Fusion of Multi-spectral Palmprint Images for Improved Identification Performance

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***Abstract*-Biometric system has been actively emerging in various industries for the past few years and it is continuing to roll to provide higher security features for access control system. In this paper, we propose a multi-modal system for person identification using multi-spectral palmprint images. In this work, the observation vectors are extracted using 2D Gabor filters. Thus, the images {RED, BLUE, GREEN and Nearest-Infrared (NIR)} are filtered by a 2D Gabor filter with different orientations and then compressed using the PCA. Subsequently, we use the GMM and HMM for modeling the observation vector of each band. Finally, log-likelihood scores are used for palmprint matching. The multi-modal systems fuse information from several modalities in order to achieve better identification performance. Therefore, all bands are integrated using the fusion at the matching score level in order to construct an efficient multi-modal identification system. The experimental results showed that the designed system achieves an excellent identification rate and provide more security than uni-modal system.**

Keywords-Biometrics; Identification; Multi-spectral Palmprint; Gabor Filter; PCA; GMM; HMM; Data Fusion

I. INTRODUCTION

Automatic personal identification with the use of biometrics technologies has been an active research area in pattern recognition and computer vision in recent years. In addition to the importance of pure research, it has a number of field applications such as surveillance and security systems, physical buildings and more applications. These technologies make use of the physical and behavioural characteristics of person such as fingerprint, iris, face, palmprint, signature, and voice for personal identification, which can provide advantages over non-biometric methods such as PIN, and ID cards [1]. Among these biometric technologies, palmprint identification is one of the most stable and reliable system. Palmprint identification is a biometric technology which recognizes a person based on his/her palmprint pattern. Palmprint serves as a reliable human identifier because the print patterns cannot be duplicated. Compared with other physical biometric characteristics, palmprint identification has several advantages such as low-resolution imaging, stable line features, and low-cost capturing device [2]. It covers wider area than fingerprint and it contains abundance of useful information for identification.

In this paper, we first propose a multi-spectral palmprint identification algorithm based on single band. In this study, feature extraction module was made by using the Gabor phase response. During feature extraction stage, five orientations for Gabor filters were used. As next step, Principal Components Analysis (PCA) was applied to these features. In the modeling stage, Hidden Markov Model (HMM) was used. To compute the correct identification rate of proposed HMM classifier, it was compared to Gaussian Mixture Model (GMM) by using a data set containing 300 samples. However, uni-modal systems are not perfect and problems like noise in the sensed biometric data, non-universality, and the lack of distinctiveness of the chosen biometric trait lead to unacceptable error rates in recognizing a person. Some of the limitations imposed by single modal biometric systems can be overcome by using multiple biometric modalities [3]. The multimodal biometric systems are expected to be more reliable due to the presence of multiple templates security. For that, the paper presents a section for fusing information from palmprint images captured under different light spectrum (different band) at the matching score level.

The rest of the paper is organized as follows: The proposed uni-modal identification scheme is presented in Section II. Section III gives a brief description of the region of interest extraction. The feature extraction and modeling process, including an overview of the Gabor filter, HMM and GMM, is presented in Section IV. The obtained results, prior to fusion and after fusion, are evaluated in Section V. Finally, conclusions and future work are given.

II. UNI-MODAL SYSTEM DESCRIPTION

The proposed system is composed of two or more sub-systems exchanging information in matching score level. Each sub-system exploits different modalities (band images). Each uni-modal biometric system (for example, Fig. 1) shows a uni-modal biometric identification system based on RED modality. This system performs on each band image of the palm surface of the hand. In the pre-processing module, the band image is segmented using a segmentation procedure described in [4]. In the next module, firstly the observation vectors describing the shape of the band are computed using Gabor phase response, and are compressed using PCA technique. Afterwards, the observation vectors are modelled and these models are then stored in the system database. In the matching module, the matching between the observation vectors and the models previously stored in the database is performed using log-likelihood score. Finally, in the decision module, the output of the matching module is compared with the security threshold, and the final decision is made.

