Abstract— In recent years there is a tremendous attention is paid on multimodal biometric system because they are efficient and gives reliable performance over unimodal system. By using multimodal biometric we can prevent system from spoof attacks. In this paper, we are going to fuse face and palm print images at different levels. These levels are sensor level fusion, feature level fusion, score level fusion, and decision level fusion. Here, we are going to use LDA (Linear Discriminant Analysis) and LPQ (Local Phase Quantization) feature extraction algorithms and these algorithms are used for feature level fusion. Here, we will perform different experiments on face and palm print images to perform fusion at different levels.

Index Terms—Face, Palm print, fusion, Multimodal biometrics, LDA, LPQ.

I. INTRODUCTION

All the researchers now days find the great importance over the biometric system because of their reliability and efficiency. Biometric system is nothing but a science which determines the behavioral and physical characteristics of person.

Unimodal biometric has disadvantages as, it has input data with noise content, easily attacked by the spoof attackers, and hence it affects on the overall performance as well as security of the system. So, in order to overcome these limitations and to provide better authentication purpose we use multimodal biometric system.

In multimodal biometric system, more than one biometric modal is used so, it increases degree of freedom, efficiency, gives high performance and able to overcome spoofing attacks.

In this paper, we are going to fuse two biometric modalities as face and palm print. These two modalities are fused at four different levels as,

(a) Sensor level fusion, here two different images from two different sources are combined.

(b) Feature level fusion, where feature extraction algorithms are performed on two different modalities and then fusion of those two images are carried out.

(c) Score level fusion, where matching score levels of different matching systems are combined.

(d) Decision level fusion, where the final decision is carried out as accepts or rejects.

At these four levels of fusion different techniques are used to fuse face and palm print images. Here, performance parameters are carried out by fusing these both face and palm print modalities under clean and noisy conditions.

It is preferable to use two modalities as face and palm print because they has several advantages such as non-intrusiveness in nature (for face), strongly available feature extraction algorithm for both modalities. In order to evaluate the deployment of these two modalities in real time scenarios, performance parameters are needs to be carried out under noisy conditions, so that we are evaluate better performance under both clean and noisy condition.

II. PROPOSED WORK

Biometric system based on single modality has different limitations so, to overcome these limitations and for better performance multimodal biometric system is used here. This fusion of face and palm print images at four different levels are based on multi resolution system.

Here, we are going to consider two different feature extraction algorithms as LDA (Linear Discriminant Analysis) and LPQ (Local Phase Quantization) for face and palm print images respectively.

The two algorithms are used for extracting the features from input images and also for dimensional reduction. These algorithms are also used for class seperability and also increase the security of the system at different levels by fusing the face and palm print images.

Block diagram of multimodal biometric system of face and palm print at four different levels is shown below. For fusion of face and palm print images two conditions are considered as,

(a) Matching related fusion, here different information from different sensors is carried out either at sensor level or feature level and then fusion is performed and fused information is carried out.
(b) Post matching fusion, here matching information is carried out at score level after matching and classification of final result is carried at decision level.

**Fig. 1** Block diagram on different levels of fusion of face and palmprint

In our multimodal biometric system we fuses two modalities as face and palm print at four different levels and they are given as,

1. **Fusion of face and palm print at sensor level:** Here, we are going to use wavelet based image fusion scheme [2]. This is used to fuse two modalities input images as face and palm print. DWT (Discrete Wavelet Transform) is performed on two modalities input images and then their wavelet coefficients are fused in wavelet transform domain. Here we have used Daubechies (db2) wavelet transform at level three.

2. **Fusion of face and palm print at feature level:** Here, first we are going to use feature extraction algorithms for two different modalities. We have used Linear Discriminant Analysis (LDA) for face and Local Phase Quantization (LPQ) for palm print modality. Then we used different fusion methods as different normalization techniques namely Min-Max, Z-Score and Hyperbolic tangent (Tanh) [9].

3. **Fusion of face and palm print at score level:** Here, we considered different fusion methods such as Sum, Max and Min rule, to combine the two matching scores.

4. **Fusion of face and palm print at decision level:** Here, we considered logical AND and logical OR to combine the output decisions by different matchers [11]. We are going to calculate False Accept error rate and False Reject error rates of the combined biometric by using both AND an OR fusion methods.

III. **RESULTS**

Here, results are obtained by applying different techniques on face and palm print images. In this section, we describe the experimental setup made in our project work. For face image we have used ORL database and for palm print image we have used PolyU database. Both ORL and PolyU database contains 40 persons and each person contains 10 images. In all experiments training was performed by considering three views of each user and seven views were used for subsequent testing. The performance was studied under both clean and noise conditions. Noisy database is obtained by adding different noise to face and palm print images. Here, we have added Gaussian noise of 0.1 mean and 0.003 variance to face modality and Salt-and-Pepper with 0.05 noise density to palm print modality [15].

**Fig 2** Fusion of face and palm print images of clean database
Z-score and tanh normalization schemes in feature level fusion show same performance. This is due to the fact that feature set of face and palmprint are same. Hence, after normalization done using these measures (Z-score and tanh), feature sets were transformed into a unique range.

Score level fusion using Sum rule shows highest accuracy. This is because the scores of palmprint and face give best discriminatory information after their fusion.

Decision level fusion, the OR rule performance is better than AND rule. This is because of, if any one of the matchers classifies the test sample as genuine, the final decision will be regarded as genuine. This is unlike the AND rule where both matchers have to show the test sample as genuine to classify the sample as genuine.
Sensor level fusion shows below the performance even under noisy conditions. This behavior is already explained in previous subsection.

Feature level fusion, the tanh normalization scheme shows robust results compared to Zscore and min-max normalization schemes. This displays the fact that tanh measure are known to perform well under noisy conditions.

Score level fusion, the sum rule continued to exhibit its robust nature even under noise conditions for the reasons stated in above subsection. So, we can show that for face and palmprint modalities, the optimal results (both under clean and noise conditions) can be obtained by fusing at score level using the sum rule.

At decision level fusion, the same behavior was shown as that of clean test conditions.

IV. CONCLUSION

By using 3 levels DWT operation we have fused the face and palmprint images and also draw the ROC curve for modality system at different levels of fusion. From this ROC curve we have find the percentage rate of False Accept Rate and Genuine Accept Rate.

In all our experiments, the performance of multimodal system (at all levels of fusion) performance is much better than their unimodal counterparts except sensor level fusion.

For fusing face and palmprint modalities, the score level fusion adopting the sum rule obtained best results under both clean and noise conditions.

Sensor level fusion of face and palmprint modalities leads to undesired result. In fact, the performance is worst than its unimodal counterparts.

REFERENCES


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