SIViP (2011) 5:477–483
DOI 10.1007/s11760-011-0251-7

ORIGINAL PAPER

Personal identification using feature and score level fusion of palm- and fingerprints

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Received: 31 July 2010 / Revised: 14 December 2010 / Accepted: 17 February 2011 / Published online: 18 August 2011

Abstract The ever increasing demand of security has resulted in wide use of Biometric systems. Despite overcoming the traditional verification problems, the unimodal systems suffer from various challenges like intra class variation, noise in the sensor data etc, affecting the system performance. These problems are effectively handled by multimodal systems. In this paper, we present multimodal approach for palm- and fingerprints by feature level and score level fusions (sum and product rules). The proposed multimodal systems are tested on a developed database consisting of 440 palm- and fingerprints each of 55 individuals. In feature level fusion, directional energy-based feature vectors of palm- and fingerprint identifiers are combined to form joint feature vector that is subsequently used to identify the individual using a distance classifier. In score level fusion, the matching scores of individual classifiers are fused by sum and product rules. Receiver operating characteristics curves are formed for unimodal and multimodal systems. Equal Error Rate (EER) of 0.538% for feature level fusion shows best performance compared to score level fusion of 0.6141 and 0.5482% of sum and product rules, respectively. Multimodal systems, however, significantly outperform unimodal palm- and fingerprints identifiers with EER of 2.822 and 2.553%, respectively.

Keywords Multimodal · Personal identification · Fusion

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1 Introduction

Modern networked society requires more reliability in providing high level security to access and transaction systems. Traditional personal identity verification systems i.e. token and password based can easily breached when the password is disclosed or the card is stolen. The traditional systems are not sufficiently reliable to satisfy modern security requirements as they lack the capability to stop the fraudulent user who illegally acquires the access privilege. The pronounced need for establishing secured identity verification systems has turned the world's attention toward the field of biometrics which utilizes unique behavioral or physiological traits of individual for the recognition purpose and therefore inherently possesses the capability of differentiating genuine users from imposters [1,2]. These traits include palmprint, palm-geometry, fingerprint, palm vein, finger-knuckle-print, face, retina, iris, voice, gait, signature and ear etc. Unimodal systems that use single biometric trait for recognition purposes suffer several practical problems like non-universality, noisy sensor data, intra-class variation, restricted degree of freedom, unacceptable error rate, failure-to-enroll and spoof attacks [3]. Several studies have shown that in order to address some of the problems faced by unimodal systems and improved recognition performance, multiple sources of information can be consolidated together to form multi-biometrics systems [4–6]. Multi-biometrics system can be developed by utilizing different approaches: (a) multisensor systems combine evidences of different sensors using a single trait, (b) multi-algorithm systems process single biometric modality using multiple algorithms, (c) multi-instance systems consolidate multiple instances of the same body trait, (d) multi-sample systems use multiple samples of same biometric modality using a single sensor, (e) multimodal systems are developed by fusing the information of different biometric traits of the individual to establish identity [3]. Multimodal system can be developed by fusing information of different biometric modalities at pre-classification level that includes fusion at feature extraction level and post-classification fusion that includes fusion at matching score level and decision level [3,7].

At feature level fusion, feature vectors extracted from different biometric modalities are combined together and subsequently used for classification [8]. Fusion at score level is performed by combining the matching scores originating from different classifiers pertaining to various modalities, and depending upon the score threshold, a classification decision is made. For decision level fusion, final outputs of different classifiers are fused together through different fusion techniques like Bayesian Decision Fusion [6]. In this paper, we present multimodal systems at feature level and score level fusions using our already reported unimodal palmprint and fingerprint identifiers [9,10]. The unimodal finger- and palmprint identification systems utilize directional energies of texture as features, extracted using contourlet transform. The rest of the paper is organized as follows: Sect. 2 gives a literature overview. Section 3 briefly describes the unimodal palmprint and fingerprint systems, followed by the feature level fusion of palmprint and fingerprint identifiers for multimodal system in Sect. 4 and score level fusion in Sect. 5, respectively. The details of experiments and results are given in Sect. 6. Section 7 concludes the paper by presenting discussion and comparison of result of the developed multimodal system to already reported results in literature.

