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Personal authentication using multiple palmprint representation

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Abstract

Although several palmprint representations have been proposed for personal authentication, there is little agreement on which palmprint representation can provide best representation for reliable authentication. In this paper, we characterize user's identity through the simultaneous use of three major palmprint representations and achieve better performance than either one individually. This paper also investigates comparative performance between Gabor, line and appearance based palmprint representations and using their score and decision level fusion. The combination of various representations may not always lead to higher performance as the features from the same image may be correlated. Therefore we also propose product of sum rule which achieves better performance than any other fixed combination rules. Our experimental results on the database of 100 users achieve 34.56% improvement in performance (equal error rate) as compared to the case when features from single palmprint representation are employed. The proposed usage of multiple palmprint representations, especially on the peg-free and non-contact imaging setup, achieves promising results and demonstrates its usefulness.
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Keywords: Biometrics; Palmprint authentication; Fusion; Multiple classifiers; Fixed combination rules; Gabor filters

1. Introduction

The widespread penetration of information technology into our daily lives has triggered the real need for reliable and user friendly mechanism to authenticate individuals. Personal authentication using palmprint has emerged as a promising component of biometric study [1]. While palmprint based authentication approaches have shown promising results, efforts are still required to achieve higher performance for their use in high security applications. Prior work on palmprint authentication has shown promising results on inked [2], scanned [3], and constrained [4] images, there is great need for better performance in images acquired from unconstrained peg-free setup [5] and this paper attempts to address this problem. One of the possible approaches to achieve higher performance is to integrate palmprint with other biometrics (multimodal systems) or combine various classifiers (intramodal systems) that have shown promising results in palmprint authentication. In the context of recent work [6–8] on intramodal biometric systems, palmprint also deserves careful evaluation.

Earlier studies have revealed that the palmprint contains mainly three types of information, i.e., texture information, line information, and appearance based information. A generic online palmprint based authentication system [4] considers only texture information while ignoring line- and appearance-based information. Thus the use of single palmprint representation has become the bottleneck in producing high performance. An ideal palmprint based personal authentication system should be able to

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reliably discriminate individuals using all of the available information. The main contributions of this paper [19] can be summarized as follows; we propose a new palmprint authentication system using a combination of three major representations of the palmprint. The experimental results show that the combination of palmprint representations, on the same palmprint image, can provide better performance than either one individually. Secondly, this paper provides comparative performance between Gabor-, line- and appearance-based palmprint authentication approaches and their fusion using score level fusion strategies. Thirdly, we propose a new fixed combination rule, i.e., product of sum (POS) rule, that can achieve higher performance than other fixed combination rules. Finally, the performance improvement using fusion of multiple decisions (decision level fusion) from each of the palmprint representations, as compared to those from individual palmprint representation, is also investigated.

1.1. Prior work

Personal authentication using palmprint images has received considerable attention during the last 5 years and numerous approaches have been proposed in the literature [2–5,9–15]. The available approaches for palmprint authentication can be divided into three categories primarily on the basis of extracted features; (i) texture-based approaches [4,10–12,26,28] (ii) line-based approaches [2,3,5,13], and (iii) appearance-based approaches [14,15,27]. A detailed description of these approaches is beyond the scope of this paper. However a summary of these approaches with the typical references can be seen in Table 1. Researchers have shown promising results on inked images [2], images acquired directly from the scanner [3] and images acquired from digital camera [4] using constrained pegged setup. However efforts are still required to improve the performance of unconstrained images [5] acquired from peg-free setup. Therefore this paper utilizes such images to investigate the performance improvement. A summary of prior work in Table 1 shows that there has not been any attempt to investigate the palmprint authentication using its multiple representations.

Several matching score level fusion strategies for combining various biometric modalities have been presented in the literature. It has been shown that the performance of different fusion strategies is different. However, there has not been any attempt to combine the decisions of various score level fusion strategies to achieve performance improvement. The organization of rest of this paper is as follows; Section 2 described the block diagram of the proposed system. This section also details feature extraction methods employed in the experiments. Section 3 details the matching criterion and the proposed fusion strategy. Experiment results and their discussion appear in Section 4. Finally the conclusions of this work are summarized in Section 5.