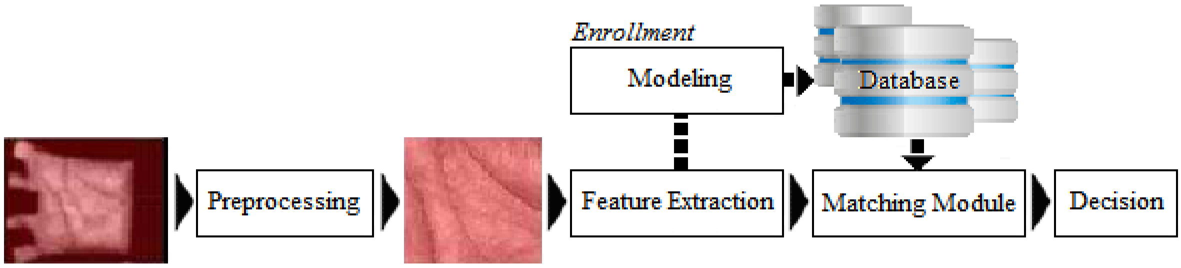

Fig. 1 An illustration of a typical uni-modal palmprint identification system based on RED band modality

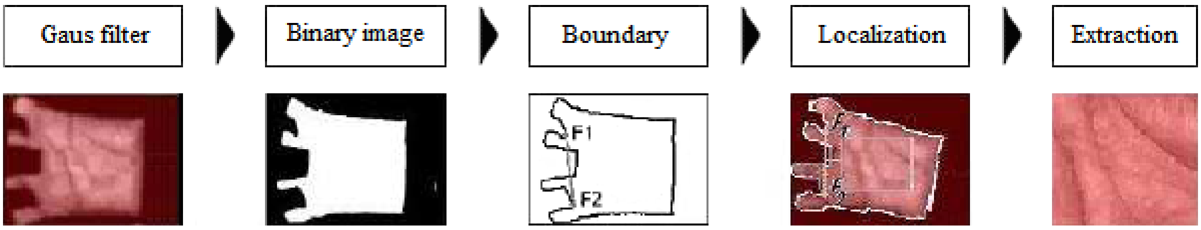

Fig. 2 Various steps in a typical region of interest extraction algorithm: (a) the filtered image; (b) the binary image; (c) the boundaries of the binary image and the points for locating the ROI pattern; (d) the central portion localization; (e) the pre-processed result (ROI)

III. PALMPRINT PRE-PROCESSING

In order to localize the palm area, the first step is to preprocess the palm images. We use the preprocessing technique described in [4] to align the palmprints. In this technique, Gaussian smoothing filter is used to smoothen the image before extracting the Region of Interest (ROI) and its features. After that, Otsu's thresholding is used for binarization of the hand. A contour-following algorithm is used to extract the hand contour. The tangent of the two stable points on the hand contour (they are between the forefinger and the middle finger and between the ring finger and the little finger) are computed and used to align the palmprint. The central part of the image, which is 128x128, is then cropped to represent the whole palmprint. Fig. 2(see above) shows the palmprint pre-processing steps.

IV. FEATURE EXTRACTION AND MODELING

The feature extraction module processes the acquired biometric data and extracts only the salient information to form a new representation of the data. Ideally, this new representation should be unique for each person. In our method, the band modality is typically analysed using Gabor filter and a PCA technique. After the decomposition transform of the Gabor phase response, some of vector components are selected to construct observation vectors.

A. Observation Vector Generation

Gabor filters can be used to extract components corresponding to different scales and orientations from images. The 2D Gabor filter can be represented as a complex sinusoidal signal modulated by a Gaussian function (envelope). Specifically, a 2D Gabor filter hθ(x, y) can be formulated as follows [5]:

$$h_\theta(x,y) = \frac{1}{2\pi\sigma^2} e^{((x^2+y^2)/2\sigma^2)} e^{2\pi iu(x\cos\theta + y\sin\theta)} \quad (1)$$

Where $i=\sqrt{-1}$, u is the frequency of the sinusoidal signal, θ controls the orientation of the function, and σ is the standard deviation of the Gaussian envelope. In order to select Gabor filters for band pass filtering, three parameters have to be determined: frequency u, orientation θ, and space constants σ. The values of θ only in the interval [-90o, 90o] are considered, since other values are redundant due to symmetry.

In this work, the parameters of Gabor filters were empirically determined for the acquired palmprint band images. These were set as; u = 0.0916, and σ = 5.6179. Gabor filters with five different values of θ (-60o,-30o, 0o, 30o, 60o) were employed. Filtering the image I(x, y) with the Gabor filter hθ (x, y), can be defined by the following equation:

$$I_\theta(x,y) = h_\theta(x,y) * I(x,y) = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} h_\theta(m,n) I(x-m, y-n) \quad (2)$$

Where * denotes discrete convolution and the Gabor filter mask is of size NxN, with N = 16. Thus every image is filtered with a bank of five filters to generate five filtered images. The results Re{Iθ}, and Im{Iθ} of a pair of a real and an imaginary filter are combined in the Gabor phase response, ψθ as follows:

$$\psi_\theta = \arctan\left[\frac{\operatorname{Im}\{I_\theta\}}{\operatorname{Re}\{I_\theta\}}\right] \quad (3)$$

The features are generated from ψθ by PCA technique [6]. This feature-extraction technique has been widely used for pattern recognition, as well as in the field of biometrics. Applying the PCA technique to the vectors ψθ for each filtered images (ψθ), we decorrelate the vectors of ψθ, and concentrate the information content on the first components of the transformed vectors. The observation vector is formed by taking some components of the transformed vectors (for each orientation, θ) and concatenating all transformed vectors on one vector (observation vector). Fig. 3 (see above) illustrates the proposed feature extracted method.

