An Effective Classifier Fusion Approach for Palmprint Based Identity Verification

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Abstract—*Palmprint is a trusted media for user identity proof due to its rich of information presented in friction ridge impression. Palmprint recognition uses the palm region of a person as a biometric for identifying or verifying the identity of a person. Palmprint provides large quantity of stable physical characteristics of a human and hence more stable biometric than any other biometric. It has enough information for identity verification of a person. In this work we have concentrated on a palmprint verification method. The palmprint verification method followed by four basic steps such as (i) image acquisition, (ii) palmprint preprocessing, (iii) feature extraction or encoding and (iv) palmcode comparision or matching. Our method exploits a ROI detection technique and a classification method. The goal of ROI detection is to obtain a sub-palmprint image for feature extraction and to eliminate the variation caused by rotation and translation. An appropriate fusion of classifier for proximity measures can increase the reliability of identity verification through palmprint biometric. The proposed method for fusion of classifiers is based on a dynamic selection of a threshold point. The classification method works based on various similarity measures for the matching scores obtained at various threshold values. A classifier is designed to support the verification system for two randomly selected palmprint samples, whether they belong to the same person or not based on the distance measures using different didtances like hamming distance(HD), Weighted Euclidean distance(WED), and Jaccard distance(JD) and designing a fusion rule for classification using HD, WED and JD. The effectiveness of the method has been established using several benchmark databases.*

1. INTRODUCTION

Palmprint is a hand-based biometric, rich of information presented in friction ridge impression. It provides information of the raised portion of the epidermis (the outermost layer of skin) containing ridge structure, ridge characteristics and ridge flow details. Palmprint recognition uses the palm region of a person as a biometric for identifying or verifying identity of the person. The palm is the inner surface of our hand from the wrist to the root of fingers.

The palmprint provides large quantity of information and have many advantages. It deals with more stable physical characteristics and hence more stable biometric. It is mostly acceptable biometric due to its permanence and uniqueness. Even identical twins have different principle lines, wrinkles, minutiae, datum point features and texture images [11]. The basic advantages [6], [7] of using palmprint as a promising biometric are its (i) high distinctiveness, (ii) permanence, (iii) high performance, (iv) non-intrusiveness, (v) low-resolution imaging, (vi) user-friendliness, (vii) low price palmprint devices, and (viii) high stability. However, the palmprint has a serious disadvantage also. The palmprint may undergo changes depending on the type of work the person is doing over a long duration of time.

A palmprint basically shows certain skin pattern of a palm, composed of many physical characteristics like lines, points, and texture of the skin. The palmprint epidermis may be as thick as 0.8 mm comparing to other part of our body which is 0.07 to 0.12 mm thick. In response to continuous pressure and friction after birth, the epidermis gradually becomes thicker. Palm in general contains three flexion creases (i) Permanent creases (principal lines), (ii) secondary creases (wrinkles) and (iii) ridges. These three major flexions are genetically dependent [3].

In this work we have concentrated on a palmprint verification method. The method exploits a ROI detection technique and a classification method. The classification method performs using various similarity measures for the matching scores obtained at various threshold values. The performance of the method was established using benchmark datasets and results have been found satisfactory. Next, we describe the prior related work.

2. PRIOR RELATED WORK

Personal verification using palmprint biometric has received considerable attention and numerous approaches have been proposed in the literature. Use of Sobel and Morphological operations of palm print was found to be suitable in many network-based applications analyzed by Chin chuan Han et al [7]. In this paper they have suggested region extraction steps to obtain a square region in a palm table which is called region of interest (ROI). A method of locating and segmenting the palm print into region of interest (ROI) using elliptical halfrings has been reported by Poon et al [18] to improve the identification.

The use of ROI while applying correlation fillter classifiers for palm print identification and verification has been reported by Pablo Hennings [6]. In this work three different regions of pixel sizes: 64×64, 96×96, 128× 128 has been used. Two reference points were first determined from the hand geometry, and square regions are extracted after aligning these two points with the vertical axis.

J.Z. Wang, J. Li, and G. Wiederhold have proposed an integrated region matching (IRM) scheme which allows for matching a region of one image to several regions of another image and thus decreases the impact of inaccurate segmentation by smoothing over the imprecision. The scheme is implemented as SIMPLIcity system [7].

