Learning Gabor Magnitude Features for Palmprint Recognition

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Abstract. Palmprint recognition, as a new branch of biometric technology, has attracted much attention in recent years. Various palmprint representations have been proposed for recognition. Gabor feature has been recognized as one of the most effective representations for palmprint recognition, where Gabor phase and orientation feature representations are extensively studied. In this paper, we explore a novel Gabor magnitude feature-based method for palmprint recognition. The novelties are as follows: First, we propose an illumination normalization method for palmprint images to decrease the influence of illumination variations caused by different sensors and lighting conditions. Second, we propose to use Gabor magnitude features for palmprint representation. Third, we utilize AdaBoost learning to extract most effective features and apply Local Discriminant Analysis (LDA) to reduce the dimension further for palmprint recognition. Experimental results on three large palmprint databases demonstrate the effectiveness of proposed method. Compared with state-of-the-art Gabor-based methods, our method achieves higher accuracy.

1 Introduction

Biometrics is an emerging technology by using unique and measurable physical characteristics to identify a person. The physical attributes include face, fingerprint, iris, palmprint, hand geometry, gait, and voice. Biometric systems have been successfully used in many different application contexts, such as airports, passports, access control, etc. Compared with other biometric technologies, palmprint recognition has a relatively shorter history and has received increasing interest in recent years.

Various techniques have been proposed for palmprint recognition in the literature [1,2,3,4,5,6,7,8,9,10]. They can be mainly classified into three categories according to the palmprint feature representation method. The first category is based on structure features, such as line features [1] and feature points [2]. The second one is based on holistic appearance features, such as PCA [3], LDA [4] and KLDA [5]. The third one is based on local appearance features, such as PalmCode [7], FusionCode [8], Competitive Code [9] and Ordinal Code [10].

Among these representation methods, Gabor feature is one of the most efficient representations for palmprint recognition. Zhang et al. [7] proposed a texture-based method for online palmprint recognition, where 2D Gabor filter was used to extract the

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phase information (called PalmCode) from low-resolution palmprint images. Kong and Zhang [8] improved the efficiency of PalmCode method by fusing the codes computed in four different orientations (called FusionCode). Multiple Gabor filters are employed to extract phase information on a palmprint image. To further improve the performance, Kong and Zhang [9] proposed another Gabor based method, namely competitive code. The competitive coding scheme uses multiple 2D Gabor filters to extract orientation information from palm lines based on the winner-take-all competitive rule [9]. Combined with angular matching, promising performance has been achieved.

Gabor phase and orientation features have been extensively studied in existing works [7,8,9]. In this paper, we attempt to explore Gabor magnitude feature representation for palmprint recognition. First, to increase the generalization capacity and decrease the influence of illumination variations due to different sensors and lighting environments, we propose an illumination normalization method for palmprint images. Second, multi-scale, multi-orientation Gabor filters are used to extract Gabor magnitude features for palmprint representation. The original feature set is of high dimensionality. Then, we utilize AdaBoost learning to select most effective features from the large number of candidate feature set, followed by Local Discriminant Analysis (LDA) for further dimensionality reduction. Experimental results demonstrate the good performance of proposed method. Compared with state-of-the-art Gabor-based method, our method achieves higher accuracy. Moreover, the processing speed of the method is very fast. In the testing phase, the execution time for the illumination normalization, feature extraction, feature space to LDA subspace projection and matching for one image are 30ms, 20ms, 1.5ms and 0.01ms, respectively.

The rest of this paper is organized as follows. In Section 2, we introduce the illumination normalization method. In Section 3, we describe the Gabor magnitude features for palmprint representation. Section 4 gives the details of statistical learning for feature selection and classifier. Experimental results and conclusions are presented in Section 5 and Section 6, respectively.

2 Illumination Normalization

Due to different sensors and lighting environments, the palmprint images are varied significantly, as shown in the top row of Fig. 1. A robust illumination preprocessing method will help to diminish the influence of illumination variations and increase the robustness of recognition method.

In general, an image $I(x, y)$ is regarded as product $I(x, y) = R(x, y)L(x, y)$, where $R(x, y)$ is the reflectance and $L(x, y)$ is the illuminance at each point (x, y). The reflectance R depends on the albedo and surface normal, which is the intrinsic representation of an object. The luminance L is the extrinsic factor. Therefore, the illumination normalization problem reduces to how to obtain R given an input image I.