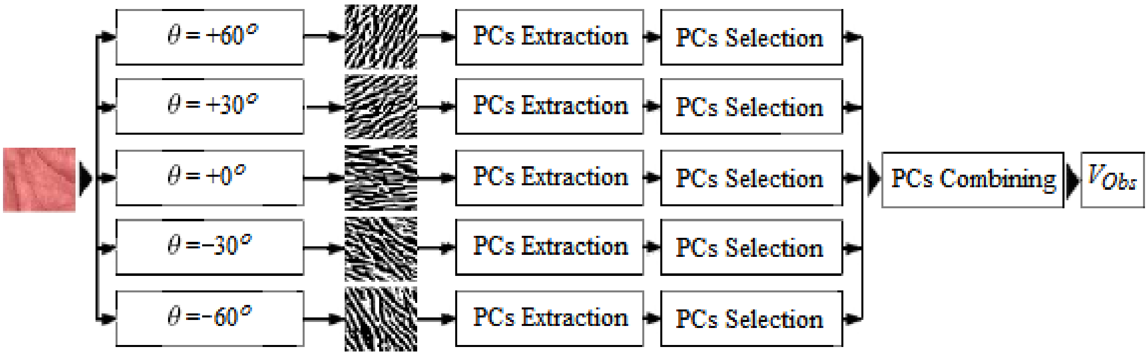

Fig. 3 The observation vector extraction algorithm

B. Modeling Process

1) Gaussian Mixture Model:

Gaussian mixture model is a pattern recognition technique that uses an approach of the statistical methods [7]. The observation vector of each class measurement can be described by normal distribution, also called Gaussian distribution. Each class measurement may be then defined by two parameters: mean (average) and standard deviation (variability). Suppose that the observation vector is the discrete random variable VObs. For the general case, where vector is multidimensional, the probability density function of the normal distribution is a Gaussian function:

$$P(V_{obs} / \mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^d |\Sigma|}} \exp\left[-\frac{1}{2}(V_{obs} - \mu)^T \Sigma^{-1} (V_{obs} - \mu)\right] \quad (4)$$

Where μ is the mean, Σ is the covariance matrix and d is the dimension of feature vector. Covariance matrix is the natural generalization to higher dimensions of the concept of the variance of a random variable. If we suppose the random variable measurement is not characterized only with simple Gaussian distribution, we can then define it with multiple Gaussian components. GMM is a probability distribution that is a convex combination of other Gaussian distributions:

$$P(V_{obs}) = \sum_{i=1}^{M} \pi_i P(V_{obs} / \mu_i, \Sigma_i) \quad (5)$$

Where M is the number of Gaussian mixtures and πi is the weight of each of the mixture. After GMM is trained, the model of each user will be the final values of πi, μi and Σi. Thus, the compact notation θ, such that $\theta = \{\pi_i, \mu_i, \Sigma_i\}_{i=1}^{N}$, is used to represent a model. To estimate the density parameters of a GMM statistic model, Expectation-Maximization algorithm (EM) is adopted [8].

2) Hidden Markov Model:

A hidden Markov model is a collection of finite states connected by transitions. Each state is characterized by two sets of probabilities: a transition probability and either a discrete output probability distribution or continuous output probability density function which, given the state, defines the condition probability of emitting each output symbol from a finite alphabet or a continuous random vector [9]. An HMM can be written in a compact notation λ= (A, B, π) to represent the complete parameter set of the model, where A is the state transition probability distribution, B is probability distribution of observation symbols for each state, and π is the initial state distribution of any given state. Finally, forward backward recursive algorithm, Baum-Welch or otherwise EM algorithm, and Viterbi algorithm are used to solve evaluating, training, and decoding, respectively [10].