Ying-Han Pang et al have used various moments (ZM, PZM and LM) as feature descriptors [8]. In the first stage of their experiment a localization of palm print region has been implemented as per methodology given by Tee Connie et al [9]. Different methods in Palm print Feature extraction using Region-of-Interest has been analyzed by Kasturika et al [10].

3. BACKGROUND OF THE WORK

Palmprint recognition steps comprises four basic steps such as (i) image acquisition, (ii) palmprnt preprocessing, (iii) feature extraction or encoding, (iv) palmcode comparison or matching. Fig. 1 shows a generic palmprint verification system. Next we discuss each of these steps in detail.

3.1 Image Acquisition

In this step, a sensor scans the palmprint of the user and acts as the interface between the user and the verification system. The palmprint image acquisition may be off line or on-line. In case of off-line verification, all palmprint samples are inked, which are then transmitted into a computer with a scanner. Whereas, in case of on-line identifacation, the samples are captured with a palmprint scanner which is connected to a computer for storage.

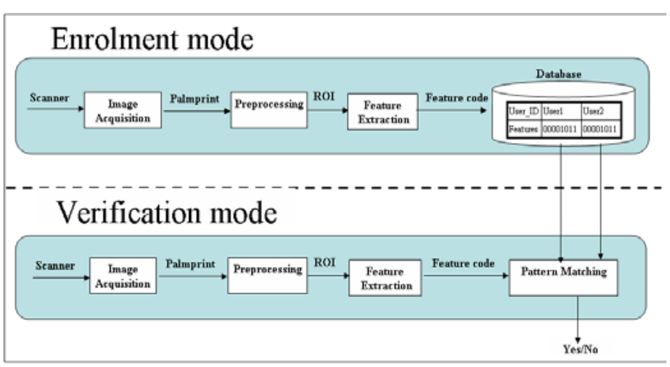

Fig. 1: A palmprint verification system

3.2 Palmprint Preprocessing

Palmprint preprocessing involves alignment of different palmprints under the same coordinate system so that the expected area of each palmprint, called region of interest (ROI) can be extracted for use in feature extraction and matching. Many ROI detection algorithms involve the detection of key points between finngers. In general, palmprint preprocessing have five steps, (i) binarization, (ii) contour detection of the finger and/or palm region, (iii) detecting the key points, (iv) establishing a coordinate system and (v) extracting the central parts. The details of the steps are as follows:

3.2.1. Binarization. Image thresholding operation is used to obtain a binary palmprint image. As image background is stable (black), after computing a threshold value, can be subsequently used for other images.

3.2.2. **Contour Detection of the Palm Region.** Here, we obtain the binary image contour by first applying the canny edge detection method [13] and then finding the boundary of the image.

3.2.3. **Key Points Detection.** The key points detection of the hand boundary is useful for proof of transformation invariance of the palmprint representation. The key point detection algorithms are of different types. It may be of (a) finger-based, (b) bisector based and (c) tangent based.

3.2.4. Establishing a Coordinate System. To establish the coordinate system using finger based key point detection, Han proposes one approach, based on the index, middle and ring fingers [8]. This is a wavelet based multiple finger approach that uses a set of predefined boundary points on the three fingers to construct lines in the middle of the three fingers so that the lines from index and ring fingers are used to set the orientation of the coordinate system and the line from the middle finger is used to set its position. Another approach given by Han et al. [7] is based on the middle finger that uses a wavelet to detect the finger trip and the middle point in the bottom finger and draw a line passing through these two points. In the tangent-based approach, two convex curves are drawn as a boundary, one from index finger and middle finger and other from ring finger and last finger. The intersection points between the tangent to these curves give the key points for establishing the coordinate system. In case of bisector-based approach [10], [9], a line is drawn between the center of gravity of a finger boundary and the middle of its start and end points. Their intersection points give a key point.

3.2.5. Extracting the ROI. The goal of ROI detection is to obtain a sub-palmprint image for feature extraction and to eliminate the variation caused by rotation and translation. The details of our preprocessing steps are shown in the Fig. 2 to Fig. 5.

