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ACCURATE PERSONAL IDENTIFICATION BY COMBINING LEFT AND RIGHT PALMPRINT IMAGES

Engineering

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ABSTRACT

Providing authorized users with secure access to the services are a challenge to the personal identification systems. A real time personal identification system should meet the conflicting dual requirements of accuracy and response time. Multimodal biometric systems perform better than unimodal biometric systems. Recently, palmprint based identification systems have been receiving more attention from researchers because of its good performance. The left and right palmprint images are combined and obtain better results. This paper propose a novel framework to combine both left and right palmprint images by generating three kinds of scores and performs matching score level fusion. Based on the obtained fusion score the Support Vector Machine (SVM) classifier classifies the outcome as identical or not. The first two kinds of scores were, respectively generated from the left and right palmprint images and can be obtained by Robust Line Orientation Code (RLOC) method and the third kind of score was obtained using a specialized algorithm. This paper also exploits the similarity of the left and right palmprint of the same subject.

I. INTRODUCTION

In today's complex, geographically mobile, electronically wired information society, to achieve highly accurate automatic personal identification is a crucial problem that needs to be solved properly. The e-commerce applications are growing rapidly and it requires reliable and automatic personal identification for effective security control. Biometrics refers to metrics related to human characteristics. Biometrics authentication is used in computer science as a form of identification and access control. Biometric identifiers are the distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorized as physiological versus behavioral characteristics. Physiological characteristics are related to the shape of the body. Examples include fingerprint, palm veins, face recognition, DNA, palm print, hand geometry, iris recognition, retina and odour/scent. Behavioral characteristics are related to the pattern of behavior of a person, including typing rhythm, gait, and voice [1] A biometric authentication system works by acquiring biometric data from a user and comparing it against the template data stored in the database in order to identify a person or to verify a claimed identity. Among various biometric systems, palmprint recognition is a promising one due to its simplicity, feature extraction, matching feature, high precision, real time computation, and the resolution of used images. Palm is the inner surface of the hand and between the wrist and fingers. Palm area contains huge number of features such as principal lines, wrinkles, minutiae, datum point features and texture. Palmprint identification has emerged as one of the popular and promising biometric modalities for forensic and commercial applications.

Palmprint features are considered promising in identifying people. There are two types of palmprint features with reference to the field at which palmprint systems are used. The first type of features are the principal lines and wrinkles which could be extracted from low resolution images (<100 dpi) and it is used for identification in the commercial applications. The second type of features are the singular point, ridges and minutiae point which could be extracted from high resolution images (>100dpi) and it is used for forensic applications such as law enforcement applications[2] A palmprint recognition system normally consists of four parts: palmprint scanner, pre-processing, feature extraction and matcher. The palmprint scanner is to gather palmprint images. Pre-processing is an arrangement of a coordinate system to align the palmprint images, and to segment a fraction of the palmprint image for feature extraction. Feature extraction is to acquire effective features from the pre-processed palmprints. Finally, a matcher evaluates the two palmprint features.

The proposed method uses the preprocessed image that is the Region of Interest (ROI) extracted palmprint images from the IITD database. This defines a co-ordinate system for the further processing of palmprint images

II. LITERATURE REVIEW

Huanga, Jiaa and Zhang [3] have proposed the palmprint authentication system based on principal line extraction. Modified finite Radon transform has been employed for feature extraction. A line matching technique has been used which is based on the pixel-to-area algorithm Type fonts are required. Please embed all fonts, in particular symbol fonts, as well, for math, etc. Zhang, Kong, You and Wong [4] had proposed Online Palmprint Identification. The proposed scheme takes online palmprints, and utilizes low resolution images. Low pass filter in addition to boundary tracking algorithm is used in the pre-processing phase. A normalized hamming distance is used for matching.

Anil K Jain, ArunRose [5] proposed Multibiometric systems which describes about the limitations imposed by unimodal systems can be solves by using multimodal systems. Yong Xu, Lunke Fei, and David Zhang [6] proposed the paper Combining Left and Right Palmprint Images for More Accurate Personal Identification. The proposed framework shows that the left and right palmprint images of the same subject are somewhat similar. The proposed method carefully takes the nature of the left and right palmprint images into account, and designs an algorithm to evaluate the similarity between them. Moreover, by employing this similarity, the proposed weighted fusion scheme uses a method to integrate the three kinds of scores generated from the left and right palmprint images.