V. EXPERIMENT RESULTS AND DISCUSSIONS

A. Experimental Database

Experiments are performed on the multi-spectral palm print database from the Hong Kong polytechnic university (PolyU) [11]. The database contains images captured with visible and infrared light. Multi-spectral palmprint images were collected from 300 volunteers, including 195 males and 105 females. The age distribution is from twenty to sixty years old. It has a total of 14400 images obtained from about 300 different palms. These samples were collected in two separate sessions. In each session, the subject was asked to provide six images for each palm. Therefore, twenty-four images of each illumination from two palms were collected from each subject. The average time interval between the first and the second sessions was about nine days.

B. GMM-based Identification

1) Open Set Identification:

When an unknown sample is presented to the identification system, the system generates an observation vector and calculates the Log-likelihood score of this vector given each model stored in the database. Thus, a Min-Max normalization scheme was employed to transform the Log-likelihood scores computed into similarity scores in the same range, [0...1]. In this section, the proposed method was tested through the open-set identification. In all experiments, the impostor and genuine distributions are generated by 2700 and 403650 comparisons, respectively. All the Experiments are performed on the multi-spectral palmprint (MSP) database from Hong Kong Polytechnic University.

a) Number of Gaussian in the GMM: A series of experiments were carried out using the MSP database to select the best number of Gaussian in GMM, and this is carried out by comparing all k Gaussian, k = 1 to 5, and finding the number of Gaussian in GMM that gives the best identification rate. The problem we address is as follows: we want the chosen number of Gaussian in GMM such that the Equal Error Rate (EER) is minimized. In Fig. 4.(a), we compare the system performance under different number of Gaussian in GMM. The results show the benefits of using one Gaussian in GMM.

b) Single band palm-print image: The goal of this experiment was to evaluate the system performance when we using information from each bands. Fig. 4.(b) compares the performance of the system for deferent bands. It can safely be seen the benefits of using the BLUE band than the other bands in terms of EER. It can achieve an EER equal to 0.327 % at the threshold To = 0.8035. Therefore, the system can achieve higher accuracy at the BLUE band when compared with the other bands. Finally, the ROC curve obtained by the proposed scheme is plotted in Fig. 4.(c). Table I shows the False Acceptance Rate (FAR) and False Rejection Rate (FRR) with percentage using all bands at deferent thresholds.

c) Multiple band palmprint image: At the matching score level fusion, the matching scores output by multiple matchers (subsystem) are integrated. In our system, two combinations of bands (RGB and RGBN) and different fusion rules, such as Sum-score (SUM), Min-score (MIN), Max-score (MAX), Mul-score (MUL) and Sum-weighting score (WHT), were tested to find the combination that optimizes the system accuracy. Thus, to find the better of the all fusion rules and combinations, with the lowest EER, Table II tabulates EER for the two combinations and fusion rules. As can be seen, the best result was obtained with the combination of RGBN and the fusion rule was MUL rule, it can achieve even higher precision, an EER of 0.005 % and a To of 0.6184.

2) Closed-set Identification:

In the case of a closed set identification, a series of experiments were carried out to select the best color band (best combination).

a) Single band palm-print image: For the evaluation of the closed set identification, Table III presents the experiments results obtained for all color bands. From this Table, it can be seen that the GREEN band done the best performance. Thus, the performance of the closed set identification system is significantly improved by using this band. The Rank-One Recognition (ROR) rate = 97.556 % with a lowest Rank of Perfect Recognition (RPR) of 110.

b) Multiple band palmprint images: A performance comparison of all fusion rules of all bands combination (RGB and RGBN) is made in Table IV. This table shows that the SUM rule with RGBN combination offers better results in terms of the ROR (ROR = 99.815 % with RPR = 8). The results suggests that always SUM rule has performed better than other fusion rules, in the case of RGB combination (ROR = 99.667 % with RPR = 9).

3) Summary Study:

According to the experimental results, multimodal biometrics performs better than the individual biometrics in both cases closed set and open set identification (see Fig. 5.(a) and Fig. 5.(b). This shows that multimodal biometrics have the ability to improve the identification accuracy over individual biometrics. This result is shown clearly at the case of RGBN combination.

C. HMM-based Identification

1) Open-set Identification:

In this section, the results for our proposed method were obtained using the HMM modeling. In order to evaluate the benefit of the HMM modeling, we perform just as the experiments presented in the previous section (GMM modeling).

a) Number of states in the HMM: The experimental setup is similar to that described in the first part of this section. However, the following gives the results of our method as a ROC curves, which shows the FAR and FRR at each threshold value. Fig. 6.(a) shows ROC curves generated by five states of HMM, from which we can see that two states perform the best among the others evaluated in terms of EER. Note that the number of Gaussian in each state is equal to 1.

b) Single band palmprint image: In this section, we compare the performance of all bands. Fig. 6.(b) compares the performance of the system for deferent bands. The experimental results indicate that the BLUE band performs better than the others (EER = 0.377 % with To = 0.7878). Finally, the ROC curve obtained by the proposed scheme is plotted in Fig. 6.(c). Table V provides the performance of the system under all bands.

c) Multiple band palmprint images: To find the better fusion rules and the best combination, Table VI is generated. This table shows that the SUM, WHT, and MUL rule offers better results in terms of the EER (EER = 0.037 % with To = 0.7670, To = 0.7789, and To = 0.4425, respectively). Finally, the results show the benefits of using the GMM modeling in the uni-modal and multi-modal system.