Table 1
Methods for personal authentication using palmprint

Approach	Method	References
Texture-based	1. Gabor filter	[4,26]
	2. Laws mask	[9]
	3. Discrete Fourier transform	[10]
	4. Discrete cosine transform	[11]
	5. Wavelets	[12,28]
Line-based	1. Line matching	[2]
	2. Line detection	[5]
	3. Crease detection	[13]
	4. Morphological operators	[3]
Appearance-based	1. Principal component analysis	[14]
	2. Linear discriminat analysis	[15,27]

2. Proposed system

Unlike previous work, we propose an alternative approach to palmprint authentication by the simultaneous use of different palmprint representations with the best pair of fixed combination rules. The block diagram of the proposed method for palmprint authentication using the combination of multiple features is shown in Fig. 1. The hand image from every user is acquired from the digital camera. These images are used to extract region of interest, i.e. palmprint, using the method detailed in Ref. [5]. Each of these images is further used to extract texture-, line- and appearance-based features using Gabor filters, Line detectors, and principal component analysis (PCA) respectively. These features are matched with their respective template features stored during the training stage. Three matching scores from these three classifiers are combined using fusion mechanism and a combined matching score is obtained, which is used to generate a class label, i.e., genuine or imposter, for each of the user. The experiments were also performed to investigate the performance of decision level fusion using individual decisions of three classifiers. However, the best experimental results were obtained with the proposed fusion strategy which is detailed in Section 4.

2.1. Extraction of Gabor features

The texture features extracted using Gabor filters have been successfully employed in fingerprint classification, handwriting recognition and recently in palmprint verification [4]. In spatial domain, an even-symmetric Gabor filter is a Gaussian function modulated by an oriented cosine function. The impulse response of even-symmetric Gabor filter in 2-D plane has the following general form:

$$h(x', y') = \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right]\cos(2\pi u_0 x), \qquad (1)$$

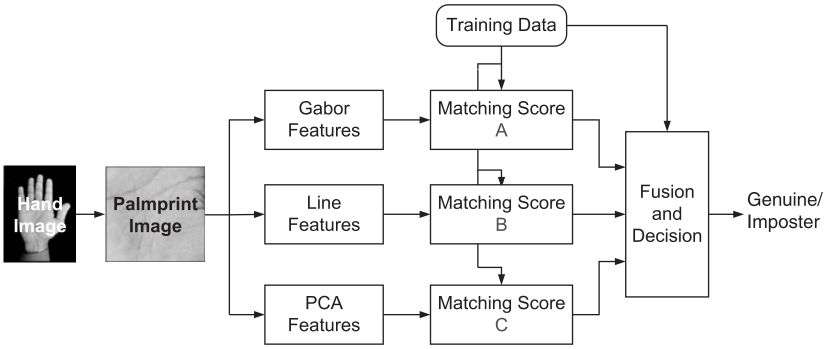

Fig. 1. Block diagram of the experimental setup for personal authentication using palmprint.

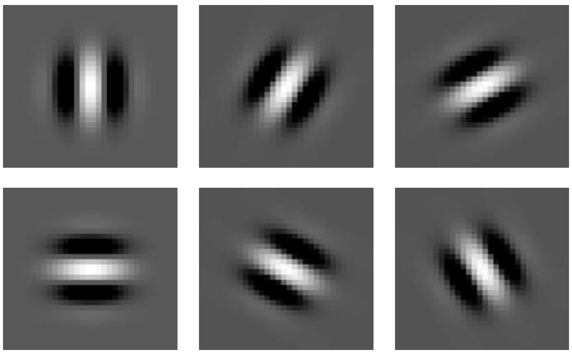

Fig. 2. Spatial-domain representation of typical even symmetric Gabor filters in six different directions.

where $x' = x \sin \varphi + y \cos \varphi$, $y' = x \cos \varphi - y \sin \varphi$, and u_0 denotes the radial frequency of sinusoidal plane wave along direction φ from *x*-axis. The space constants σ_x and σ_y define the Gaussian envelope along *x*- and *y*-axes respectively. Fig. 2 shows spatial domain representation of typical even-symmetric Gabor masks.

In order to select Gabor filters for bandpass filtering, three parameters have to be determined; frequency u_0, orientation φ, and space constants σ_x and σ_y. The values of φ only in the interval $[0^\circ, 180^\circ]$ are considered, since other values are redundant due to symmetry. The filter frequency u_0 is selected as $(1/C_w)$, where C_w is the average width of prominent lines i.e., creases and principal lines. A large value of u_0 results in spurious creases and smaller values unites two nearby creases. The bandwidth of Gabor filter is a tradeoff between these two conflicting goals and is determined from the space constant of Gaussian envelope i.e., σ_x and σ_y. Large values of σ_x and σ_y results in smoothing of lines and creases but better suppression of background noise. On the other hand, smaller values of σ_x and σ_y is prone to background noise and generates spurious lines.