However, estimating the reflectance and the illuminance is an ill-posed problem. To solve the problem, a common assumption is that the illumination L varies slowly while the reflectance R can change abruptly. In our work, we introduce an anisotropic approach to compute the estimate of the illumination field $L(x, y)$, which has been used

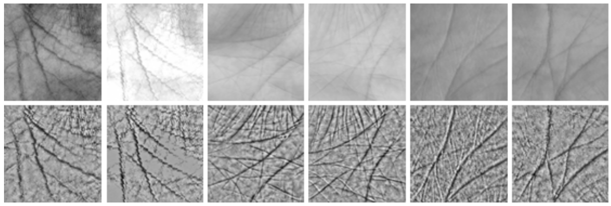

Fig. 1. Examples of the palmprint images from different sensors before and after illumination normalization. Top: Original palmprint images. Bottom: Corresponding processed palmprint images. The images are taken from the PolyU Palmprint Database [12] (first two columns), UST Hand Database [13] (middle two columns) and CASIA Palmprint Database [14] (last two columns).

for face recognition [11]. Then, we estimate the reflectance $R(x, y)$ as the ratio of the image $I(x, y)$ and $L(x, y)$ for palmprint image,

The luminance function was estimated as an anisotropically smoothed version of the original image, which can be carried out by minimizing the cost function:

$$J(L) = \int_y \int_x \rho(x,y)(L - I)^2 dxdy + \lambda \int_y \int_x (L_x^2 + L_y^2) dxdy \tag{1}$$

where the first is the data term while the second term is a regularization term which imposes a smoothness constraint. The parameter λ controls the relative importance of the two terms. ρ is Weber's local contrast between a pixel a and its neighbor b in either the x or y directions [11]. The space varying permeability weight $\rho(x, y)$ controls the anisotropic nature of the smoothing constraint.

By Euler-Lagrange equation, Equ. (1) transforms to solve the following partial differential equation (PDE):

$$L + \frac{\lambda}{\rho}(L_{xx} + L_{yy}) = I \tag{2}$$

The PDE approach is easy to implement. By the regularized approach, the influence of the illumination variations is diminished, while the edge information of the palmprint image is preserved. Fig. 1 show some examples from several different palmprint database before and after processing with the method. In section 5, we will further evaluate the effectiveness of the illumination normalization method on a large palmprint database.

3 Gabor Magnitude Features for Palmprint Representation

Gabor features exhibit desirable characteristics of spatial locality and orientation selectively, and are optimally localized in the space and frequency domains. The Gabor kernels can be defined as follows [15]:

$$\psi_{\mu,v} = \frac{k_{\mu,v}^2}{\sigma^2} exp(\frac{k_{\mu,v}^2 z^2}{2\sigma^2})[exp(ik_{\mu,v} z) - exp(-\frac{\sigma^2}{2})] \tag{3}$$

where μ and v define the orientation and scale of the Gabor kernels respectively, $z = (x, y)$, and the wave vector $k_{\mu,v}$ is defined as follows:

$$k_{\mu,v} = k_v e^{i\phi_\mu} \tag{4}$$

where $k_v = k_{max}/f^v$, $k_{max} = \pi/2$, $f = \sqrt{2}$, $\phi_\mu = \pi\mu/8$. The Gabor kernels in Equ. 3 are all self-similar since they can be generated from one filter, the mother wavelet, by scaling and rotating via the wave vector $k_{\mu,v}$. Each kernel is a product of a Gaussian envelope and a complex plane wave, while the first term in the square brackets in Equ. (3) determines the oscillatory part of the kernel and the second term compensates for the DC value. Hence, a bank of Gabor filters is generated by a set of various scales and rotations. In our experiment, we use Gabor kernels at five scales $v \in \{0, 1, 2, 3, 4\}$ and eight orientations $\mu \in \{0, 1, 2, 3, 4, 5, 6, 7\}$ with the parameter $\mu = 2\pi$ to derive the Gabor representation by convoluting palmprint image with corresponding Gabor kernels.

Let $I(x, y)$ be the gray level distribution of an palmprint image , the convolution of image I and a Gabor kernel $\psi_{\mu,v}$ is defined as:

$$F_{\mu,v}(z) = I(z) * \psi_{\mu,v}(z) \tag{5}$$

where $z = (x, y)$, $*$ denotes the convolution operator. Gabor magnitude feature is defined as

$$M_{\mu,v}(z) = \sqrt{Im(F_{\mu,v}(z))^2 + Re(F_{\mu,v}(z))^2} \tag{6}$$

where $Im(\cdot)$ and $Re(\cdot)$ denote the imaginary and real part, respectively. For each pixel position (x, y) in the palmprint image, 40 Gabor magnitudes are calculated to form the feature representation.

