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### FEATURE LEVEL FUSION USING FACE AND PALMPRINT BIOMETRICS FOR SECURED AUTHENTICATION

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#### ABSTRACT

Multibiometric systems utilize the evidence presented by multiple biometric sources (e.g., face and fingerprint, multiple fingers of a user, multiple matchers, etc.) in order to determine or verify the identity of an individual. Information from multiple sources can be consolidated in several distinct levels, including the feature extraction level, match score level and decision level. While fusion at the match score and decision levels have been extensively studied in the literature, fusion at the feature level is a relatively understudied problem. In this paper fusion at the feature level in 3 different scenarios: (i) fusion of PCA and LDA coefficients of face; (ii) fusion of LDA coefficients corresponding to the R,G,B channels of a face image; (iii) fusion of face and hand modalities is discussed. Preliminary results are encouraging and help in highlighting the pros and cons of performing fusion at this level. The primary motivation of this work is to demonstrate the viability of such a fusion and to underscore the importance of pursuing further research in this direction. Partitioning around medoids (PAM) algorithm is used to partition the set of n invariant feature points of the face and palm print images into k clusters.

**Index terms:** Multibiometric, PCA, LDA, PAM.

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#### I INTRODUCTION

The pronounced need for establishing identity in a reliable manner has spurred active research in the world of biometrics. It is now apparent that a single biometric is not sufficient to meet the variety of requirements including matching performance imposed by several large-scale authentication systems. Multibiometric systems seek to alleviate some of the drawbacks encountered by unibiometric systems by consolidating the evidence presented by multiple biometric traits/sources. These systems can significantly improve the recognition performance of a biometric system besides improving population coverage, deterring spoof attacks, increasing the degrees-of-freedom, and reducing the failure-to-enroll rate. Although the storage requirements, processing time and the computational demands of a multibiometric system are much higher (than a unibiometric system), the above mentioned advantages present a compelling case for deploying multibiometric

systems in large-scale authentication systems. Evidence in a multibiometric system can be integrated in several different levels as described below:

**1. Sensor level:** The raw data acquired from multiple sensors can be processed and integrated to generate new data from which features can be extracted. For example, in the case of face biometrics, both 2D texture information and 3D depth (range) information (obtained using two different sensors) may be used to generate a 3D texture image of the face which could then be subjected to feature extraction and matching.

**2. Feature level:** The feature sets extracted from multiple data sources can be used to create a new feature set to represent the individual. The geometric features of the hand, for example, may be augmented with the Eigen-coefficients of the face in order to construct a new high-dimension feature vector. A feature selection/transformation procedure may be adopted to elicit a minimal feature set from the high-

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dimensional feature vector.

**3. Match score level:** In this case, multiple classifiers output a set of match scores which are used to generate a single scalar score. As an example, the match scores generated by the face and hand modalities of a user may be combined via the simple sum rule in order to obtain a new match score which is then used to make the final decision.

**4. Rank level:** This type of fusion is relevant in identification systems where each classifier associates a rank with every enrolled identity (a higher rank indicating a good match). Thus, fusion entails consolidating the multiple ranks associated with an identity and determining a new rank that would aid in establishing the final decision. Techniques such as the Borda count may be used to make the final decision.

**5. Decision level:** When each matcher outputs its own class label (i.e., accept or reject in a verification system, or the identity of a user in an identification system), a single class label can be obtained by employing techniques like majority voting, behavior knowledge space, etc.

Fusion at the match score, rank and decision levels have been extensively studied in the literature. Fusion at the feature level, however, is a relatively understudied problem. Fusion at this level involves the integration of feature sets corresponding to multiple information sources. Since the feature set contains richer information about the raw biometric data than the match score or the final decision, integration at this level is expected to provide better authentication results. However, fusion at this level is difficult to achieve in practice because of the following reasons: (i) the feature sets of multiple modalities may be incompatible (e.g., minutiae set of fingerprints and Eigen-coefficients of face); (ii) the relationship between the feature spaces of different biometric systems may not be known; (iii) concatenating two feature vectors may result in a feature vector with very large dimensionality leading to the 'curse of dimensionality' problem; and (iv) a significantly more complex matcher might be required in order to operate on the concatenated feature set. In this paper fusion at the feature level in 3 different contexts: (i) fusion of PCA and LDA co-efficient of face; (ii) fusion of LDA co-efficient corresponding to the R,G,B channels of a face image; (iii) fusion of face and hand modalities are discussed. A distance measure known as the Threshold Absolute Distance (TAD) to be used along with the Euclidean distance metric is also introduced.