In this work, the parameters of Gabor filters were empirically determined for the acquired palmprint images. These were set as; $u_0 = 1/5$, and $\sigma_x = \sigma_y = 4$. Gabor filters with six different values of $\varphi(0^\circ, 30^\circ, 60^\circ, 90^\circ, 120^\circ, 150^\circ)$ were employed. Filtering the image $I'(i, j)$ with the Gabor filter $h_\varphi(i, j)$, can be defined by the following equation:

$$I'_\varphi(i, j) = h_\varphi(i, j) * I'(i, j), \\ = \sum_{k=1}^{W} \sum_{l=1}^{W} h_\varphi(k, l) I'(i - k, j - l), \quad (2)$$

where '$*$' denotes discrete convolution and the Gabor filter mask is of size $W \times W$. Thus every palmprint image is filtered with a bank of six Gabor filters to generate six filtered images. Each of the filtered images accentuates the prominent palmprint lines and creases in corresponding direction i.e., φ while attenuating background noise and structures in other directions. The components of palmprint creases and lines in six different directions are captured by each of these filters. Each of these images filtered images is divided into several overlapping blocks of same size. The feature vector from each of the six filtered images is formed by computing the standard deviation in each of these overlapping blocks. This feature vector is used to uniquely represent the palmprint image and evaluate the performance.

2.2. *Extraction of line features*

Palmprint identification using line features has been reported to be powerful and offers high accuracy. The extraction of line features used in our experiments is same as detailed in Ref. [5]. Four directional line detectors are used to probe the palmprint creases and lines oriented at each of the four directions, i.e. 0°, 45°, 90° and 135°. The spatial extent of these masks was empirically fixed as 9×9. The resultant four images are combined by voting of gray-level magnitude from corresponding pixel position. The combined image represents the combined directional map of palm-lines and creases in the palmprint image. This image is further divided into several overlapping square blocks. The standard deviation of grey-level in each of the overlapping blocks is used to form the feature vector for every palmprint image.

2.3. Extraction of PCA features

The information content of palmprint image also consists of certain local and global features that can be used for identification. This information can be extracted by registering the variations in an ensamble of palmprint images, independent of any judgment of palmprint lines or creases. Every $N \times N$ pixel palmprint image is represented by a vector Φ of $1 \times N^2$ dimension using row ordering. The available set of K training vectors is subjected to PCA which generates a set of orthonormal vectors that can optimally represent the information in the training dataset. The covariance matrix of normalized vectors Θ_j can be obtained as follows:

$$\mathbf{C} = \frac{1}{K} \sum_{j=1}^{K} \Phi\Phi^{\mathrm{T}}. \tag{3}$$

The computation of eigenvector of $N^2 \times N^2$ covariance matrix $\mathbf{C}$ is cumbersome due to the memory and computational constraints. Therefore the simplified method suggested in Ref. [16] is adopted. Thus the eigenvectors $Z = [z_1, z_2, \ldots, z_K]$ of the $M \times M$ matrix Γ are first computed:

$$\Gamma = \Phi^{\mathrm{T}}\Phi. \tag{4}$$

The eigenvectors of covariance matrix $\mathbf{C}$, say u_j ($j = 1, 2, \ldots, K$), are computed from the product of Θ_j and z_j.

$$[u_1, u_2, \ldots, u_K] = [\Theta_1, \Theta_2, \ldots, \Theta_K][z_1, z_2, \ldots, z_K], \text{ or}$$

$$U = \Phi Z. \tag{5}$$

Each of the basis vectors u_j in Eq. (5) is the ordered principal components of covariance matrix $\mathbf{C}$. These basis vectors are used to compute characteristic features for each of the training palmprint images. This is achieved by computing a set of projection coefficients for each of the training palmprint images, on a set of K' basis vectors. Thus the features vector $x_j^{\mathrm{T}} = [x_1, x_2, \ldots, x_{K'}]$ for jth training palmprint image is obtained as follows:

$$x_i = u_i^{\mathrm{T}} \Theta_j \quad i = 1, 2, \ldots, K', \quad j = 1, 2, \ldots, K, \quad K' \leqslant K. \tag{6}$$

The set of feature vector $\mathbf{x}_j$ from training images and set of basis vectors $\mathbf{u}_j$ are stored during training phase. The feature vector for every test image is computed in similar manner, using Eq. (6), and used to uniquely represent the palmprint image.

