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PERFORMANCE EVALUATION OF FUSION METHODS FOR PALMPRINT AND PALM VEIN MULTIMODAL BIOMETRICS BASED IDENTIFICATION AND VERIFICATION

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Abstract: There are increasing applications which require biometric methods for identifying and verifying a person. A biometric system using a single physical characteristic does not have good performance parameters, which can be improvised by using a multimodal biometric system. Palm prints and palm veins have many biometric features that are unique and distinctive. They can be acquired in a touchless acquisition setup. This paper investigates the performance of multimodal biometrics with fusion of palm prints and palm vein images. The fusion can be carried out at sample level, feature level or score level. The effect of fusion on identification as well as verification is studied and evaluated. The analysis of results obtained is presented in the paper.

Index Terms - **Biometric, verification, identification, fusion, multimodal, touchless**

I. Introduction

The methods of identification and verification using biometric systems are known to have many advantages. Identification is used to find the identity of a person. The feature vectors of the person to be identified are compared with all the feature vectors in the enrolment database to locate the best possible match. Verification is used to examine whether the person is genuine user or an imposter, wherein the feature vectors of user are compared only with the enrolled feature vectors of the same person [7]. In order to make biometric systems more reliable and to increase safety from spoof attacks, multimodal systems are useful [3,18].

The biometric features of palmprints and palm veins are stable. They have unique patterns and can be easily acquired [1,2,9]. In this work, palm print and palm vein are used as the two biometrics. The advantage of combining palm print and palm vein is that the palmprint and palm vein images can be acquired simultaneously. These images are subjected to digital image processing stages for pre-processing, extracting ROI, feature extraction and feature matching.

Palm images have been selected from CASIA Multispectral database for the study in this work [5]. The information of preprocessing, ROI extraction, feature extraction and feature matching incorporated; and techniques used for analyzing the results is explained in Section II of this paper. The methodology and the sequence of processing carried out is explained in Section III. The experimental work undertaken for identification is given in Section IV and that for verification is explained in section V. Finally, the results and discussion is given in Section VI.

II. Basic Information

Initial preprocessing operations are performed to segment the palm from the background followed by palm alignment. The processing stages incorporated for segmenting the hand is converting colour image to gray scale image, binarising the image, filling the holes, eliminating small objects and boundary detection. In a touchless setup palmprint images may be captured at different times and rotated at different angles so the images have to be aligned to have same orientation. A preprocessing algorithm has been developed to deal with these variations, which allows the palm to be facing the sensor in any orientation. The algorithm for alignment determines the angle to rotate the palm image such that the resulting image has the palm's outer edge in the vertical direction with fingers in the upwards direction. The algorithm is simple and works in two stages. The first stage deals with coarse alignment and orients the image in the vertical direction with fingers upwards. The second stage deals with the fine alignment of the image based on the outer edge of the palm. The new algorithm which partitions the hand image into finger and palm region has been used to extract a central square shaped Region of Interest. The corner points of ROI are determined with respect to the end points of the partitioning line. The ROI is cropped from the palm image, normalized and sharpened [15].

The next step is to extract features from the ROI. Extraction of appropriate features and accurate feature matching are important factors in improving the performance of any biometric identification or verification. Texture provides a high-order description of the local image content [20]. The advantage of texture analysis is that the information can be extracted from low resolution. Principal Component Analysis is reported to have good characteristics for palmprint recognition. PCA describes images with reduced dimensions [17,19,22]. Considering these merits, texture and appearance based features have been used for feature extraction. The ROI is partitioned into equal size non overlapping subparts. Features from all subparts are combined to form the feature vector. Statistical features, wavelet transform based features; and appearance features using Principal Component Analysis have been extracted. Statistical feature using standard deviation values showed distinguishing features [17]. Normalized wavelet energy has high recognition accuracy when feature vector is formed from square shaped non overlapping regions [14]. PCA feature vector is derived using the largest Eigen values [4,16,21].