2) Closed Set Identification:

In this section, we compare the performance of all bands in the case of closed set identification.

a) Single band palmprint image: In this case, a series of experiments were carried out to select the best palmprint band. This has been done by comparing all bands and finding the band that gives the best identification rate. Table VII shows the results for all bands. From this table, it is clear that our system achieves a best performance when using BLUE band (ROR = 97.296 % and RPR = 142).

b) Multiple band palmprint images: Table VIII shows the close set identification results of the multimodal system. This Table shows that MUL fusion rule and RGBN combination performs better than the other rules and improves the original performance by ROR = 99.815 % and RPR = 32. Also, we can see that SUM rule followed by WHT rule fusion can produce a best performance, ROR equal to 99.778 % (RPR = 38) and 99.741 % (RPR = 42), respectively.

3) Summary Study:

Fig. 7.(a) and Fig. 7.(b) show the comparison of uni-modal and multimodal systems in the closed/open set identification, respectively. Results show that the identification rate of multimodal identification based on fusion of all bands is higher than that of the identification adopting the uni-modality.

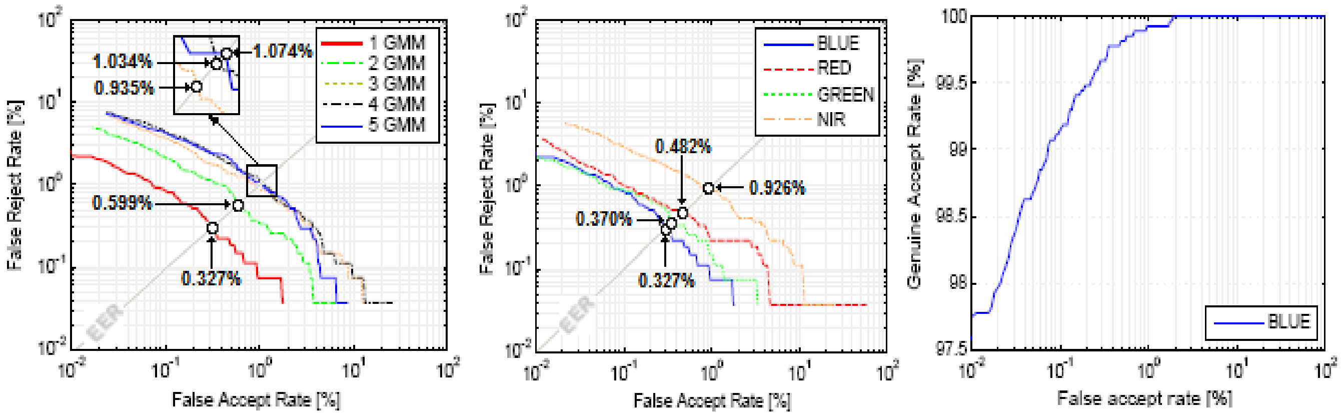

Fig. 4 GMM-based uni-modal biometric identification test results: *(a)* the ROC curves under different number of Gaussian; *(b)* the ROC curves for all palm-print bands and *(c)* the ROC curve for the blue band

TABLE I GMM-BASED OPEN SET UNI-MODAL SYSTEMS PERFORMANCES

DB SIZE	BLUE			GREEN			RED			NIR		
	T_o	FAR	FRR	T_o	FAR	FRR	T_o	FAR	FRR	T_o	FAR	FRR
300	0.6700	2.121	0.000	0.6200	3.804	0.000	0.6100	4.882	0.037	0.6200	5.207	0.222
	0.8035	0.327	0.327	0.7856	0.370	0.370	0.7870	0.482	0.482	0.7858	0.926	0.926
	1.0000	0.007	2.704	1.0000	0.008	2.444	1.0000	0.011	3.778	1.0000	0.021	0.889

