, Australia in 1992. She was a lecturer at the University of South Australia and senior lecturer at Griffith University from 1993 till 2002.Currently she is a professor at the Hong Kong Polytechnic University. Her research interests include image processing, pattern recognition, medical imaging, biometrics computing, multimedia systems and data mining.