2 Related work

Different approaches have been proposed in the literature for developing unimodal and multimodal biometric systems. Multi-biometric systems are developed by fusing different biometric features pertaining to various biometric modalities at different levels. Many researches have shown that the multimodal systems outperform the unimodal systems, giving better discrimination of genuine from imposters.

A unimodal palmprint-based identification system is presented in [11]. For system development, firstly, a simple alignment method called direction alignment based on morphology was used. Then, for database development, palmprint features were extracted from ROIs and classified into Local Features, Global Features and Combination Features. Finally, Eucledian distance classifier differentiates between genuine and imposters.

Li et al. [12] proposed a Palmprint Recognition based on Translation Invariant Zernike Moments and Modular Neural Network. In the paper, Translation invariant Zernike moments (TIZMs) are utilized as palm features and a modular neural network (MNN) is used as a classifier. Experimental results on Polyu Palmprint database [13] have demonstrated the identification (99.5%) and recognition (98.7%) rate of the proposed method. In the approach proposed in [14], adjacent orientation vector (AOV) fingerprint feature is used for fingerprint matching. AOV is used to find minutiae pairs, which are further used for a preliminary matching to ensure reliability and for fine matching to overcome possible distortion. Snelick et al. [15] present a multimodal biometric authentication system using fingerprint and face biometric systems on a population of 1,000 individuals. After normalizing the scores, different fusion methods including Simple-Sum (SS), Min-Score (MIS), Max-Score (MAS), Matcher Weighting (MW) and User Weighting (UW) are utilized. The minimum EER achieved out of these methods is 0.63%. Kumar and Zhang [16] proposed a multimodal system by combining palmprint, fingerprint and hand shape. For fusion purposes, matched minutiae scores from fingerprint images are combined with the scores of palmprint and hand-shape images that are based on distance of feature vectors. Wang et al. [17] combined palmprint and palm vein images to develop a multimodal system at image level fusion. Integrated Line-preserving and contrast enhancing fusion methods are used to perform fusion. Fused images are obtained by combining modified multiscale edges of palmprint and palm vein images. The resultant interaction points (IPs) of the palmprints and vein lines and image contrast are enhanced. Laplacianpalm feature is extracted from the fused images and further used for recognition purposes.

3 Unimodal biometric identifiers

3.1 Palmprint identifier

The present work is continuation of our research on unimodal Palmprint system [9]. Of 55 individuals, 440 palmprints are collected with the help of the developed palm acquisition platform as shown in Fig. 1. The palm capturing system is an enclosed black box, simple in construction