## II PROBLEM AND ANALYSIS

### 2. FEATURE LEVEL FUSION

In this work, feature level fusion is accomplished by a simple concatenation of the feature sets obtained from multiple information sources. Let  $X = [x_1; x_2; \dots; x_m]^T$  and  $Y = [y_1; y_2; \dots; y_n]^T$  denote feature vectors ( $X \in \mathbb{R}^m$  and  $Y \in \mathbb{R}^n$ ) representing the information extracted via two different sources. The objective is to combine these two feature sets in order to yield a new feature vector,  $Z$ , that would better represent the individual. The vector  $Z$  is generated by first augmenting vectors  $X$  and values of  $Z^0$ . This results in a new feature vector  $Z = [z_1; z_2; \dots; z_k]^T$ . The criterion function to perform feature selection is defined to be the average of the Genuine Accept Rate (GAR) at four different False Accept Rate (FAR) values (0:05%, 0:1%, 1%, 10%) in the ROC (Receiver Operating Characteristics) curve pertaining to the training data. The reason for choosing this criterion is explained below.

#### 2.1. Criteria for Feature Selection

The feature selection algorithm relies on an appropriately formulated objective function to elicit the optimal subset of features from the complete feature set. In the case of a biometric system it is difficult to identify a single parameter that would characterize the matching performance across a range of FAR/FRR values. Note that the single-valued parameters commonly used in the biometric literature - the Equal Error Rate (EER) and the d-prime measure - do not summarize the matching performance across all matching thresholds. An alternative would be to define the objective function at a fixed GAR/FAR value. However, this would also result in maximizing the performance at only those specific points. In order to optimize the performance gain across a wide range of thresholds, the objective function to be the average of GAR corresponding to 4 different FAR's (0:05%, 0:1%, 1%, 10%).

#### 2.2. Match Score Generation

Consider feature vectors  $fX_i; Y_i$  and  $fX_j; Y_j$  obtained at two different time instances  $i$  and  $j$ . The corresponding fused feature vectors may be denoted as  $Z_i$  and  $Z_j$ , respectively. Let  $s_X$  and  $s_Y$  be the normalized match (Euclidean distance) scores generated by comparing  $X_i$  with  $X_j$  and  $Y_i$  with  $Y_j$ , respectively, and let  $s_{match} = (s_X + s_Y)/2$  be the fused match score obtained using the simple sum rule. Figure 1 shows the distribution of  $s_{match} - P(S_{match})$  -

under the genuine and impostor hypothesis. The critical region is defined as a range of scores,  $[t^-; t^+]$ , where the probability distributions of the genuine and impostor scores have substantial overlap. By utilizing the fused vectors  $Z_i$  and  $Z_j$ , the ambiguity presented by the critical region may be resolved.

In order to accomplish this we observe that in the case of genuine pairs, a high match score is typically

the effect of a few feature values constituting the fused vector, while a similar score for an impostor pair is typically the cumulative effect of all feature values. This observation is fairly intuitive since the feature selection process eliminates features that are redundant as well as those that are correlated with other features.