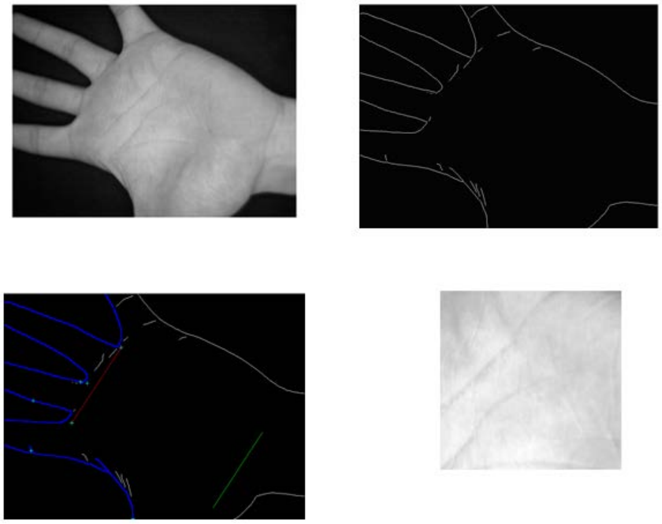

Fig. 2,3,4,5: ROI detection steps resectively:.(i) An original palmprint image (ii) Binarization of the image, (iii) Contour and co-ordinate point detection of the image, (iv) ROI of the image

3.3 Palmprint Feature Extraction

Palmprint contains large number of different types [3] of features that are used to identify a person uniquely which are used to divide into three different categories like (i) Point features, (ii) Line features and (iii) Texure features.

(i) Point features: These are the features that can be obtained from palmprint images with high resolution.

- Datum Points features: These are two end points obtained by using the principal lines. Distance between these two points give the size of a palm.
- Delta point features: A delta point is the center of a delta-like region in the palmprint. They provide unique and stable measurements for palmprint recognition.
- Ridge features (Minutiae details): The ridge structures of a palm region are the outer cellular layer of the skin Minutiae details of ridge section give finer details about palmprint as another measure for identity verification.

(ii) Line features: These features include three relevant palmprint principal lines, due to flexing the hand and wrist in the palm, and other wrinkle lines and curves (thin and irregular).

- Principal-line features: They are the flexure creases that may vary from person to person.
- Wrinkle features: Wrinkles are the lines to provide the skin with a certain amount of stretch ability. In a palmprint, there are many wrinkles, which are different from the principal lines in that they are thinner and more irregular.

(iii) Texture features: Palmprint are rich of texture information. These are the geometry features like width, length and area of a palm's shape. The texture features have advantages over other features that, images can be obtained at low spatial resolution and hence can be smaller in size and the system is less sensitive to noise. Out of these features, the point features can be obtained [3].

3.4 Palmcode Comparison or Matching

Matching a pair of palmprint means to measure how different they are or to decide whether they belong to the same individual or not. As our goal is to verify palmprint by classifying between imposter and genuine users, pattern matching can be performed using the Hamming Distance (HD). The effectiveness of the method is done with the help of other distance measures also. The details of the distance measures that are used are as follows:

- Hamming Distance (HD) was chosen as a metric for recognition since bit-wise comparisons were necessary. Two templates are considered to have been generated from the same palmprint if the HD produced is lower than a user specified threshold values of HD which is defined as

$$HD = \frac{1}{M}\sum_{J=1}^{M} X_J\,(XOR) Y_J \tag{1}$$

and calculates the amount of different bits in binary sequences X and Y over total number of M bits by the sum of the exclusive-OR between X and Y.

- Weighted Euclidean Distance (WED) is a measure of dissimilarity of collection of values between two palmprint templates. The WED is defined as

$$WED(k) = \sum_{i=1}^{N} \frac{(f_i - f_i^{\,k})^2}{(\delta_i^k)^2} \tag{2}$$

Where

f_i : i^{th} feature of unknown palmprint

f^k_i : i^{th} feature of palmprint template k

δ_i^k : standard deviation of the i^{th} feature in palmprint template k

The unknown palmprint template is matched with the palmprint template k if WED is minimum at k.

- Jaccard distance(JD) is a distance measure between binary feature vectors. Jaccard distance is defined as

$$JD(i,k) = \frac{x^T y}{x^T y + x^T Y + X^T y} \tag{3}$$

The value of JD ranges from 0 to 1.