TABLE II GMM-BASED OPEN SET MULTI-MODAL SYSTEMS PERFORMANCES

COMBINATION	SUM		WHT		MIN		MAX		MUL	
	T_o	EER	T_o	EER	T_o	EER	T_o	EER	T_o	EER
RGB	0.8184	0.029	0.8331	0.026	0.7670	0.098	0.8764	0.185	0.6169	0.024
RGBN	0.8614	0.006	0.8438	0.010	0.7461	0.100	0.9243	0.148	0.6184	0.005

TABLE III GMM-BASED CLOSED SET UNI-MODAL SYSTEMS PERFORMANCES

DB SIZE	BLUE		GREEN		RED		NIR	
	ROR	RPR	ROR	RPR	ROR	RPR	ROR	RPR
300	97.296	41	97.556	110	96.222	251	94.111	201

TABLE IV GMM-BASED CLOSED SET MULTI-MODAL SYSTEMS PERFORMANCES

COMBINATION	SUM		WHT		MIN		MAX		MUL	
	ROR	RPR	ROR	RPR	ROR	RPR	ROR	RPR	ROR	RPR
RGB	99.667	9	99.556	11	99.370	99	96.222	38	99.667	10
RGBN	99.815	8	99.778	10	99.407	99	94.407	41	99.815	9

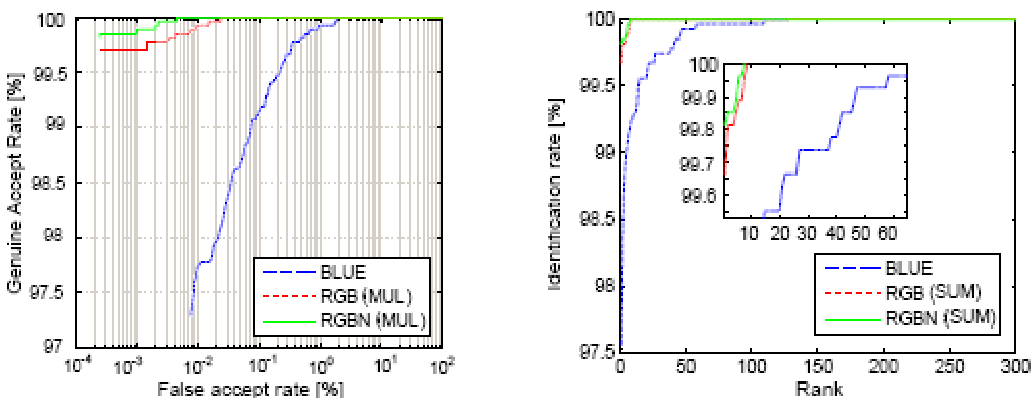

Fig. 5 Comparison of different GMM based systems: *(a)* open set identification systems and *(b)* closed set identification systems

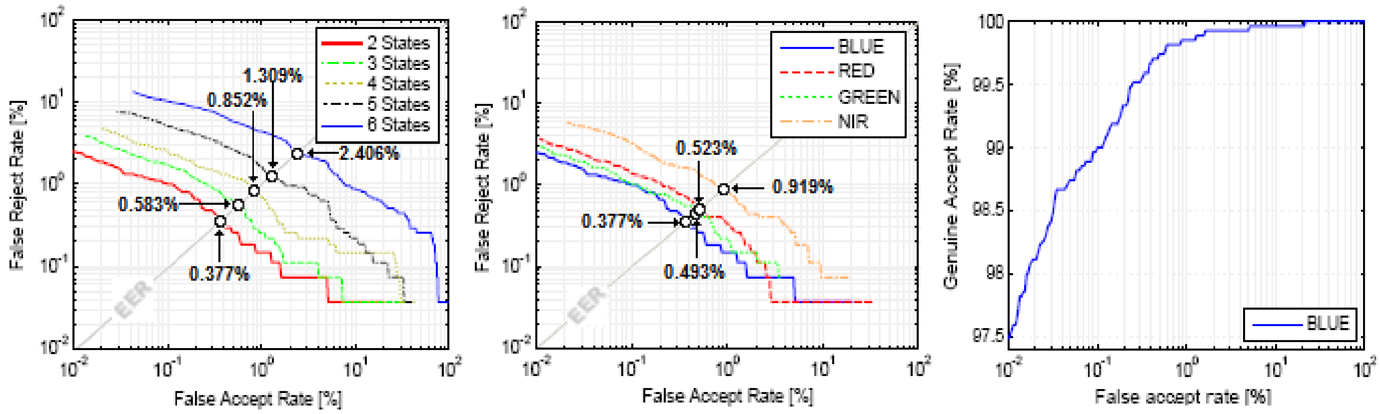

Fig. 6 HMM-based uni-biometric identification test results: *(a)* the ROC curves under different number of states; *(b)* the ROC curves for all palm-print bands; *(c)* the ROC curve for the blue band