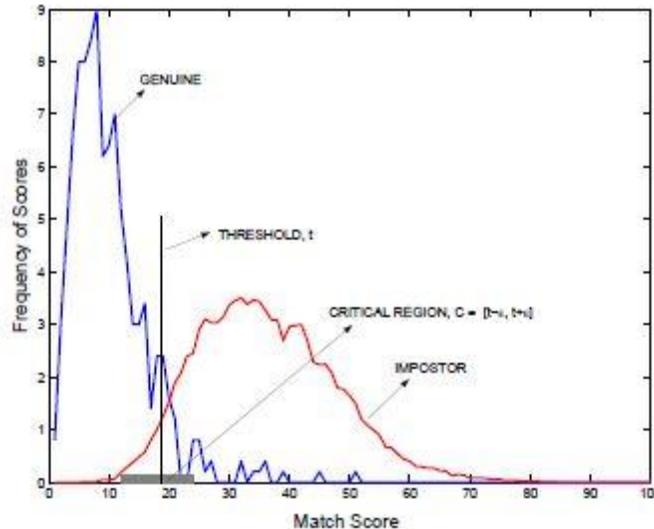


Figure 1. Distribution of  $s_{match} - P(S_{match})$

Two different distance measures to compare  $Z_i$  and  $Z_j$  are employed

$$s_{euc} = \sum_{r=1}^k (z_{i;r} - z_{j;r})^2 \quad (\text{Euclidean distance}) \quad (1)$$

$$s_{tad} = \sum_{r=1}^k I(|z_{i;r} - z_{j;r}|; t) \quad (\text{Thresholded absolute}) \quad (2)$$

Here,  $I(y; t) = 1$ , if  $y > t$  (and 0 otherwise), and  $t$  is a pre-specified threshold. The TAD measure determines the number of normalized feature values that differ by a magnitude greater than  $t$ . The  $s_{euc}$  and  $s_{tad}$  values are consolidated into one feature level score,  $s_{feat}$ , via the simple sum rule.

### III SOLUTION AND MECHANISM

#### 3.EXPERIMENTAL RESULTS

Set of 500 face images and hand images were acquired from 100 users (5 biometric samples per user per biometric) at West Virginia University (WVU). The hand data was obtained using a commercial-off-the-shelf (COTS) hand geometry system installed at WVU.

The feature set is a 9-byte value comprising of different geometric measurements of the hand. The face data was acquired using the Sony EVI-D30 PTZ

Color camera. Each face image was decomposed into its component R, G, B channels. Further, the grayscale rendition of the color image - I - was also computed. The Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) were performed on these component images (i.e., R, G, B, I) in order to extract representational features. Thus, a component image was represented using PCA coefficients as well as LDA coefficients. Details of these methods may be obtained from the paper by Belhumeur et al. The proposed technique was tested on three different scenarios: (i) fusion of PCA and LDA

coefficients corresponding to I (intra-modal); (ii) fusion of LDA coefficients corresponding to the R,G,B channels (intra-modal); (iii) fusion of face and hand modalities (inter-modal).

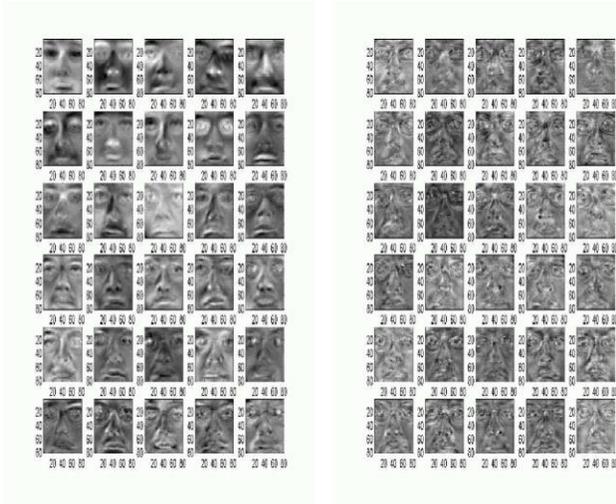


Figure 2. a) PCA and (b) LDA techniques

### 3.1. Fusion of PCA and LDA Coefficients

The basis images corresponding to PCA (eigenfaces) and LDA (sherfaces) are shown in Figure 3. Each grayscale face image was represented using 25 eigen-coefficients and 27 sher-coefficients. The feature fused vector had 28 features. The results of fusion are summarized in Figure 3. It is observed that the performance of the LDA-based matcher performance.