Although in the literature, there are many proximity measures for binary data handling, we have chosen these three proximity measures because of the following reasons.

- In case of Hamming distance (HD), it is easy to implement and two palmcode pattern generated from two similar palmprint will be of highly correlated in nature. Moreover, it has faster response and established for wide range of application domains of binary data. But for two binary pattern of genuine or imposter classification, if the HD provides equal weights to all responsible bits in the binary palmcode, the performance of the system may degrade.
- More reasonable way is to put different weight for different elements of the binary descriptors. Assigning the weight would not effectively put all the measurements on the same scale in case of WED. As WED is used for numeric data only, converting the binary feature vectors to a numeric one, it is used as a proximity measure. It is giving a good result from the benchmark CASIA V1. palmprint dataset we have used in our palmprint verification method.
- To compare and test our result with another binary feature vector measure we have adopted JD because it is also used for a wide range of application domains of binary data handling and its responses are faster.

4. MOTIVATION

The motivation of this research is to develop

i) a palmprint verification method using a 2-D circular Gabor filter and to generate a feature code (PF_Code) from the extracted ROI. For each location in the region of interest, Gabor response is converted into a binary format. This can be considered as a feature reduction method, as Gabor response will be 1 or 0. Afterwards, pattern matching is done using hamming distance.

ii) a classifier to support the verification system for two randomly selected palmprint samples, whether they belong to the same person or not based on the distance measures using different distances like HD, WED and JD and by designing a fusion rule for classification using HD, WED and JD. and by designing a fusion rule for classification using HD, WED and JD.

5. PROPOSED METHOD.

In this work, a method has been developed for verification of identity using palmprint information. It follows three basic steps for palmprint recognition: (i) apply an adjusted circular Gabor fillter initially to the preprocessed palmprint images, (ii) Codify the signs of the filltered images as a feature vector, and (iii) Measure the difference between two plamprint representations using the normalized hamming distance. It also provides robustness against varying brightness and contrast in images. In biometric research, Gabor filters have been applied to feature extraction iris, face and fingerprint recognition.

To support palmprint based classification, a palmprint featurecode (PF-code) is generated where the proposed method for palmprint verification comprises of distinct stages as shown in Fig. 9 for algorithm of PF_code computation as depicted in Fig. 8.

5.1 Our method

After detection of ROI, segmentation and normalization (size and orientation) steps, we calculate a set of palmprint texture features. As the proposed method has been developed with reference to generated features of palmprint image, a method called PF_code is proposed, the short review of which is given in the following algorithm.

1: Input a palm image.
2: Extract ROI.
3: Obtain a palmprint vector: $\{x_1,x_2,...x_{256}\}$ from ROI.
4: Apply an adjusted circular Gabor _lter:
5:

$$G(x, y, \theta, u, \sigma) = \frac{1}{2\pi\sigma^2} \exp\{-\frac{x^2+y^2}{2\sigma^2}\} \exp\{2\pi i(ux\cos\theta + uy\sin\theta)\}$$

6: Obtain feature vector, PF_code as the sign of the filtered image.
7: Measure and find out the difference between two PF_code using distance measures.

Fig. 6: Algorithm for PF_Code computation

To generate a meta representation called PF_code based on the feature extraction for palmprint image we develop a routine called PF_code() which is shown in Fig. 9. For illustration of working of our method let us assume that x : $\{x_1, x_2, ...x_d\}$ and y : $\{y_1, y_2, ...y_d\}$ denote two feature sets generated from palm print biometrics.

Let c(x) denotes the class of the person that x belongs to. As the matching is based on distance measure, two distributions are generated viz. intra distance (or within person) that occurs when c(x) = c(y) and inter-distance (for two different persons) when c(x) $\neq$ c(y). So by assuming that the distributions are normal, we find a decision threshold to minimize the FAR (False Acceptance Rate) and FRR (False Rejection Rate).

As the palmprint code comparison or matching is done to check if the two palmprint belong to the same person or not, hence a distance measure give the intra distance distribution tends to be close to 0 while the inter distance distribution tends to be far from 0.

We calculate Hamming distance of the palmprint template. However for evaluation of the effectiveness of the method we also test with the other proximity measures like Weighted Euclidean distance (WED) and the Jaccard distance(JD).