4 Statistical Learning of Best Features and Classifiers

The whole set of Gabor magnitude features is of high dimension. For a palmprint image with size of 128×128 , there are about 655,360 features in total. Not all of them are useful or equally useful, and some of them may cause negative effect on the performance. Straightforward implementation is both computationally expensive and exhibits a lack of efficiency. In this work, we utilize AdaBoost learning first to select the most informative features and then apply linear discriminant analysis (LDA) on the selected Gabor magnitude features for further dimension reduction.

4.1 Feature Selection by AdaBoost Learning

Boosting can be viewed as a stage-wise approximation to an additive logistic regression model using Bernoulli log-likelihood as a criterion [16]. AdaBoost is a typical instance of Boosting learning. It has been successfully used on face detection problem [17] as an effective feature selection method. There are several different versions of AdaBoost algorithm [16], such as Discrete AdaBoost, Real AdaBoost, LogitBoost and Gentle AdaBoost. In this work, we apply Gentle AdaBoost learning to select most discriminative Gabor magnitude features and remove the useless and redundant features. Gentle AdaBoost is a modified version of the Real AdaBoost algorithm and is defined in Fig. 2.

Input:	Sequence of N weighted examples: $\{(x_1, y_1, w_1), (x_2, y_2, w_2), \ldots, (x_N, y_N, w_N)\}$;
Initialize:	$w_i = \frac{1}{N}, i = 1, 2, ..., N, F(x) = 0$
	Integer T specifying number of iterations;
For t = 1, . . . ,T	
(a) Fit the regression function $f_t(x)$ by weighted least squares of y_i to x_i with weights w_i.	
(b) Update $F(x) \leftarrow F(x) + f_t(x)$	
(c) Update $w_i \leftarrow w_i e^{-y_i f_t(x_i)}$ and renormalize.	
3. Output the classifier $sign[F(x)] = sign[\sum_{t=1}^{T} f_t(x)]$	

Fig. 2. Algorithm of Gentle AdaBoost

Empirical evidence suggests that Gentle AdaBoost is a more conservative algorithm that has similar performance to both the Real AdaBoost and LogitBoost algorithms, and often outperforms them both, especially when stability is a crucial issue [16].

While the above AdaBoost procedure essentially learns a two-class classifier, we convert the multi-class problem into a two-class one using the idea of intra- and extra-class difference [18]. However, here the difference data are derived from each pair of Gabor magnitude features at the corresponding locations rather than from the images. The positive examples are derived from pairs of intra-personal differences and the negative from pairs of extra-personal differences.

In this work, the weak classifier in AdaBoost learning is constructed by using a single Gabor magnitude feature. Therefore, AdaBoost learning algorithm can be considered as a feature selection algorithm [17,19]. With the selected feature set, a series of statistical methods can be used to construct effective classifier. In the following, we introduce LDA for dimension reduction further and use cosine distance for palmprint recognition and expect it can achieve better performance.

4.2 LDA with Selected Features

LDA is a famous method for feature extraction and dimension reduction that maximizes the extra-class distance while minimized the intra-class distance. Let the sample set be $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n\}$, where $\mathbf{x}_i$ is the feature vector for the i-th sample. The within-class scatter matrix $\mathbf{S}_w$ and the between-class scatter matrix $\mathbf{S}_b$ are defined as follows:

$$\mathbf{S}_w = \sum_{i=1}^{L} \sum_{\mathbf{x}_j \in C_i} (\mathbf{x}_j - \mathbf{m}_i)^T (\mathbf{x}_j - \mathbf{m}_i) \tag{7}$$

$$\mathbf{S}_b = \sum_{i=1}^{L} n_i (\mathbf{m}_i - \mathbf{m})^T (\mathbf{m}_i - \mathbf{m}) \tag{8}$$

where $\mathbf{m}_i = \frac{1}{n_i} \sum_{\mathbf{x}_j \in C_i} \mathbf{x}_j$ is the mean vector in class C_i, and $\mathbf{m} = \frac{1}{n} \sum_{i=1}^{L} \sum_{\mathbf{x}_j \in C_i} \mathbf{x}_j$ is the global mean vector.