3. Matching criterion

The classification of extracted feature vectors using each of three methods is achieved by nearest neighbour (NN) classifier. The NN classifier is a simple nonparametric classifier which computes the minimum distance between the feature vector of unknown sample g and that of for g_m in the mth class:

$$L(g, g_m) = \min_m L(g, g_m). \tag{7}$$

The class label corresponding to closet training sample is assigned to feature vector g. Three distance measures were used in our experiments to evaluate the performance of different feature sets.

$$L_1 = |g - g_m| = \sum_n |g^n - g_m^n|, \tag{8}$$

$$L_2 = \|g - g_m\|^2 = \sum_n (g^n - g_m^n)^2, \tag{9}$$

$$L_{\cos} = 1 - \frac{g \cdot g_m}{\|g\| \cdot \|g_m\|} = 1 - \frac{\sum_n g^n \cdot g_m^n}{\sqrt{\sum_n (g^n)^2 \sum_n (g_m^n)^2}}, \tag{10}$$

where g^n and g_m^n respectively represent the nth component of feature vector of unknown sample and that of mth class. Each of the three feature sets obtained from the three different palmprint representations were experimented with each of the above three distance measures (8)–(10). The distance measure that achieved best performance was finally selected for the classification of feature sets from the corresponding palmprint representation.

4. Fusion strategies

The fusion strategy aims at improving the combined classification performance than that from single palmprint representation alone. There are three general methods of combining classifiers; at feature level, at score level and at decision level. Due to the large and varying dimension of feature vectors, the fusion approach at feature level has not been considered in this work. A summary [20] of employed approaches for multimodal fusion suggests that the score level fusion of feature sets has been the most common approach for fusion and has shown to offer significant improvement in performance. The goal of evaluating various score level fusion strategies is to produce best possible performance in palmprint authentication using given set of images. Let $L_{Gabor}(g, g_m)$, $L_{Line}(g, g_m)$ and $L_{PCA}(g, g_m)$ denote the matching distance produced by Gabor, Line and PCA classifiers respectively. The combined matching score $L_C(g, g_m)$ using the well-known fixed rules can be obtained

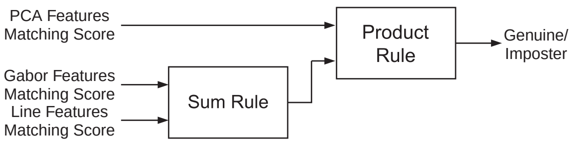

Fig. 3. Combining Gabor, Line, and PCA matching scores using product of sum rule.

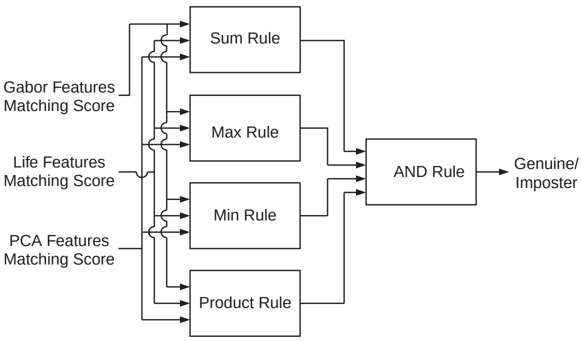

Fig. 4. Hybrid fusion scheme to combine Gabor, Line, and PCA based features.

as follows:

$$L_c(g, g_m) = \Xi\{L_{Gabor}(g, g_m), L_{line}(g, g_m), L_{PCA}(g, g_m)\}, \quad (11)$$

where Ξ is the selected combining rule, i.e. Ξ represents maximum, sum, product or minimum rule (abbreviated as MAX, SUM, PROD and MIN respectively), evaluated in this work. One of the shortcomings of fixed rules is the assumption that individual classifiers are independent. This assumption may be poor, especially for the Gabor and Line based features. Therefore SUM rule can be better alternative for consolidating matching scores while combining Gabor and Line features. These consolidated matching scores can be further combined with PCA matching scores using PROD rule (Fig. 3) as the PROD rule is estimated to perform better on the assumption of independent data representation [17].