5.2 Effective Verification using classifier fusion

To improve the matching performance, a classifier based on decision level fusion is designed with the fusion of different proximity measures. Based on an experimental study we decide the expression for decision level fusion for those chosen dissimilarity measures as follows:

$$f(x) = \begin{cases} 1, if WED \langle t_b \\ HD, if t_b \leq WED \leq t_a \\ 0, if WED \geq t_a \end{cases} \qquad (4)$$

Here we have used only HD and WED because of the superior performance over other synthetic and benchmark dataset.

6. PERFORMANCE EVALUATION.

The performance protocol given by [5,7] is used to measure the accuracy of the palmprint verification system. To evaluate similarity measures for binary features, we chose two types of errors, false accept rate (FAR) and false reject rate (FRR).

In order to check validity of the sample data taken for training and testing, we use a k-fold cross-validation method. It is a generalization approach which partitions data into disjoint subsets of size n/k and then trains, validates and takes average over the k partitions where n is the total number of training data points.

The algorithm use for cross validation check is shown in Fig. 7. cross-validation has several advantages such as (i) the method with the highest crossvalidation accuracy is chosen, (ii) cross validation generates an approximate estimate of how well the classifier will do on 'unseen' data and (iii) by averaging over different partitions it is more robust than just a single train/validate partition of data.

```
for i=1:k
train on 90% of data,
Acc(i)= accuracy on other 10 %
end
CrossValidationAccuracy = 1/k
    ∑ Acc(i)
```

Fig. 7: Algorithm for k-fold cross validation

6.1 Environment used

The experiments were carried out on a workstation with Intel dual-core processor (1.86 GHz) with 1 GB of RAM. We used MATLAB 7.2 (R2006a) version in windows (64-bits) platform for the performance evaluation.

6.2 Datasets used

We have used CASIA(V1) palmprint dataset for verification of palmprint. The dataset contains 312 subjects and total 5502 samples. The samples are of 8-bit gray-level JPEG files. The palmprint dataset is available in [17]. For the verification experiments, the datasets are divided into two parts training and test sets. The results are generated using k-fold error validation method. The dataset used for cross-comparison of samples is as shown in the Table 1.

Table 1: Datasets used for cross-comparison of 300 subjects and 8 samples

Class	Data sample types	
	Samples	DB per k fold
Intra class	Training	216
	Testing	24
Inter class	Training	216
	Testing	24

6.3 Experimental results and analysis

In this section, we carry out two different experiments to evaluate the performance of our method.

Experiment 1: A randomized k-fold cross validation method is adopted by dividing the 2400 palmprint images into k parts on a per subject basis.

From the CASIA V.1 Palmprint dataset, we have taken 2400 samples of 300 subjects containing 8 samples per subjects and divided entire samples into two partitions of 1200 and 1200 samples of intra class and inter class palmprint samples for balanced classification. The details of the data samples are as shown in the Table 1.

A comparison of experimental results are made by using cross-validation with k=5. From palmprint dataset (CASIA V.1), we obtain the matching scores for different palmprint images and the corresponding error rates are generated using different threshold values for each of the fillter level of the Gausian fillter. From the result of our experiment we have obtained ROC curves for this method in terms of FAR and FRR for palmprint biometric as shown in Fig. 8. The FAR and FRR values are reported in Table 2 with best values among all the five sets of data samples. It can be seen from the table as well as from the Fig. that result is satisfactory.

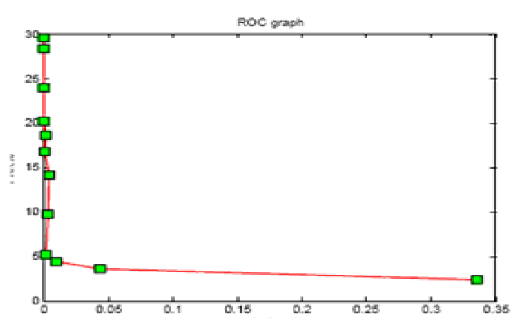

Fig. 8: ROC curve of Palmprint verification (CASIA V1) dataset

Table .2: FAR/FRR values of Palmprint V.1 dataset

Filter No.	FAR	FRR
1	0.0185	0.25
2	0.0231	0.2222
3	0.0231	0.213
4	0.0278	0.1852
5	0.0324	0.162
6	0.0417	0.1157
7	0.0509	0.0926
8	0.0556	0.0823
9	0.0648	0.0694
10	0.0741	0.0556
11	0.0926	0.0463
12	0.1111	0.037