LDA aims to find projection matrix $\mathbf{W}$ so that the following object function is maximized:

$$J = \frac{tr(\mathbf{W}^T \mathbf{S}_b \mathbf{W})}{tr(\mathbf{W}^T \mathbf{S}_w \mathbf{W})} \tag{9}$$

The optimal projection matrix $\mathbf{W}_{opt}$ can be obtained by solving the following generalized eigen-value problem

$$\mathbf{S}_w^{-1} \mathbf{S}_b \mathbf{W} = \mathbf{W} \mathbf{\Lambda} \tag{10}$$

where $\mathbf{\Lambda}$ is a diagonal matrix whose diagonal elements are the eigenvalues of $\mathbf{S}_w^{-1}\mathbf{S}_b$.

Given two input vectors $\mathbf{x}_1$ and $\mathbf{x}_2$, their subspace projections are calculated as $\mathbf{v}_1 = \mathbf{W}^T\mathbf{x}_1$ and $\mathbf{v}_2 = \mathbf{W}^T\mathbf{x}_2$, and the following cosine distance is used for the matching:

$$H(\mathbf{v}_1, \mathbf{v}_2) = \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{\|\mathbf{v}_1\| \, \|\mathbf{v}_2\|} \tag{11}$$

where $\|.\|$ denotes the norm operator. In the test phase, the projections $\mathbf{v}_1$ and $\mathbf{v}_2$ are computed from two input vectors $\mathbf{x}_1$ and $\mathbf{x}_2$, one for the input palmprint image and another for an enrolled palmprint image. By comparing the score $H(\mathbf{v}_1, \mathbf{v}_2)$ with a threshold, a decision can be made whether $\mathbf{x}_1$ and $\mathbf{x}_2$ belong to the same person.

5 Experiments

To evaluate the performance of the proposed palmprint recognition method, three large palmprint databases are adopted, including PolyU Palmprint Database [12], UST Hand Image Database [13] and CASIA Palmprint Database [14]. These databases are among the largest in size in the public domain. We train the classifiers and evaluate the effectiveness of illumination normalization method on PolyU Palmprint Database. To explore the generalization of the classifier, we further evaluate the performance of proposed palmprint recognition method on the other two databases, and compare with the state-of-the-art Gabor-based recognition methods [7,8,9].

5.1 Evaluate on PolyU Palmprint Database

PolyU Palmprint Database[12] contains 7752 images corresponding to 386 different palms. Around twenty samples from each of these palms were collected in two sessions. There are some illumination variations between the two sessions. We select 4000 images from 200 different palms collected in two sessions as the testing set, with 20 images per palm. The rest 3752 images from 186 different palms are used for training. All the input palmprint images are normalized to 128×128 using the method proposed in [7].

In the training phase, the training set of positive samples were derived from intra-class pairs of Gabor features, the negative set from extra-class pairs. Two Gabor magnitude feature-based classifiers are trained. One is an AdaBoost learning based classifier, and another is an LDA based classifier using AdaBoost-selected features. These two methods are named “GMBoost” and “GMBoostLDA”, respectively. Moreover, to evaluate the effectiveness of the illumination normalization method, we also train two classifiers and test the performance on the palmprint images without illumination normalization.

The first two classifiers are trained using the palmprint images without illumination normalization. 882 most effective features are selected by the AdaBoost procedure from the original 655,360 Gabor magnitude features with the training error rate of zero on the training set. For LDA, the feature dimension retained is 181, which is optimal in the test set.

The other two classifiers are trained using the palmprint images with illumination normalization. 615 most effective features are selected with the training error rate of zero on the training set. The optimal feature dimension for LDA is 175 found in the test set. The first 5 most effective features learned by Gentle AdaBoost are shown in Fig. 3, in which the position, scale and orientation of corresponding Gabor kernels are indicated on an illumination normalized palmprint image.

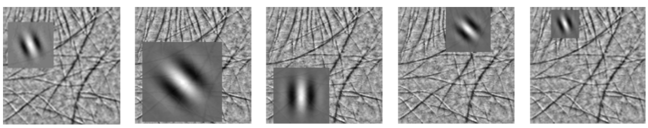

Fig. 3. The first 5 features and associated Gabor kernel selected by AdaBoost learning

In the testing phase, we match palmprints from different sessions. Each image from the first session is matched with all the images in the second sessions. This generated 20,000 intra-class (positive) and 380,000 extra-class (negative) pairs. Fig. 4 shows the ROC curves derived from the scores for the intra- and extra-class pairs. From the result, we can see that all these Gabor magnitude feature-based methods achieve good verification performances. The performance of “GMBoostLDA” methods are better than that of “GMBoost” methods. This indicates applying LDA with AdaBoost-selected features is a good scheme for palmprint recognition. Among these classifiers, “GMBoostLDA with Illumination Normalization” performs the best, which demonstrates the effectiveness of the proposed illumination normalization method.