III. THE PROPOSED FRAMEWORK

A. Similarity Between the Left and Right Palmprints

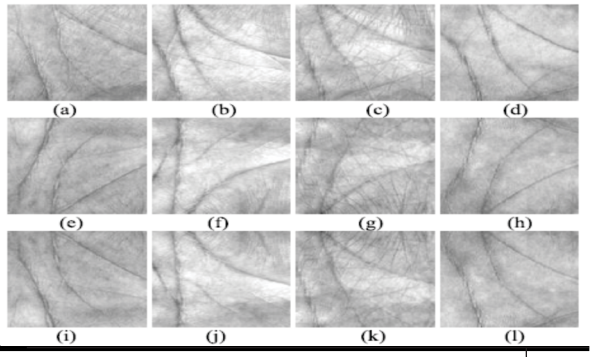
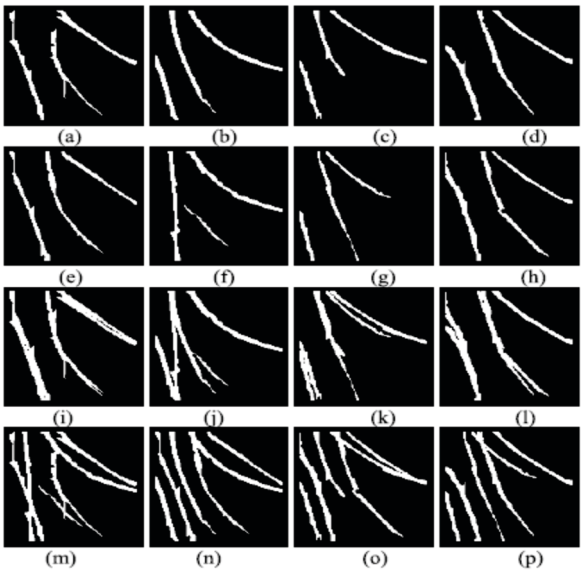


Fig.1. Palmprint images of four subjects. (a)-(d) are four left palmprint images; (e)-(h) are four right palmprint corresponding to (a)-(d); (i)-(l) are the reverse right palmprint images of (e)-(h).

Images in Fig. 1 (i)-(l) are the four reverse palmprint



images of those shown in Fig. 1 (e)-(h). It can be seen that the left palmprint image and the reverse right palmprint image of the same subject are somewhat similar

Fig. 2 (a)-(d) depicts the principal lines images of the left palmprint shown in Fig. 1 (a)-(d). Fig. 2 (e)-(h) are the reverse right palmprint principal lines images corresponding to Fig. 1 (i)-(l). Fig. 2 (i)-(l) show the principle lines matching images of Fig. 2 (a)-(d) and Fig. 2 (e)-(h), respectively. Fig. 2 (m)-(p) are matching images between the left and reverse right palmprint principal lines images from different subjects. The four matching images of Fig. 1 (m)-(p) are: (a) and (f) principal lines matching image, (b) and (e) principal lines matching image, (c) and (h) principal lines matching image, and (d) and (g) principal lines matching image, respectively.

Fig. 2 (i)-(l) clearly show that principal lines of the left and reverse right palmprint from the same subject have very similar shape and position. However, principal lines of the left and right palmprint from different individuals have very different shape and position, as shown in Fig. 2 (m)-(p). This demonstrates that the principal lines of the left palmprint and reverse right palmprint can also be used for palmprint verification/identification.

Fig. 2. Principal lines images. (a)-(d) are four left palmprint principal lines images, (e)-(h) are four reverse right palmprint principal lines image, (i)-(l) are principal lines matching images of the same people, and (m)-(p) are principal lines matching images from different people.

A. Principle Line Extraction using Canny Egde Detection Method

Principle lines are one of the key features of palmprint images. A palmprint could be represented by some line features from low resolution image. Algorithms such as Canny [7] are able to extract the principal lines. In order to extract principle line, edges of the image needs to detect. Edge detection is the process of finding sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects. John F Canny developed an algorithm which is optimal with regard to detecting real edge points and localizing it as close as possible to real edges. Here the principle lines are extracted by applying Canny edge detection method.

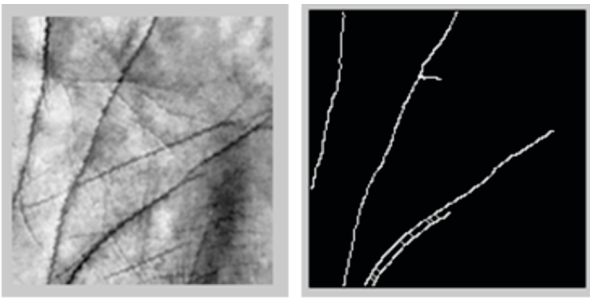


Fig. 3 (a) ROI of left palmprint image given to Canny Edge detector (b)Image after applying canny edge detector