TABLE V HMM-BASED OPEN SET UNI-MODAL SYSTEMS PERFORMANCES

DB SIZE	BLUE			GREEN			RED			NIR		
	T_o	FAR	FRR	T_o	FAR	FRR	T_o	FAR	FRR	T_o	FAR	FRR
300	0.6000	4.153	0.074	0.6100	3.687	0.000	0.6300	2.850	0.037	0.6500	4.528	0.296
	0.7878	0.377	0.377	0.7655	0.493	0.493	0.7624	0.523	0.523	0.7794	0.919	0.919
	1.0000	0.008	2.704	1.0000	0.010	3.000	1.0000	0.011	3.741	1.0000	0.020	5.963

TABLE VI HMM-BASED OPEN SET MULTI-MODAL SYSTEMS PERFORMANCES

COMBINATION	SUM		WHT		MIN		MAX		MUL	
	T_o	EER	T_o	EER	T_o	EER	T_o	EER	T_o	EER
RGB	0.7495	0.105	0.7608	0.099	0.7618	0.111	0.8878	0.148	0.4885	0.098
RGBN	0.7670	0.037	0.7789	0.037	0.7577	0.096	0.9187	0.148	0.4425	0.037

TABLE VII HMM-BASED CLOSED SET UNI-MODAL SYSTEMS PERFORMANCES

DB SIZE	BLUE		GREEN		RED		NIR	
	ROR	RPR	ROR	RPR	ROR	RPR	ROR	RPR
300	97.296	142	97.000	126	96.259	239	94.037	211

TABLE VIII HMM-BASED CLOSED SET MULTI-MODAL SYSTEMS PERFORMANCES

COMBINATION	SUM		WHT		MIN		MAX		MUL	
	ROR	RPR	ROR	RPR	ROR	RPR	ROR	RPR	ROR	RPR
RGB	99.630	44	99.556	48	99.000	131	95.963	66	99.630	40
RGBN	99.778	38	99.741	42	99.185	110	93.963	86	99.815	32

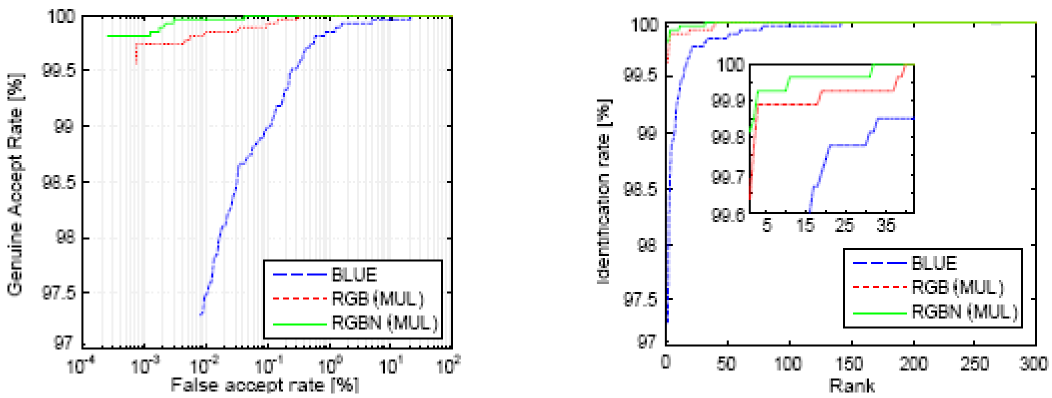

Fig. 7 Comparison of different HMM based systems: *(a)* open set identification systems and *(b)* closed set identification systems

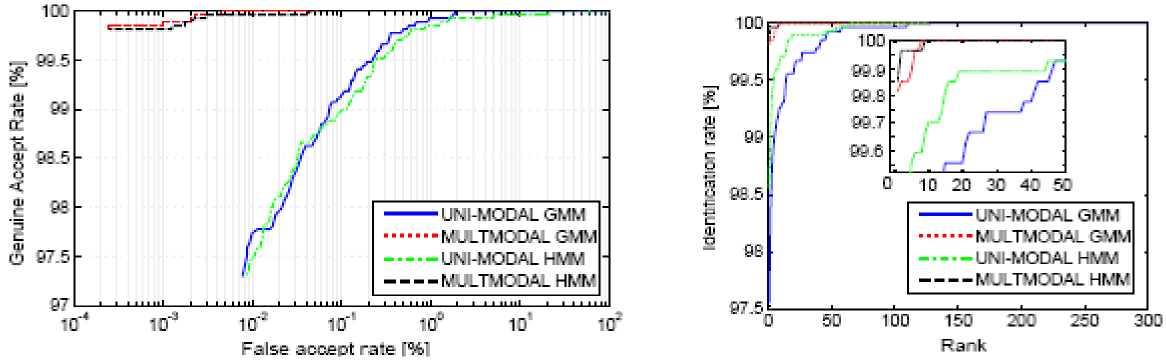

Fig. 8 Comparison of the GMM-based and HMM-based systems: *(a)* open set identification systems and *(b)* closed set identification systems