The individual decisions from the three palmprint representations were also combined (majority voting) to examine the performance improvement. The performances of various score level fusion strategies are different. Therefore the performance from simple hybrid fusion strategy that combines decisions of various fixed score level fusion schemes, as shown in Fig. 4, was also investigated in this work. Instead of using fixed combination rules, the matching scores from the training set can also be used to adapt a classifier for two class, i.e. genuine and imposter, classification. Therefore the combined classification of three matching scores using feed-forward neural network (FFN) and support vector machine (SVM) classifier has also been investigated.

5. Experiments and results

The proposed palmprint authentication method was investigated on a dataset of 100 users. This data set consists of 1000 images, 10 images per user, which were acquired from digital camera using unconstrained peg-free setup in indoor environment. Fig. 5 shows typical acquisition of a hand image using the digital camera with live feedback. The hand images were collected over a period of 3 months from the users in the age group of 16–50 years. The hand images were collected in two sessions from the volunteers, which were not too cooperative. During image acquisition, the users were only requested to make sure that (i) their fingers do not touch each other and (ii) most of their hand (back side) touches the imaging table. The automated segmentation of region of interest, i.e. palmprint, was achieved by the method detailed in Ref. [5]. Thus the palmprint image of 300 × 300 pixels were obtained and employed in our experiments. Each of the acquired images was further histogram equalized. Five image samples per user were used for the training and the remaining five samples were

Fig. 5. Acquisition of hand images using digital camera.

Table 2
Performance of Gabor, Line and PCA based features

		E_{ER}	FAR_{TME}	FRR_{TME}	$Threshold_{TME}$
Gabor features	L_1	12.11	10.93	12.80	0.199
	L_2	12.38	11.58	12.80	0.056
	$L_{\cos}$	**4.89**	**0.82**	**7.200**	**0.249**
Line features	L_1	9.28	3.93	12.20	0.204
	L_2	10.20	5.06	11.40	0.059
	$L_{\cos}$	**6.19**	**2.95**	**7.60**	**0.190**
PCA features	L_1	6.56	2.52	8.80	0.496
	L_2	**5.83**	**2.74**	**7.20**	**0.111**
	$L_{\cos}$	6.60	3.71	8.40	0.134

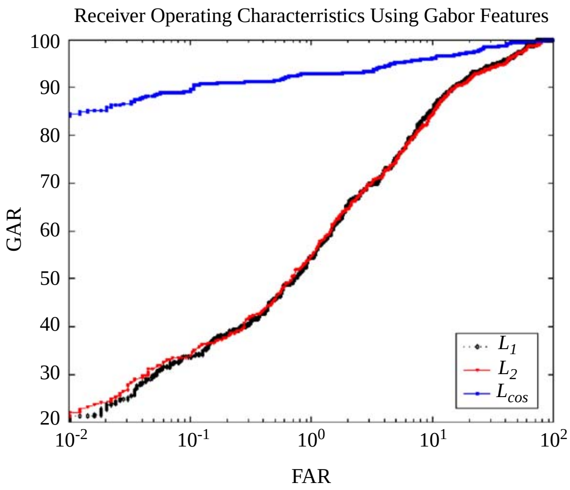

Fig. 6. Comparative ROC using Gabor features.

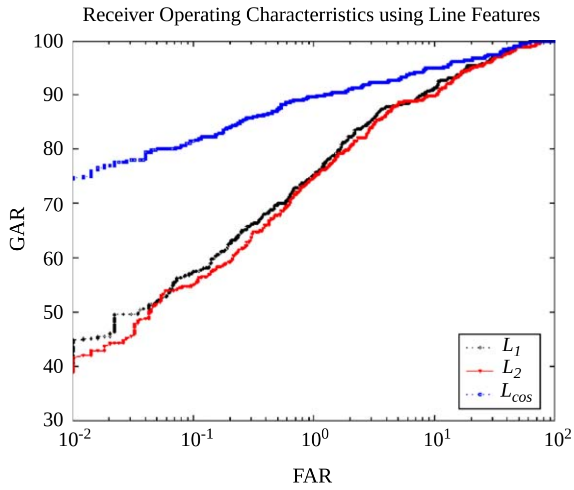

Fig. 7. Comparative ROC using Line features.