A. Matching score calculation

NAminjjiBjiABAS)),(&),((),(11åå===The task of palmprint matching is to calculate the degree of similarity between a test image and a training image. The pixel-to-area matching strategy is adopted for principal lines matching in Robust Line Orientation Code (RLOC) method [3]

$$S(A,B) = \left(\sum_{i=1}^{m}\sum_{j=1}^{n} A(i,j) \,\&\, \overline{B}(i,j)\right) \Big/ N \quad (1)$$

Where A and B are two palmprint principal lines images, "&" represents the logical "AND" operation, N_A is the number of pixel points of A, and *.B (i, j)* represents a neighbour area of *B(i, j)*. For example, *.B (i, j)* can be defined as a set of five pixel points, *B(i*-1, *j*), *B(i* +1, *j*), *B(i, j*), *B(i, j* –1), and *B(i, j* +1). The value of *A(i, j)* & *.B(i, j)* will be 1 if *A(i, j)* and at least one of *.B (i, j)* are simultaneously principal lines points, otherwise, the value of *A(i, j)* & *.B (i, j)* is 0. Theoretically speaking, *S(A,B)* is between 0 and 1, and the larger the matching score the greater the similarity between *A* and *B*. The matching score of a perfect match is 1. From the definition of *S(A,B)*, it can be seen that it is robust for slight translations and slight rotations between two images. That is, the matching score will change little if the translation is not to exceed one pixel and the rotation is not to exceed 3 .However, because of imperfect pre-processing, there might have large translations in practical applications

A. Procedure of the Proposed Framework

*thresholdmatchXscoreSimkkjY_*),(_~[3]In the proposed work, a palmprint image is given, and it is verified against the stored template. Score of input image with each class is generated. Then fusion score is generated and the fusion score is given to the Support Vector Machine (SVM) classifier to check whether the generated fusion score is greater than the threshold value set. If so the output is shown as identical person else it is the non-identical person. Procedure for the proposed work is explained below. The framework first works for the left palmprint images and uses the RLOC method explained in section C to calculate the score of the test sample with each class. Then it applies for the right palmprint images and calculates the score of the test sample with each class using the same method used for the left palmprint images. Then crossing matching score is calculated by using the left palmprint and the reversed right palmprint images. Then the proposed framework performs matching score level fusion to integrate these three scores and given it to the SVM classifier to obtain the identification result.

$Sim_score(\widetilde{Y}_j^k, X^k)$ $match_rfpcqfmjb$

Suppose that there is C subjects, each of which has m available left palmprint images and m available right palmprint images for training. Let X_k^i and Y_k^i denote the ith left palmprint image and i^{th} right palmprint image of the kth subject respectively, where $i = 1, \ldots, m$ and $k = 1, \ldots, C$. Let $Z1$ and $Z2$ stand for a left palmprint image and the corresponding right palmprint image of the subject to be identified.$Z1$ and $Z2$ are the so-called test samples

Step1: Generate the reverse $\widetilde{W}$images of the right palmprint images Yik. Both Yik and will be used as training samples. is obtained by

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(l=1…LY, c=1…CY) where LY and CY are row number and column number of Yik respectively.

Step 2: Use Z1, Xik s, calculate the score of Z1 with respect to each class by using the equation of Robust Line Orientation Code method. The score of Z1 with respect to the ith class is denoted by s_i.

Step 3: Use Z2, Y_i^k s, calculate the score of Z2 with respect to each class using the equation of Robust Line Orientation Code method. The score of Z2 with respect to the ith class is denoted by t_i

Step4 $\tilde{Y}_j^k (j = 1,..., m', m' \le m)$ which have the property of are selected from as additional training samples, where *m-*a-tc-h_th-reshold* is a threshold. is defined as $Sim_score(Y_j^k, X^k)$

$$Sim_score(\tilde{Y}_j^k, X^k) = \sum_{i=1}^{T} (S(\hat{I}_i, X^k)) / T$$

Where Y is a palmprint image. X^k are a set of palmprint images from the kth subject and X_i^k is one image from X_k. $X\hat{}_i^k$ and $Y\hat{}$ are the principal line images of X_i^k and *Y*, respectively. *T* is the number of principal lines of the palmprint and *t* represent the tth $\tilde{W}_t$ principal line.

Step 5: Treat s obtained in Step 4 as the training samples of Z1. Calculate the score of Z1 with respect to each class. The score of the test sample with respect to $\tilde{W}_t$ the s of the ith class is denoted as g_i

Step 6: The weighted fusion scheme fi = w1si + w2ti +w3gi, where 0 ≤ w1, w2 ≤ 1 and w3 = 1-w1-w2, is used to calculate the score of Z1 with respect to the ith class.