In sample or sensor level fusion, the images from different sensors are combined to form a single image. It is essential that the images from the different sensors must be compatible i.e. they must have the same resolution [4]. Sample level fusion is reported in literature with 'Min-Max' method with fusion as minimal of approximation components and the maximal details components. Competitive coding method is used as features. It resulted in EER of 0.0696%. [8]. Another method of fusion is 'Avg-Max' with average rule to combine the approximation coefficients and the maximum rule to combine the detail coefficients. This approach was used on palmprint and palm dorsal images in touch based setup. Lines like features were used as features and SVM for matching resulting in GAR as 98.8% [6].

In feature level fusion, the feature vectors of both biometrics are combined to generate a large feature vector. Fusion of features should ideally result in better identification. But the drawback is that the dimension of feature vector increases. Also the relationship between feature vectors of different sensors is not known and hence discarding the correlated features becomes difficult. Hence very few researchers have studied integration at the feature level [4]. Feature level fusion is reported on palmprint and face biometrics [11].

Score level fusion is performed by combining the scores obtained by matching different data to decide the final outcome. Score normalization is essential prior to fusing the scores. Min-max normalization method is used to set the scores in the range (0 to 1). Fusion rules are simple sum, weighted sum, minimum score, maximum score or product rule [11,12]. Sum based score level fusion is reported in contactless system using palmprint and palm vein. Directional coding is used for feature extraction and SVM for matching. It has given overall increase of 3.4% in accuracy compared to single biometrics [10]. Matching score level fusion has also lead to improving identification accuracy in a system using left and right hand palmprint images [23].

II. METHODOLOGY

The work presented in this paper has an objective of implementing palm print biometric recognition in a touch-less acquisition setup. The 'WHT' images and '940nm' images from CASIA Multispectral database have been used as palmprint and palm vein images respectively. The ROI is extracted with algorithm mentioned in section II and normalized. Features of standard deviation, normalized wavelet energy and PCA components are determined from the ROIs of both palmprint and palm vein images. The two biometrics are fused at different levels. These levels are shown in figure 1.

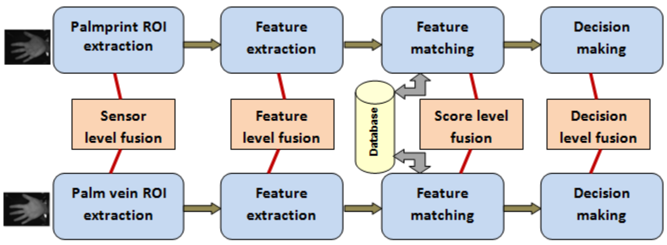

Figure 1: Levels of fusion

In this paper, the effect of image level fusion, feature level fusion and score level fusion on the outcome of multimodal biometric performance has been studied. All the programs have been implemented using MATLAB software with version R2016 on a 3.1GHz Intel ® Core ™ i5-2400 CPU. Feature matching has been implemented with distance measure. The correctness of identification is evaluated in terms of Genuine Acceptance (GA) and Genuine Rejection (GR). The incorrect identification is evaluated as False Acceptance (FA) and False Rejection (FR). These parameters are also expressed in percentages as rates and together they indicate the accuracy of corrections in authentication. Repetitive experiments have been carried out to optimize the size of feature vector, threshold values for decision making and other relevant parameters in feature extraction and matching algorithms. The selection of threshold value is a balancing act of False Acceptance Rate and False Rejection Rate, because decreasing one causes the other to increase. In applications of access control, the threshold needs to be selected such that an imposter is not falsely accepted.

III. EXPERIMENTAL WORK

The parameters of feature extraction and feature matching are first optimized for individual biometrics and then fusion is performed.

4.1. Optimizing the size of feature vector

In the beginning, experimentation was undertaken to optimize the size of feature vector. The images of 100 persons from CASIA multispectral database with White light and 940nm have been have been selected as palm print and palm vein images respectively. Sample images are shown in figure 2.