D. Comparison Study

To find the better methods, GMM modeling or HMM modeling, graphs showing the ROC curves for the closed set and open set identification using uni-modal and multimodal system, were generated (see Fig. 8.(a) and Fig. 8.(b)). By the analysis of those plots, it can be observed that the performance of the identification system is significantly improved by using the fusion. In the case of open set identification, the GMM modeling gives the best result (EER = 0.005 %). The best result (ROR = 99.8150) in the case of closed set identification is given when using HMM modeling. However, it can be concluded that the fusion of all modalities yields much better identification results compared with uni-modality. Therefore, the developed system is expected to give higher accuracy.

VI. CONCLUSION AND FURTHER WORK

This paper proposes an efficiency scheme for MSP identification using the GMM (HMM) modeling. Firstly the observation vector is given by Gabor phase response with different orientations and compressed using PCA. Subsequently, we use the GMM (HMM) for modeling the observation vector of each band. The experimental results showed that the proposed methods obtained a highest recognition rate and the information fusion at the matching scores level improved the results. For further improvement of the system, our future work will focus on the performance evaluation using large size database and using other feature extraction techniques such as Independent Component Analysis (ICA).

REFERENCES

[1] Arun A. Ross, K. Nandakumar and A. K. Jain, “Handbook of Multibiometrics”, Springer Science+Business Media, LLC, New York, 2006.

[2] Uma Biradar, Smita Jangale, Manisha Dale and M. A. Joshi, “Palmprint recognition using wavelet”, international conference on contours of computing technology, Thinkquest 2010, Pp. 266-269, 13-14 march 2010.

[3] Abdallah Meraoumia, Salim Chitroub and ahmed Bouridane, “Efficient person identification by fusion of multiple palmprint representations”, 4th international conference-ICISP, LNCS 6134, pp. 182-191. Trois-Rivires, QC, Canada (2010).

[4] David Zhang, Zhenhua Guo, Guangming Lu, Lei Zhang, and Wangmeng Zuo, “An Online System of Multispectral Palmprint Verification”, IEEE transactions on instrumentation and measurement, Vol. 59, No. 2,pp. 480-490, february 2010.

[5] Wai kin kong and david zhang, “Palmprint Texture Analysis On Low Resolution Images For Personal Authentication”, IEEE Trans. on Pattern Analysis and Machine Intelligence, 2002.

[6] M.S. Bartlett, J.R.Movellan, and T.J. Sejnowski, “Face recognition by independent component analysis”, IEEE Trans. on Neural Networks, 13(6):1450-1464, 2002.

[7] Peter Varchol, Dũsan Levický, “Using of Hand Geometry in Biometric Security Systems”, Radioengineering, VOL. 16, NO. 4, pp:82-87, December 2007.

[8] Dimitrios Ververidis and Constantine Kotropoulos, “Gaussian mixture modeling by exploiting the Mahalanobis distance”, IEEE Trans. Signal Processing, vol. 56, issue 7B, pp. 2797-2811, 2008.

[9] Harun Uguz, Ahmet Arslan, Ibrahim Turkoglu, “A biomedical system based on hidden Markov model for diagnosis of the heart valve diseases”, Pattern Recognition Letters 28, pp: 395-404, 2007.

[10] Fabien Cardinaux, Conrad Sanderson, Samy Bengio, “Face Verification Using Adapted Generative Models”, 6th IEEE Int. Conf. Automatic Face and Gesture Recognition, Seoul, 2004, pp. 825-830, 2004.

[11] The Hong Kong Polytechnic University Multi-spectral Palmprint Database,http://www.comp.polyu.edu.hk/biometrics/MultispectralPalmprint/MSP.htm.

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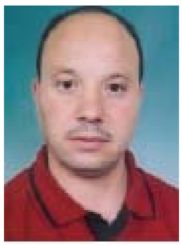

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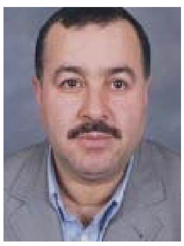

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