A. Fusion score calculation

Since, three score values are obtained a fusion score is to be calculated by using three weights. The weighted fusion scheme is done by

$$f_i = w_1 s_i + w_2 t_i + w_3 g_i \quad \text{Where } 0 \le w_1, w_2 \le 1 \text{ and } w_3 = 1 - w_1 - w_2$$

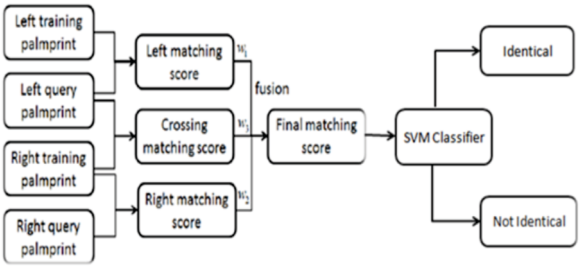


Fig 4. Architecture of the Proposed Framework

A. svm classification

The generated fusion score is given to SVM Classifier which classifies the result as identical or not. Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges [9]. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, perform classification by finding the hyper-plane that differentiate the two classes very well In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible [9]. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

In this work a database file is created with values as possible scores given into one field, corresponding to that the values one or zero is given. The scores below a threshold value is set as value 0 and the score above the threshold value is set as 1.When the fusion score is generated it is given to the SVM classifier, then the score corresponding to which value that is zero or one is given as the output from the SVM classifier. If the value obtained is 1 then the person is the identified person otherwise who the non-identified person is.

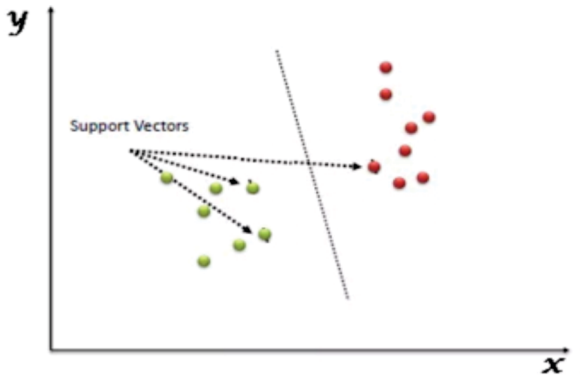
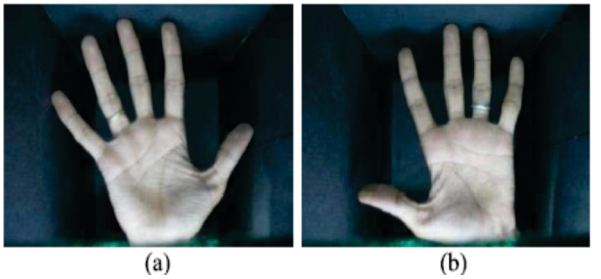


Fig 5. SVM hyper-plane that differentiate the two classes

IV. EXPERIMENTAL RESULTS

A. Palmprint Databases

There are different palmprint databases are available which contain a number of palmprint images. The databases available are PolyU databases, IITD Databases. The PolyU palmprint database (version 2) [10] contains 7,752 palmprint images captured from a total of 386 palms of 193 individuals. The samples of each individual were collected in two sessions, where the average interval between the first and second



sessions was around two months. In each session, each individual was asked to provide about 10 images of each palm Fig 6: (a) and (b) are a pairs of the left and right hand images of one subjects from IITD database

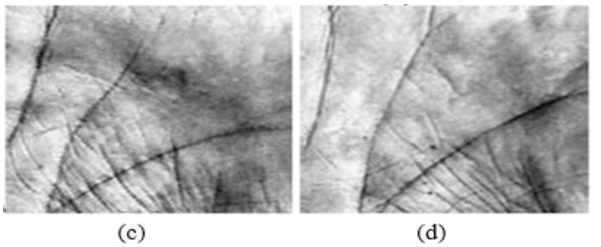


Fig 7: (c) and (d) are the corresponding ROI images extracted from (a) and (b).