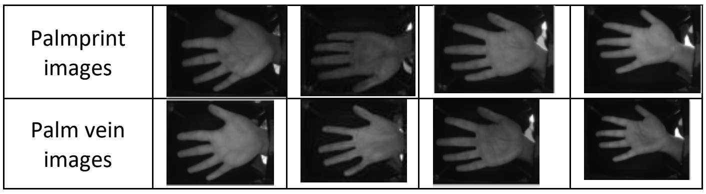

Figure 2: Sample Palm print and Palm vein images

There are 6 images of each person in the database. Hence 5 images of each person have been chosen for training and 1 image of each person totalling 100 images are used for testing. Features have been extracted based on principal components, standard deviation and wavelet energy. The feature sizes of principal components, standard deviation and wavelet energy have been varied. The value of threshold is optimized at a value corresponding to EER. It is observed that, the GAR is maximum for PCA with 70 components, standard deviation of 225 subparts and normalized wavelet energy of 225 subparts.

4.2. Sample level fusion

The two strategies of fusion with Min-Max and Avg- Max have been studied. The palmprint and palm vein images are transformed using Discrete Wavelet Transform. They are fused and then Inverse DWT is performed to generate a new fused image combining features of both. The performance parameters are given in table 1.

Table 1. Effect of Sample level fusion

		PCA	Standard deviation	Wavelet energy
Min-Max fusion	GAR (%)	12.9	96.3	16.2
	EER (%)	43.5	1.9	41.9
Avg- Max Fusion	GAR (%)	71.8	96.3	40.1
	EER (%)	14.1	1.9	29.9

Results of Avg- Max fusion are better than Min - Max fusion method. Even though Avg-Max has higher values of GAR, yet GAR for unimodal identification is better indicating that this type of fusion method is not effective in improving the identification performance as desired.

4.3 Feature level fusion

In feature level fusion, the corresponding feature vectors (PCA, Standard deviation and Wavelet energy) of palmprint and vein images have been combined to result into a fused large length feature vector. The results of identification are provided in table 2.

Table 2: Effect of feature level fusion

Feature vector	PCA	Standard deviation	Wavelet energy	PCA and Standard deviation	PCA and Wavelet energy	Standard Deviation and Wavelet energy	PCA, Standard deviation and Wavelet energy
GAR (%)	83.7	96.8	97.3	96.6	96.5	96.9	96.8
EER (%)	8.2	1.6	1.9	1.7	1.8	1.5	1.6

Thus it is observed that feature level fusion is not producing considerable improvement in GAR even though the size of feature vector is increased.

4.4 Score level fusion

Score level fusion has been incorporated by converting weighted Euclidean distance measures to similarity scores and then normalising these scores using Min-max normalisation.

$s'_k = \frac{s_k - min}{\max - min}$ [12]

Fusion of scores is implemented using weighted sum method. The numeric values of weights have been selected by adopting the strategy used in [4]. The weights are varied over the range [0, 1] in the steps of 0.1, such that the total of all weights is 1. The set of weights that minimizes the total error rate (sum of the false accept and false reject rates) at some specified threshold is chosen [4]. Finally, the threshold value of the fused score is optimized to achieve Equal Error Rate.

In this work, there are 6 feature vectors comprising three feature vectors (PCA, Standard deviation and wavelet energy) each of palmprint and palm vein. The process is optimized by going through 3 stages. In the first stage, the thresholds of all these 6 vectors are optimized at the value corresponding to individual EER. In the second stages, the weights for weighted sum are determined. For score fusion of two features vectors, the weights are varied from 0.1:0.9 to 0.9:0.1.In the third stage, the final decision threshold is optimized for EER after fusion [14]. Finally, all the six feature vectors are combined with score fusion and the results with score level fusion are given in table 3.

Table 3. Performance with score level fusion of different features of both biometrics

Feature vector	Fusion of PCA	Fusion of Standard Deviation	Fusion of Wavelet energy	Fusion of PCA, Standard deviation, Wavelet energy
GAR (%)	97.3	96.6	97.1	98.0
EER (%)	1.3	1.68	1.4	1.0

The GAR is observed to have improved after score level fusion of six feature vectors of palmprint and palm vein images.