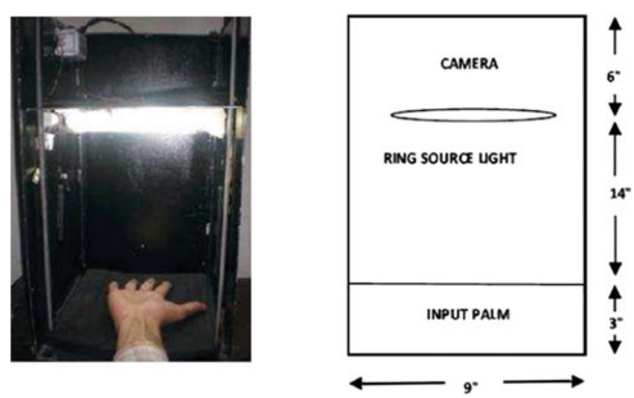

Fig. 1 Palmprint acquisition platform

Fig. 2 Distance transform applied on palmprint

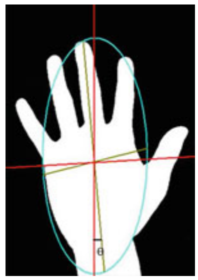

Fig. 3 Calculating the parameters of best fitting ellipse for measuring θ

and draws on ring-shaped lighting tube to ensure uniform illumination. The image acquisition setup is provided with two flat plates. The camera and the light source are fixed on the upper plate, while the bottom plate is used to place the hand for image acquisition with fixed pegs. To minimize any mismatch due to scale variance, the distance between these two plates is kept constant. After empirical testing, the distance between the plates is kept at 14 inches. Sony DSC W-35 Cyber Shot camera having resolution of 72 dpi is used for capturing the palm images. The palmprint image is binarized using Hysteresis thresholding isolating the foreground of palmprint from the background. The binarized palmprint is complemented and distance transform is calculated as shown in Fig. 2. For each pixel in the binary image, the distance transform assigns a number that is the distance between that pixel and the nearest nonzero pixel. The maximum distance obtained from the distance transform is estimated as the centre of palmprint. Although during image acquisition stage of the database development an effort was made to acquire standard palmprint images, a rotational alignment is incorporated in our proposed approach to cater any inadvertent small rotations. The longest line in a palm passes through the middle finger, and any rotation is considered with reference to this line. The second-order moment helps analyzing the elongation or eccentricity of any binary shape. By finding the eigen values and eigenvectors, we determine the eccentricity of the shape by analyzing the ratio of the eigen values. We further determine the direction of elongation by using the direction of the eigenvector with corresponding highest eigen value. The parameters of the best fitting ellipse are extracted using second order statistical moments on the binarized palmprint corresponding to the longest line as shown in Fig. 3.

After Distance Transform is used to find the center of the palm, the parameters for the best fitting ellipse help to find

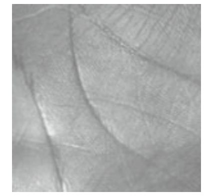

Fig. 4 Extracted region of interest (ROI)

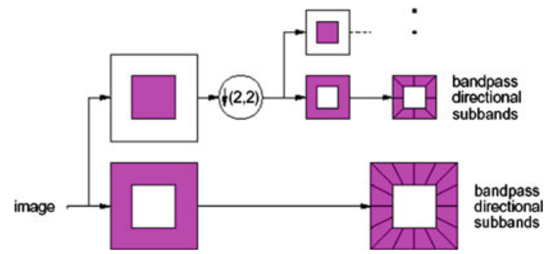

Fig. 5 Contourlet transform consisting of Laplacian pyramid and directional filter bank stages)

the alignment of hand by calculating the slant angle θ using the formula:

$$\theta = \frac{1}{2}\tan^{-1}\left(\frac{2c}{a-b}\right) \tag{1}$$

where a, b and c are the second-order normalized moments of the pixels. The second-order normalized moments a, b and c of the pixels in the image $P(x, y)$ are calculated using the following equations:

$$a = \frac{\sum_{(x,y)\epsilon P} (y-v)^2 \cdot P(x,y)}{\sum_{(x,y)\epsilon P} P(x,y)} \tag{2}$$

$$b = \frac{\sum_{(x,y)\epsilon P} (x-u)^2 \cdot P(x,y)}{\sum_{(x,y)\epsilon P} P(x,y)} \tag{3}$$

$$c = \frac{\sum_{(x,y)\epsilon P} (x-u) \cdot (y-v) \cdot P(x,y)}{\sum_{(x,y)\epsilon P} P(x,y)} \tag{4}$$

where u and v are location of centeriod. A square region of interest (ROI) of size 256×256 pixels around the center of palm aligned at θ degrees is cropped as shown in Fig. 4.

After extraction of the region of interest (ROI), iterated directional filter banks split the two dimensional (2-D) spectrums into fine slices. Textural information available on the palm is extracted with the help of contourlet transform. Contourlet, a new discrete transform, can efficiently handle the intrinsic geometrical structure containing contours. It is proposed by Do and Vetterli [18]. It provides sparse representation at both spatial and directional resolutions. Additionally, a flexible multiresolution and directional decomposition by allowing different number of directions at each scale with flexible aspect ratio is offered. Figure 5 shows a double filter bank structure of Contourlet Transform consisting of Laplacian pyramid with a directional filter bank.