The public IITD palmprint database [11] is a contactless palmprint database. Images in IITD database were captured in the indoor environment, which acquired contactless hand images with severe

variations in pose, projection, rotation and translation. The main problem of contactless databases lies in the significant intra-class variations resulting from the absence of any contact or guiding surface to restrict such variations. The IITD database consists of 3,290 hand images from 235 subjects. Seven hand images were captured from each of the left and right hand for each individual in every session. In addition to the original hand images, the Region Of Interest (ROI) of palmprint images are also available in the database. Fig. 6 and Fig 7 show some typical hand images and the corresponding ROI palmprint images in the IITD palmprint database. Compared to the palmprint images in the PolyU database, the images in the IITD database are more close to the real-applications

B. Performance Measures

Various factors such as environmental variations, noise, quality of the input devices etc which makes it very unlikely to get same values of the features extracted from the different samples of the same person at different point of time. Therefore, matching algorithm is needed to compare the samples and computes the matching score and decide if two samples belong to the same individual or not by comparing the matching score against the acceptance threshold. However, it is possible that sometimes the output of a biometrics system may be wrong. Therefore, the performance of a biometrics system is measured in terms of two errors: false accept ratio (FAR) and false reject ratio (FRR).

- **False Accept Rate (FAR)**: False acceptance is the number of times the system accepts an unauthorized user and FAR is the ratio of the false acceptance to the number of times the system is used for identification.
- **False Reject Rate (FRR)**: False rejection is the number of times the system rejects an authorized user and FRR is the ratio of the false rejection to the number of times the system is used for identification. These two factors are closely related
- **Equal Error Rate (EER)**: EER is the point where FAR is equal to FRR. It is the point where false accepts rate and false reject rate are equal

Depending upon the application of biometric system, value of the threshold is set. For example, in a high security application like access to secret government documents, a few rejection of genuine user can be tolerated but it is not desired to give access to any unauthorized user. Therefore, in this case, the threshold is set to a high value to minimize the value of FRR. For another example in an ATM, it is better to risk few false accepts rather than the annoyance of the customers if the system rejects authorized users are closely related as both depend on the acceptance threshold which is set to achieve the desired security level. If threshold is set to a very high value then false accept rate of the system may decrease but it may increase false reject ratio and a low threshold may result in decrease in false reject ratio but it may increase the false accept rate. So, the threshold is set according the requirement whether a low FAR or a low FRR is needed.

C. Experimental Results on IITD Palmprint Database

Experiments are conducted on the IITD contactless palmprint database. A square region is generally identified as the Region of Interest (ROI) before feature extraction. Thus, the relevant features are extracted and matched only in this square region. The benefit of this processing is that it can define a coordinate system to align different palmprint images captured from the same palm. Otherwise, the matching result would be unreliable. The proposed work uses the weight coefficients as w1=0.45, w2=0.5 and w3=0.05.

In the experiment a set of four palmprint images of four persons were selected to construct a training set. A database of thirty persons 6 left images and 30 persons 6 right images as selected as the test set. The left and right images of each person were selected for testing. Different threshold values were selected and the experiment was conducted. In the experiments we got FAR as 0%. That means none of the genuine persons are accepted as imposter ones. Table 1 shows the details of theFRR obtained.

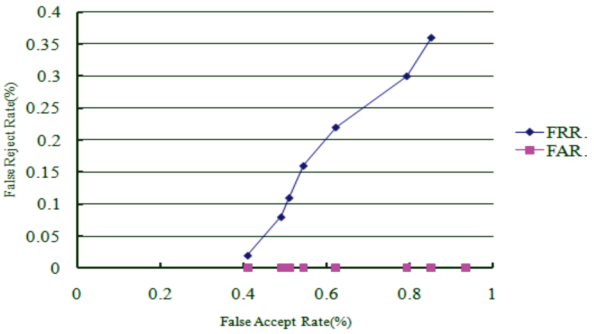


Fig 8: Graph showing FAR and FRR

TABLE 1 RESULT ANALYSIS

Threshold(R)	FRR (%)	FAR (%)
0.4088	0	0
0.4894	0.02	0
0.5088	0.08	0
0.5432	0.08	0
0.6212	0.11	0
0.7926	0.16	0
0.8517	0.22	0
0.9357	0.25	0

The following equation is used to calculate the accuracy measurement of the proposed approach[12]

$$Accuracy = 100 - \left[\frac{FAR + FRR}{2}\right]$$

According to the values of FAR and FRR obtained in Table 1 accuracy of the system obtained is 99.92%.

V. CONCLUSIONS

New personnel identification method is introduced that combine the same biometric trait, the left and right palm. The similarity of left palm and reversed right palm is considered and fusion score is calculated. The paper shows that the left and right palmprint images of the same subject are somewhat similar. The use of this kind of similarity for the performance improvement of palmprint identification has been explored in this paper. The proposed method carefully takes the nature of the left and right palmprint images into account, and designs an algorithm to evaluate the similarity between them. Moreover, by employing this similarity, the proposed weighted fusion scheme uses a method to integrate the three kinds of scores generated from the left and right palmprint images. The system achieved high accuracy

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