The processing speed of proposed method is very fast. In the testing phase, only the features selected by the AdaBoost learning need to be extracted with the Gabor filter, which largely reduce the computational cost. On a P4 3.0GHz PC, the execution time for the illumination normalization, feature extraction, feature space to LDA subspace projection and matching for one image are 30ms, 20ms, 1.5ms and 0.01ms, respectively.

In the next subsection, we will further evaluate the performance of our best classifier on the other two databases to explore the generalization capacity and compare with the state-of-the-art Gabor-based recognition methods.

5.2 Evaluate on UST Hand Image Database and CASIA Palmprint Database

UST hand image database [13] contains 5,660 hand images corresponding to 566 different palms, 10 images per palm. All images are captured using a digital camera with

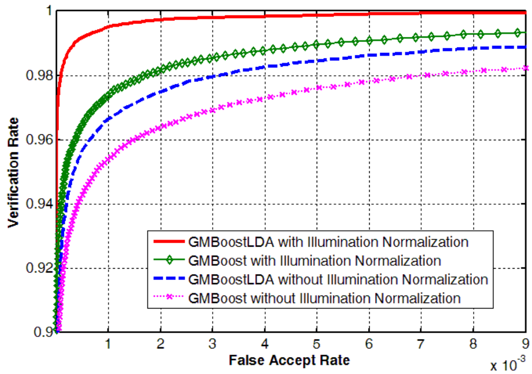

Fig. 4. Verification performance comparison on PolyU Palmprint Database

resolution of 1280 × 960 (in pixels) and 24-bit colors. There are totally 25,470 intra-class (genuine) samples and 15,989,500 extra-class (impostor) samples generated from the UST database.

CASIA palmprint database [14] contains 4,796 images corresponding to 564 different palms. All images are captured using a CMOS camera with resolution of 640x480 (in pixels) and 24-bit colors. There are 8 to 10 samples in each of these palms. There are totally 18,206 intra-class (genuine) samples and 11,480,204 extra-class (impostor) samples generated from the test set.

Fig. 5 shows the ROC curves derived from the scores for the intra- and extra-class samples. According to the ROC curves, the performance of the proposed method is better than that of the state-of-the-art Gabor-based recognition methods in both the two databases. Note that our classifier is trained on the PolyU database and tested on the UST and CASIA palmprint databases.

Two accuracy measurements are computed for further comparison in Table 1. One is the equal error rate (EER) and the other is the d' (d-prime) [20]. d' is a statistical measure of how well a biometric system can discriminate between different individuals defined as

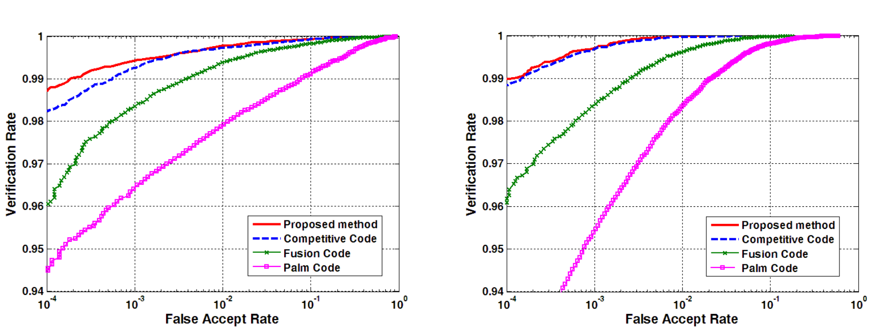

Fig. 5. Comparative results with state-of-the-art Gabor-based recognition methods. Left: ROC curves on UST Hand Image Database. Right: ROC curves on CASIA Palmprint Database.

$$d' = \frac{|m_1 - m_2|}{\sqrt{(\delta_1^2 + \delta_2^2)/2}} \tag{12}$$

where m_1 and δ_1 denote the mean and variance of intra-class feature vector respectively, while m_2 and δ_2 denote the mean and variance of extra-class feature vector. The larger the d' value is, the better a biometric system performs [20].