From the decomposed sub-band outputs, directional energy components for each block are computed. Both local

(a) (b)

Fig. 6 **a** Acquired image. **b** Enhanced image after pre-processing

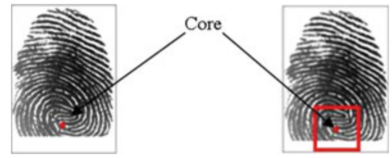

Fig. 7 Core point located to the extreme margin of the image

and global details in a palmprint are extracted as a fixed length palm code. Energy value $E_{k\theta}$ in directional sub-band, $S_{k,\theta}$ at kth resolution level is given by:

$$E_{k\theta} = \sum_{S_{k,\theta}} |F_{k,\theta}(x, y) - \overline{F}_{k,\theta}| \quad (5)$$

where $\overline{F}_{k,\theta}$ is the mean of pixel values of $F_{k,\theta}(x, y)$ in the sub-band $S_{k,\theta}$. $F_{k,\theta}(x, y)$ is the contourlet coefficient value at position (x, y). Additionally, the directional sub-bands vary from 0 to $2^n - 1$. The normalized energy value $\hat{E}_{k\theta}$ of sub-band θ at k^{th} resolution level is defined as:

$$\hat{E}_{k\theta} = \frac{E_{k\theta}}{\sum_{\theta=0}^{2^n-1} E_{k\theta}} \quad (6)$$

Taking the constant $F_{\max}$ value equal to maximum intensity level of 255, the feature value $F_{k\theta}$ is calculated as:

$$F_{k\theta} = F_{\max} \times \hat{E}_{k\theta} \quad (7)$$

These feature values are then stored to form the database. Normalized euclidian distance classifier is then used for palmprint matching of input image with the stored database.

3.2 Fingerprint identifier

Our work on fingerprint identification system is reported in the literature [10]. Fingerprint scanner of digital persona "U are U 4000-B" is used for capturing fingerprints of individuals. A total of 400 fingerprints of 55 individuals are stored. The image is 512 × 460 pixels wide and its output is a 8-bit grayscale image. JAVA platform is used in order to develop image Acquisition software. Input image is pre-processed using histogram equalization, adaptive thresholding, Fourier transform and adaptive binarization. A pre-processed fingerprint is shown in Fig. 6.

In order to extract region of interest (ROI) from the input image, core point is used as the reference point. Core point is the point located on the inner most ridge having the maximum curvature as depicted in Fig. 6. Region of interest (ROI) of 128 × 128 pixels size around the core point is extracted from input image, and contourlet transform is subsequently used for its textural analysis. With the help of Directional Filter Banks (DFBs), 2-D spectrum is fragmented into fine slices. Using five levels decomposition, total 60 blocks are formed from ROI. Let $S_{k\theta}$ denotes the sub-band image at k level and θ direction. Similarly, let $\sigma_{\theta k}$ denotes the standard deviation of the kth block in the θ direction sub-band image and $c_{\theta k}(x, y)$ is the contourlet coefficient value at pixel (x, y) in the sub-band block $S_{k\theta}$, then the value for directional energy $E_{k\theta}$ for that sub-band block is calculated using following equation [19]:

$$E_{k\theta} = n\ \mathrm{int}\left(\frac{255(\sigma_{\theta k} - \sigma_{\min})}{\sigma_{\max} - \sigma_{\min}}\right) \quad (8)$$

where

$$\sigma_{\theta k} = \sqrt{\left(\frac{1}{n}\right) \sum_{x,y \in S_{k\theta}} (c_{k\theta}(x, y) - \overline{c_{k\theta}})^2} \quad (9)$$

$n\ \mathrm{int}(x)$ is the function that returns the nearest integer value to x, $\sigma_{\max}$ and $\sigma_{\min}$ are the maximum and minimum standard deviation values for a particular sub-block. N is the number of pixels in sub-band $S_{k\theta}$. $\overline{c_{k\theta}}$ is the mean of contourlet coefficients $c_{k\theta}(x, y)$ in the sub-band block $S_{k\theta}$. The normalized energy for each block is computed as:

$$E = \frac{E_{k\theta}}{E_{k\theta(t)}} \quad (10)$$

where $E_{k\theta}$ represents directional energy of sub-band θ at k level and $E_{k\theta(t)}$ represents total directional energy of all sub-block at k level, while E is the normalized energy. Feature set for fingerprint comprises of core and delta points along with the ridge and valley orientations which have strong directionality. Euclidian distance classifier is finally employed for fingerprint matching (Fig. 7).