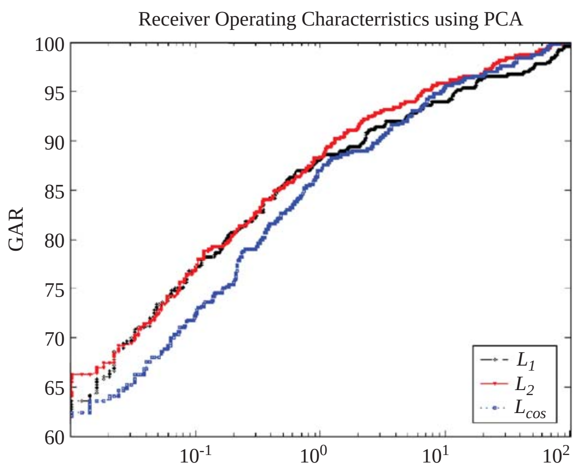

Fig. 8. Comparative ROC using PCA features.

employed for the testing. Thus the performance evaluation consisted of 500 (5 × 100) genuine matching scores and 495,00 (495 × 100) imposter matching scores for each of the three classifiers. The performance scores were quantitatively ascertained using (i) total minimum error (*TME*) and (ii) equal error rate (E_{ER}) and are quoted in percentage.

The performance for each of the individual classifiers using Gabor, Line and PCA features is shown in Figs. 6–8, respectively. The goal of these experiments was to find the best distance measure, i.e. L_1, L_2 or $L_{\cos}$, for each of the three classifiers. It can be observed from the Table 2 that the distance measure $L_{\cos}$ achieves best performance for Gabor and Line features while distance measure L_2 achieves best performance PCA features. Another conclusion that can be made from Table 2 and Figs. 6–8 is that the Gabor features achieve the best performance as compared to Line- or PCA-based features. Fig. 9 shows the distribution of genuine and

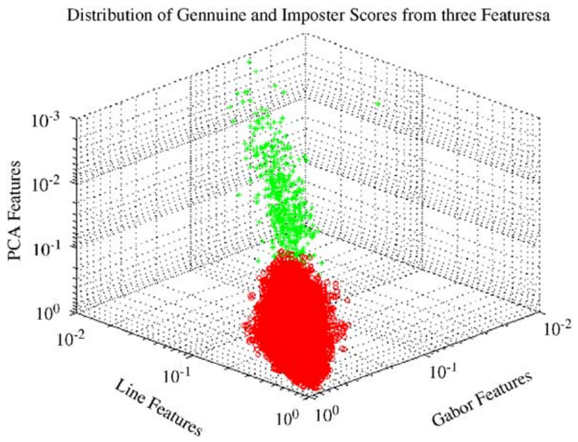

Fig. 9. Distribution of genuine (+) and imposter (o) matching scores from the three classifiers.

Table 3
Performance scores from the combination rules

	E_{ER}	FAR_{TME}	FRR_{TME}	$Threshold_{TME}$
PROD	4.6	2.44	5.00	0.172
MAX	5.00	0.70	7.20	0.249
SUM	4.80	1.70	5.60	0.202
MIN	5.60	2.05	7.80	0.104
PROD of SUM	3.20	1.04	3.60	0.179

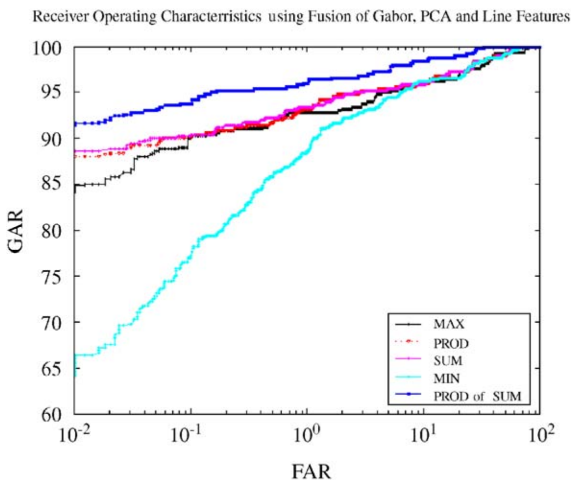

Fig. 10. Comparative ROC from the fusion schemes at score level.

imposter matching scores from the test data. The quantitative performance scores from the simple combination rules and the proposed POS rule can be ascertained from Table 3. The corresponding plots of receiver operating characteristics (ROC) are displayed in Fig. 10. Performances shown in Table 3 and Fig. 10 suggest that the performance of POS