Table 1. Comparison of accuracy measures for different classifiers on UST and CASIA databases

Algorithm	Results on UST database		Results on CASIA database	
	EER (%)	d'	EER (%)	d'
Palm Code ($\theta = 45^{\circ}$) [7]	1.77	3.39	0.95	3.58
Fusion Code [8]	0.75	3.40	0.57	3.80
Competitive Code [9]	0.38	3.51	0.19	3.81
Proposed method	**0.35**	**5.36**	**0.17**	**5.57**

From the experimental results, we can see that both the EER and the discriminating index of proposed method achieve good performance (in bold font). This also suggests the good generalization capacity of proposed method, which can work well on different types of palmprint images.

6 Conclusions

In this paper, we have proposed a Gabor magnitude feature based learning method for palmprint recognition. To decrease the influence of illumination variations, we introduced an illumination normalization method for palmprint images. Then, multi-scale, multi-orientation Gabor filters are used to extract Gabor magnitude features. Based on the Gabor magnitude features and statistical learning, a powerful classifier is constructed. The experimental results show that Gabor magnitude features with statistical learning can be powerful enough for palmprint recognition. Compared with state-of-the-art Gabor-based method, our method achieves better performance on two large palmprint database.

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References

1. Zhang, D., Shu, W.: Two novel characteristics in palmprint verification: Datum point invariance and line feature matching. Pattern Recognition 32, 691–702 (1999)
2. Duta, N., Jain, A., Mardia, K.: Matching of palmprint. Pattern Recognition Letters 23, 477–485 (2001)

3. Lu, G., Zhang, D., Wang, K.: Palmprint recognition using eigenpalms features. Pattern Recognition Letters 24, 1463–1467 (2003)
4. Wu, X., Zhang, D., Wang, K.: Fisherpalms based palmprint recognition. Pattern Recognition Letters 24, 2829–2838 (2003)
5. Wang, Y., Ruan, Q.: Kernel fisher discriminant analust-hand-databaseysis for palmprint recognition. In: Proceedings of International Conference Pattern Recognition, vol. 4, pp. 457–461 (2006)
6. Kumar, A., Shen, H.: Palmprint identification using palmcodes. In: ICIG 2004. Proceedings of the Third International Conference on Image and Graphics, Hong Kong, China, pp. 258–261 (2004)
7. Zhang, D., Kong, W., You, J., Wong, M.: On-line palmprint identification. IEEE Transactions on Pattern Analysis and Machine Intelligence 25, 1041–1050 (2003)
8. Kong, W., Zhang, D.: Feature-Level Fusion for Effective Palmprint Authentication. In: Zhang, D., Jain, A.K. (eds.) ICBA 2004. LNCS, vol. 3072, pp. 761–767. Springer, Heidelberg (2004)
9. Kong, W., Zhang, D.: Competitive coding scheme for palmprint verification. In: Proceedings of International Conference Pattern Recognition, vol. 1, pp. 520–523 (2004)
10. Sun, Z., Tan, T., Wang, Y., Li, S.: Ordinal palmprint represention for personal identification. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 279–284. IEEE Computer Society Press, Los Alamitos (2005)
11. Gross, R., Brajovic, V.: An image preprocessing algorithm for illumination invariant face recognition. In: Proc. 4th International Conference on Audio- and Video-Based Biometric Person Authentication, Guildford, UK, pp. 10–18 (2003)
12. PolyU Palmprint Database, `http://www.comp.polyu.edu.hk/biometrics/`
13. UST Hand Image database, `http://visgraph.cs.ust.hk/biometrics/Visgraph_web/index.html`
14. CASIA Palmprint Database, `http://www.cbsr.ia.ac.cn/`
15. Daugman, J.G.: Complete discret 2d gabor transforms by neural networks for image analysis and compression. IEEE Trans. ASSP 36, 1169–1179 (1988)
16. Friedman, J., Hastie, T., Tibshirani, R.: Additive logistic regression: a statistical view of boosting. Technical report, Department of Statistics, Sequoia Hall, Stanford Univerity (1998)
17. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Kauai, Hawaii, IEEE Computer Society Press, Los Alamitos (2001)
18. Moghaddam, B., Nastar, C., Pentland, A.: A Bayesian similarity measure for direct image matching. Media Lab Tech Report No.393, MIT (1996)
19. Shan, S., Yang, P., Chen, X., Gao, W.: AdaBoost gabor fisher classifier for face recognition. In: Proceedings of IEEE International Workshop on Analysis and Modeling of Faces and Gestures, Beijing, China, pp. 279–292. IEEE Computer Society Press, Los Alamitos (2005)
20. Daugman, J., Williams, G.: A Proposed Standard for Biometric Decidability. In: Proc. CardTech/SecureTech Conference, pp. 223–234 (1996)