4 Feature level fusion

Figure 8 depicts the basic methodology for feature level fusion of the multimodal system based upon palm- and fingerprints. Joint feature vector is matched with the already stored multimodal database in matching module that consists of Euclidian classifier. Depending upon the threshold, the decision module declares the result as genuine or impostor. Similarly, in case of unimodal identifiers, the extracted features are matched with respective database using a Euclidian classifier in matching module, followed by decision on the basis of selected threshold in the decision module. For feature level fusion of palmprint and fingerprint, feature vectors of palmprint and fingerprints are concatenated together to

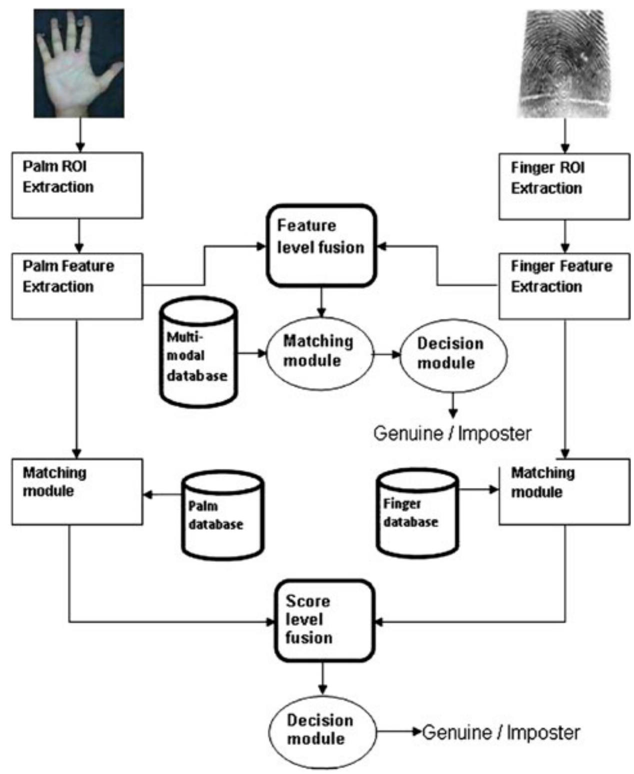

Fig. 8 Methodology of feature level and score level palm-finger multimodal systems

make combined feature vector similar to Kumar and Zhang [16]. Let $P = p_1, p_2, \ldots \cdot p_m$ and $F = f_1, f_2 \ldots f_n$ represent feature vectors containing the information extracted from palmprint and fingerprint, respectively. The objective is to combine these two feature sets after normalization in order to yield a joint feature vector (JFV). JFV is obtained by combining P and F feature sets. Problem of compatibility of feature sets is overcome inherently as feature vectors in case of both palm- and fingerprint identifiers consist of normalized energy values. Thus, need for normalizing feature sets is eliminated. One hundred and twenty-four different feature values of palmprint are concatenated with 60 different feature values of fingerprint to give a joint feature vector (JFV) of 184 feature values representing the same individual. JFVs are generated and stored in order to make multimodal database which is subsequently used for identification and verification purpose.

5 Score level fusion

Fusion at score level demands matching scores generated by comparing input test image with trained database [3]. Feature vectors of palmprint and fingerprint are compared with their respective databases using normalized euclidean distance classifier to generate the matching scores. These scores contain less amount of information as compare to feature vectors. Before fusing scores together, scores should be normalized to a common scale. As normalized energy values are used in both palmprint and fingerprint systems to generate the scores, so generated scores are already on a common scale and hence eliminate the need of using any score normalization technique. Palm and finger scores are combined using two rules: Sum Rule and Product Rule [7].