Experiment 2: In order to extend the proposed model, in this section we compared the experimental results obtained by using different distance measure also. From the two created sample sets, intra-class distance and inter-class distance sets as given in Table 1, the Palmprint verification model is tested. Each scalar distance value is classified into intra or inter person class by comparing with the threshold values as depicted in the three distribution curves in Fig. 9., Fig. 10 and Fig. 11 with respect to three distances Hamming, Jaccard and Weighted Euclidean distances are shown respectively.

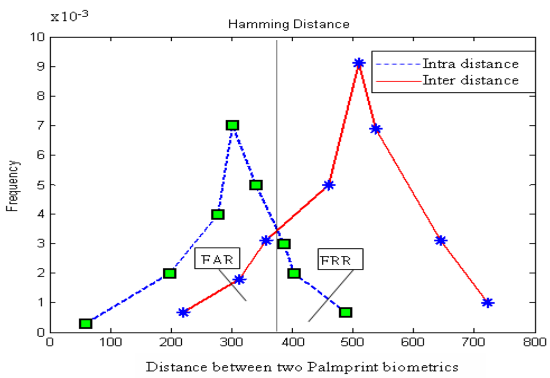

Fig. 9: Distribution curves for Inter class and Intra class w.r.t. hamming distance.

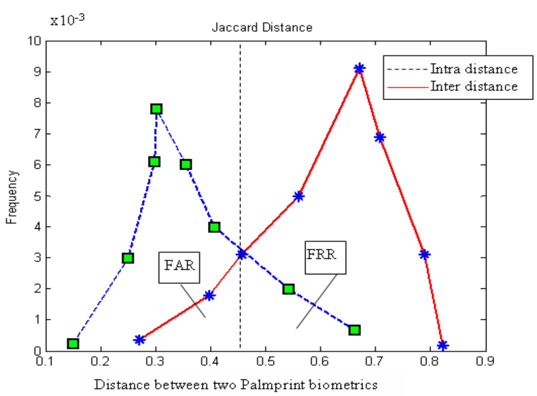

Fig. 10: Distribution curves for Inter class and Intra class w.r.t. Jaccard distance.

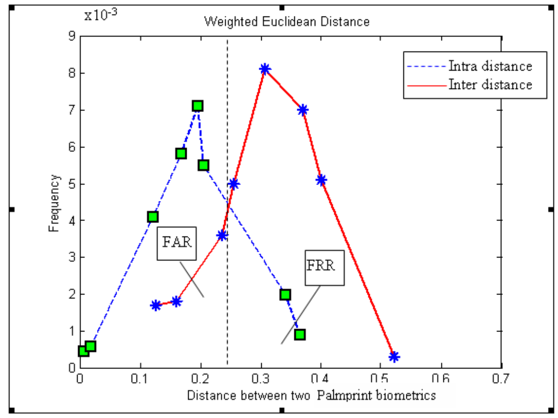

Fig. 11: Distribution curves for Inter class and Intra class w.r.t. Weighted Euclidean distance.

7. DISCUSSION

A cross-comparison was performed to build the distribution of imposter and genuine match scores. We attempted to draw distribution curves for both imposter and genuine using Hamming distance, Jaccard distance and Weighted Euclidean distance by calculating inter-class and intra-class distributions. To select an appropriate and unbiased distance measure is a difficult task as texture-based palmprint biometric verification involves measure of binary feature vector distances and verification of the identity of a person. The curve also depicts the optimization of threshold values of the individual match scores of a person with effective to specific application data. As in case of biometric verification, higher the matching score, higher the similarity between them. Access to a biometric system is granted only, if the biometric pattern to be verified is higher than a certain threshold. If we increase the threshold, there will be reduced FAR but more FRR.

A common variation is obtained using normal deviation scales on both axes which is a linear graph that eliminates the di_erences for higher performances From the distribution graph we obtained, as in Fig. 5-9 to Fig. 5-11 the matching threshold assessment for classification of genuine or imposter class can be made easily.

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