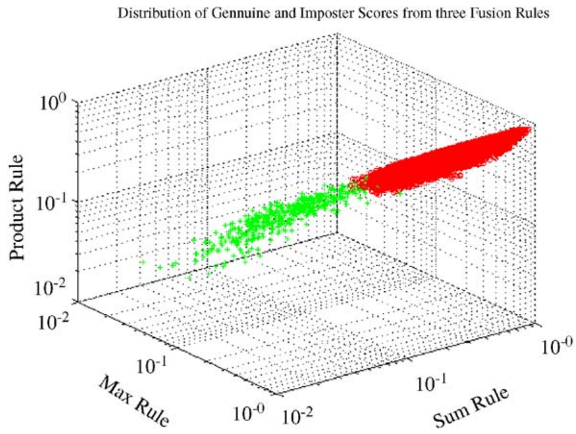

Fig. 11. Distribution of genuine (+) and imposter (o) matching scores SUM, MAX and PROD rules.

rule is the best (followed by PROD and SUM rule) and that of MIN rule is the worst. The performance improvement achieved by POS as compared to SUM, MAX, PROD or MIN rule confirms its usefulness. The performance improvement due to the combination of three palmprint representations can be observed from the comparison of Tables 2 and 3, Figs. 6–8 and 10. The best error rate, i.e., E_{ER} of 4.89% and *TME* of 8.02% (from Gabor features) has been further improved to the E_{ER} of 3.2% (34.56% improvement) and *TME* of 4.64% with the usage of POS rule. The distributions of genuine and imposter scores from the SUM, MAX and PROD rule is displayed in Fig. 11.

The SVM classifier with Radial Basis Function (RBF) and Polynomial kernel with degree five was also investigated for the fusion of matching scores. The training was achieved with C-SVM, a commonly used SVM classification algorithm [21]. The training parameter γ and ε were empirically fixed at 1 and 0.001 respectively. The performance of SVM classifiers can be observed from Fig. 12a and Table 4. The two-layer 3/1 FFN and three-layer 3/2/1 FFN was also employed with the fixed learning rate of 0.01. The hyperbolic tangent sigmoid activation function was used for input layers and a linear activation function was employed for the output layer [18]. The weights were updated using resilient backpropagation algorithm and the training was aborted if the maximum number of training steps reached to 1000. The performance of score level fusion FFN can be observed from Fig. 12b and Table 4. Comparing Tables 3 and 4 we can conclude that the trainable score level fusion strategies do not necessarily offer better performance than simple combination rules for the intramodal system [24,25].

The performance of decision level fusion and hybrid fusion scheme shown in Fig. 4 is illustrated in Table 5. The operating point (decision threshold) for each of four combination rules was fixed at total minimum error. The experiments were also performed for the direct fusion of decisions

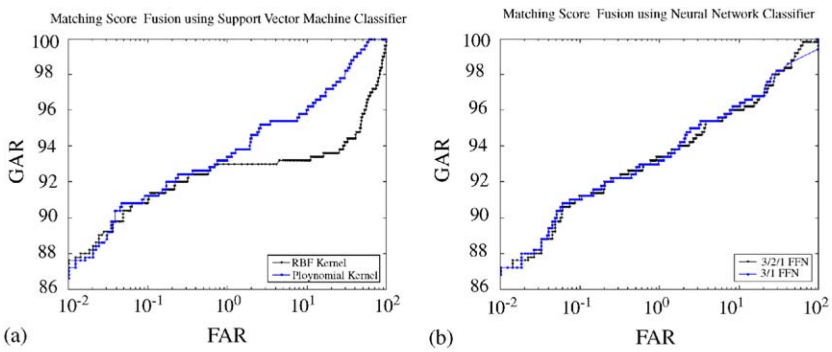

Fig. 12. The ROC from the fusion at score level using SVM in (a) and FFN in (b).

Table 4
Performance scores for SVM and FFN based score level fusion

	E_{ER}	FAR_{TME}	FRR_{TME}	$Threshold_{TME}$
SVM-RBF	6.8	0.69	7.20	0.137
SVM-Poly	4.6	2.57	4.80	0.337
NN-3/1	4.6	2.18	5.20	0.038
NN-3/2/1	4.6	0.91	6.60	0.087

Table 5
Performance scores from the decision and hybrid fusion strategy

	Total error	*FAR*	*FRR*
Decision fusion	4.68	0.08	4.6
Hybrid fusion	7.95	0.05	7.9

from three classifiers, i.e. in the absence of combination rules. The experimental results in Tables 2 and 5 suggest that the decision level fusion of multiple palmprint representations can achieve better performance than those from either one individually. The FAR of the hybrid fusion scheme is marginally improved over that from decision fusion but at the expense of increase in FRR.