5.1 Sum rule

According to sum rule, the scores of palmprint and fingerprint input images are added together to yield a new set of values. Thus, the new set of values contains more amount of information as compared to the individual unimodal systems, hence, giving more information to identify a person. Finally, the decision of input claim is established on the basis of preset threshold by the classifier. Suppose $P = p_1, p_2, \ldots p_m$ and $F = f_1, f_2 \ldots f_n$ give the scores of palm and finger images, respectively, then according to the sum rule, the combined score vector sk is obtained $s_k = p_k + f_k$. Here, 'k' represents the total number of generated score of test image corresponding to trained database. s_k is the combined score which is used for decision making.

5.2 Product rule

The scores of palmprint and fingerprint images are multiplied together to produce a new set of values consisting of combined values of both the systems. Suppose $P = p_1, p_2, \ldots p_m$ and $F = f_1, f_2 \ldots f_n$ give the scores of palm and finger images, respectively, then according to the product rule the combined score vector g_k is obtained as: $g_k = p_k \cdot f_k$. Here, 'k' represents the total number of generated score of test image corresponding to trained database, and g_k is the combined score which is used for decision making.

6 Experiments and results

Fingerprint images were collected using Digital Persona Fingerprint scanner 4000B, while palmprints with the help of developed platform. A database consisting of palm and finger images of 55 individuals has been constructed. Sixteen prints are collected from single individual with 8 records per biometric modality. Thus, multimodal database consists of $16 \times 55 = 880$ records, consisting of 440 palmprint and 440 fingerprint records. The database is developed in two sessions with an average interval of two months to focus on performance of developed multimodal system. User training is conducted prior to data acquisition phase for both palm and fingerprints. In our experiments, the developed database is divided into two non-overlapping sets: training and validation

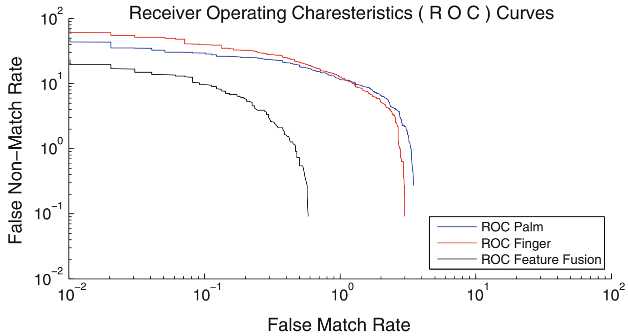

Fig. 9 ROC *curve* for Multimodal system using feature level fusion in comparison with unimodal fingerprint and palmprint identifiers

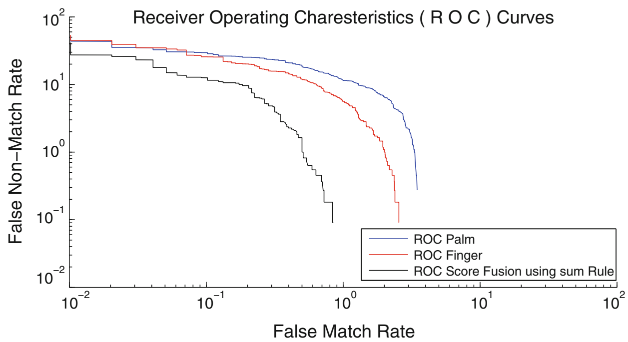

Fig. 10 ROC *curve* for Multimodal system using score level fusion (sum Rule) in comparison with unimodal fingerprint and palmprint identifiers

sets of 440 images each (220 for each modality). Palmprint- and fingerprint-based multi-modal system is implemented in Matlab on a 3.0 GB RAM, 2.0 GHz Intel CoreDuo processor PC. Training set is first used to train the system and threshold determination. Validation data set is then used to evaluate the performance of trained system. The performance of the system is recorded in terms of statistical measures like False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER), and results were plotted in terms of Receiver Operating Characteristics (ROC) curves.