V. PALM PRINT –PALM VEIN VERIFICATION

During the process of verification, the test image is compared only with the images of the same person in the database. The outcome of this limited matching is useful in access control type of applications. However, the users of biometric system may be genuine users or imposters. It is an important requirement that the imposters must be rejected by the system. Hence to test the performance of verification algorithm, tests have been carried out with genuine and imposters. Considering 100 persons with 6 images each in CASIA Multispectral database, there are in total 100 x 6 = 600 genuine verification tests and 100 x 99 x 6 = 59400 imposter verification tests.

Verification tests have been carried out on multimodal biometrics. Performance depends on by how well the algorithm can differentiate genuine and imposter matches. The optimization of final decision threshold is an important parameter to minimize errors. The value can be set either to increase security or to decrease false rejections [12].

The number of genuine match scores and imposter match scores can be found from the number of users and the number of samples per user. If there are Q users and P samples each, then these numbers are given by the following formulae

Number of genuine match scores = Q x $C_P^2 = \frac{P!}{(P-2)!2!}$

Number of imposter match scores = C_Q^2 x P x P = $\frac{Q!}{(Q-2)!2!}$ x P^2

CASIA Multispectral database contains 6 images of 100 users. Hence there are 1500 genuine match scores and 1,78,200 imposter match scores.

VI. Results and Discussion

After analyzing the results of different fusion methods, it is inferred that the GAR with score level fusion produces the best results. Hence it is desirable to incorporate score level fusion with weighted sum for decision making.

The results of identification and verification of multimodal biometrics are given in table 4.

Table 4. Comparison of Identification and Verification for multimodal biometrics

Nature of recognition	Performance	Fusion of PCA	Fusion of standard deviation	Fusion of Wavelet energy	Fusion of PCA, Standard deviation, Wavelet energy
Identification	GAR (%)	97.3	96.6	97.1	98.0
	EER (%)	1.3	1.7	1.4	1.0
Verification	GAR (%)	97.0	96.7	97.2	98.83
	GRR (%)	99.98	99.98	99.99	99.99
	FAR (%)	0.00015	0.00016	0.00011	0.00011
	FRR (%)	1.5	1.66	1.66	1.16

The results indicate that the algorithm is effective for use in verification. The thresholds set for identification to obtain EER have been retained in verification tests. The GAR with fusion of multimodal biometrics is observed very close to 100%. FAR is extremely small and further reduces with fusion of biometrics. FRR is comparatively higher than FAR, but reduces significantly with fusion. These results are favorable for access control type of applications, wherein an unauthorized person should be rejected by the algorithm. Even though an authorized person if falsely rejected, it is compromised, because overall it provides good security in attaining access.

The normalized scores of genuine matches are used to form a genuine data set and the normalized scores of imposter matches are used to form an imposter data set. The frequency of occurrence of these two data sets are plotted as genuine and imposter score distributions. The score distributions for fusion of six feature vectors is shown in figure 3.

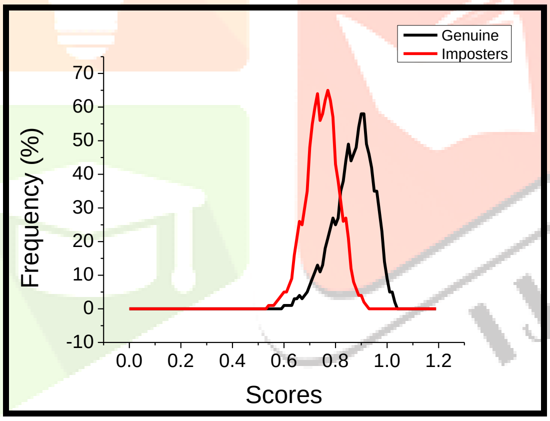

Figure 3: Score distribution for fusion of 6 feature vectors

The distributions with score level fusion of six feature vectors are separating the distributions of genuine and imposters with small area of overlap region. Thus by correct selection of threshold score, the imposters can be rejected and only genuine users be provided access.

In summary, it is studied that the performance of a biometric authentication depends on number of factors like type of biometric, feature vectors extracted as well as matching method used. In the work presented in this paper, the biometrics used are palm print and ventral palm vein images. The features extracted are principal components, standard deviation and normalized wavelet energy. Fusion at score level has resulted in best performance for identification as well as verification.

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