6. Discussion

The experimental results presented in Section 5 show that the significant improvement in the performance can be achieved from the combination of multiple palmprint representations than those from individual representations in prior work (summarized in Section 1.1). The image dataset used in our experiments was acquired from unconstrained peg-free setup as such images are more realistic and expected to show large variations. The feature extraction method employed in this work using Gabor filters uses magnitude information only from even-symmetric Gabor filters while those used in prior work [4] uses phase information from both even/odd-symmetric Gabor filters. Another reason for the high degree of computational simplicity in the proposed extraction of Gabor features is that the size of employed even symmetric Gabor masks which was empirically fixed as 15×15 while those in Ref. [4] used 35×35 for both even/odd-symmetric filters. The selection of mask size in our method is a compromise between computational simplicity and the performance. One of the shortcomings of reported performance in prior work [4,22] is that the database is formed by integrating palms of left and right and left hands. Such performance is misleading as the left and right palmprint have quite distinct orientation of textured lines and the discrimination offered is much less as compared to palmprint from same (left or right) hand.

Why the proposed POS scheme performed better than other combination schemes in Table 3? The SUM rule has been shown [17,23] to be useful for correlated feature spaces in which case the errors from the classifiers are independent. Thus the prior conclusions on the usage of SUM rule makes it most suitable for combining Gabor- and Line-based features due to the expected correlation in their feature space. However, the feature space for PCA based features is highly independent, as compared to those from Gabor- and Line-based features, and thus the PROD rule is argued to gain maximally on the assumption of independent data representation. The hybrid fusion strategy examined in Fig. 4 employed straightforward AND logic for the fusion of decisions obtained from multiple score level fusion strategies. The AND logic was employed to ensure high level of security, i.e., low FAR, since a positive authentication is only achieved when all the score level fusion strategies generate positive authentication. However, the tradeoff for low FAR, i.e., possible increase in FRR, can be justified is some applications requiring high level of security [20].

7. Conclusions

This paper has suggested a new method of palmprint authentication using the combination of palmprint representations. The experimental results presented in Section 5 demonstrate that the combination of palmprint representations can achieve better performance that may not be possible with the individual palmprint representation. The comparative performance evaluation of three major palmprint representation approaches (used in Section 5) suggests that the best performance can be achieved from the Gabor filter based representation as compared to the Line- or PCA based representations. The matching criteria, i.e., distance measure, used to compute the matching distance has important effect on the performance and this can be observed from Figs. 6–8 or Table 2. The combination of various representations may not always lead to higher performance as the features from the same palmprint image may be correlated. Therefore we also proposed new combination rule, i.e., POS rule, which achieved best performance as compared to SUM, MAX, PROD, or MIN rule. The independence of different feature spaces for various feature representations, especially in an intramodal system, is limited and therefore the selection of combination rule is important to gain maximally from the combined representation. The experimental results also illustrate that (i) selection of fusion strategy has significant effect on the performance, and (ii) trainable fusion strategies do not necessarily perform better than fixed combination rules in the intramodal authentication system. Our experimental results also demonstrated that the decision fusion from multiple palmprint representation can achieve better performance than those from either palmprint representation individually. The results shown in this paper should be interpreted in the context of images acquired from simple peg-free setup, since such images are expected to show higher variations as compared to those from setup using fixation pegs (as in Ref. [4]). The performance of various score level fusion strategies is different and therefore the decisions from these fusion strategies may be combined to ensure performance improvement. The experimental results from the hybrid fusion scheme examined in this work were not encouraging. Therefore future research should be directed/focused on the potentially promising schemes on the combination of score level fusion decisions so as to achieve performance improvement. The evaluation of fusion strategies was limited as our focus was to achieve best performance from the fixed combination rules in the context of limited training data. The nature and size of database employed in this work is reasonable as our main objective was to investigate the performance improvement from the proposed authentication system using multiple palmprint representation. However, the more reliable estimate on the performance can be obtained if significantly larger database is available and we are working to enroll more users.

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