Figure 9 shows the ROC curve of proposed multi-modal system using feature level fusion in comparison with unimodal palmprint and fingerprint systems, respectively. Figures 10 and 11 give the ROC curves for score level fusion by sum and product rules, respectively, in comparison with unimodal palmprint and fingerprint systems. It is evident from the ROC curves that multimodal system shows improved performance compared to individual unimodal systems.

Table 1 gives the comparison of Equal Error Rates of Multimodal systems with the unimodal systems. Equal Error Rate, EER of feature level fused system is 0.5380%, while that of score level fusion with sum and product rules are 0.6141 and 0.5482%, respectively. EER for multimodal systems is far less than EER values of individual palmprint (2.8224%) and fingerprint (2.5533%) identifiers. The results depict obvious improvement in performance of multimodal system as compared to unimodal systems. Amongst multi-modal systems, the feature level fusion performs best, followed by score level fusion using product rule.

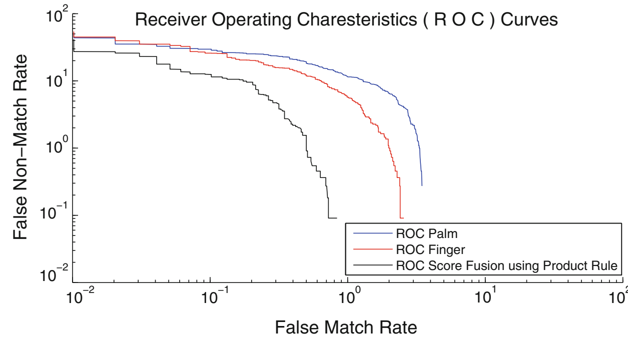

Fig. 11 ROC *curve* for Multimodal system using score level fusion (product rule) in comparison with unimodal fingerprint and palmprint identifiers

Table 1 Comparison of equal error rates of multimodal and unimodal systems

Biometric system	EER (%)
Palmprint	2.822
Fingerprint	2.553
Palm and fingerprints(feature level fusion)	0.538
Palm and fingerprints (score level fusion (sum rule))	0.6141
Palm and fingerprints (Score level fusion (product rule))	0.5482

7 Discussions and comparison of results

Multimodal biometric systems fuse two or more physical or behavioral traits to give minimum EER values and hence improving system dependability. Table 2 presents a comparison of results of different approaches proposed by Snelick et al. [15], Kumar and Zhang [16] and Wang et al. [17] to our proposed approach. Minimum EER value of proposed multimodal system as compared to different biometric systems proves the effectiveness of presented approach.

The paper presents multimodal personal identification system utilizing palmprint and fingerprint systems. The unimodal identifiers utilize directional energies for matching purpose with the help of distance-based classifier. The feature level fused multi-modal system uses a joint feature vector representing the palm and finger energy features, which is subsequently used for matching using distance classifier. In score level fused multimodal system, individual scores of unimodal palm- and fingerprint identifier systems are fused

Table 2 Comparison of equal error rates of proposed and already published multimodal systems

System	Feature	Level of fusion	EER (%)
Snelick et al. [15]	Finger + face	Score (sum rule)	0.94
Snelick et al. [15]	Finger + face	Score (min score)	5.43
Snelick et al. [15]	Finger + face	Score (max score)	0.63
Snelick et al. [15]	Finger + face	Score (matcher weighting)	1.16
Snelick et al. [15]	Finger + face	Score (user weighting)	0.63
Kumar et al. [16]	Hand shape + palmprint	Score	7.15
Kumar et al. [16]	Hand shape + palmprint + fingerprint	Score	3.53
Wang et al. [17]	Palmprint + palm vein	Image level fusion	1.016
Proposed	Palmprint + fingerprint	Feature	0.538
Proposed	Palmprint + fingerprint	Score (sum rule)	0.6141
Proposed	Palmprint + fingerprint	Score (product rule)	0.5482

by sum and product rules. ROC curves and EER values demonstrate considerable improvement in recognition results for multimodal system as compared to individual unimodal identifiers. Among the multimodal systems, the feature level fused system performs the best.

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