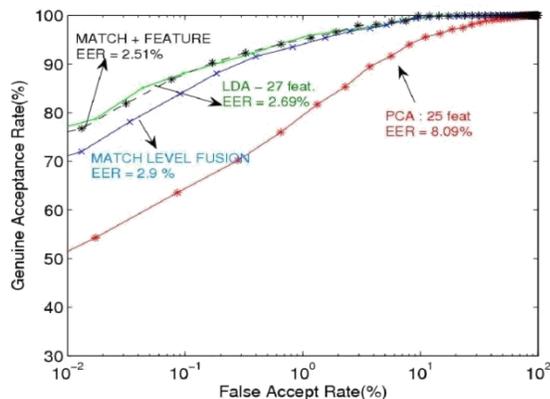


Figure 3. The results of fusion when combining the PCA and LDA coefficients of grayscale face images.

However, combining the feature level and match score level information neither degrades nor improves the matching performance. An information both at the match score level ( $s_{match}$ ) as well as the feature level

( $s_{feat}$ ) is obtained. Both these values are combined using the simple sum rule to obtain the final score  $s_{tot}$  (Figure 2). In the following experiments,  $s_{tot}$  is referred to as the score obtained by combining information at the match score level and the feature level is much higher than that of the PCA-based matcher. The difference in performance is more pronounced at lower FAR values. For example, at a FAR = 0.01% the GAR using the PCA technique is 50% and the LDA technique is 80%. Therefore, this scenario represents a case where a weak classifier is combined with a strong classifier. The application of match level fusion in this situation is observed to degrade matching match level fusion. It must be mentioned that using alternate fusion schemes (other than the simple sum rule) might result in different performance curves.

### 3.2. Fusion of R, G, B Channels

Experiments were also conducted in order to assess the efficacy of the proposed technique in an intra-modal fusion scenario involving the R,G and B color channels of the face images. In this case, three separate feature sets are denoted as LDA-R (18 features), LDA-G (32 features) and LDA-B (40 features) were generated for a face image by performing LDA on each color channel independently. These three feature sets were then subjected to fusion at both the feature and match score levels. The feature fused vector consisted of 43 features. Figure 4 summarizes the results using this data. It is observed that the proposed scheme outperforms match score level fusion by a substantial margin thereby underscoring the significance of the proposed technique.

### 3.3. Fusion of Face and Hand - Palm Biometrics

In this case, the 9-byte hand feature set and the LDA-coefficients (27 features) of the grayscale face image were combined. Figure 6 presents the ROC curves for this scenario. The matching performance of the proposed scheme is seen to result in a marginally inferior performance compared to fusion at the match score level.palmprint images to obtain the partitioned of features which can provide more discriminative and meaningful clusters of invariant features. The algorithm can be given below.

This experiment was also conducted using the Michigan State University (MSU) dataset consisting of hand and face information pertaining to 50 users with each user providing 5 samples of each biometric. The hand feature set was extracted using the technique described by Jain et al. In this case, the performance of

the proposed fusion scheme was observed to be superior to that of match score level fusion (Figure 7). Currently, we are analyzing the reasons for such differences in performance across datasets. It is clear, however, that the performance of constituent matchers and the relationship between the feature sets generated by individual modalities have a large role to play in determining the efficacy of the proposed technique. A more formal framework may be necessary to better understand this phenomenon.

### 3.3 Correspondence between Clusters of Face and Palmprint Images

To establish correspondence between any two clusters of face and palmprint images, it has been observed that more than one keypoint on face image may correspond to single keypoint on the palmprint image. To eliminate false matches and to consider the only minimum pair distance from a set of pair distances for making correspondences, first it needs to verify the number of feature points that are available in the cluster of face and that in the cluster of palmprint. When the number of feature

points is less than that of the cluster for palmprint, many points of interest from the palmprint cluster needs to be

discarded. If the number of points of interest on the face cluster is more than that of the palmprint cluster, then a single interest point on the palmprint cluster may act as a match point for many points of interest of face cluster. Moreover, many points of interest on the face cluster may have correspondences to a single point of interest on the cluster for palmprint. After computing all distances between points of interest of face cluster and palmprint cluster that have made correspondences, only the minimum pair distance is paired. After establishing correspondence between clusters for face and palmprint images, isomorphic graph representation for each cluster has been formed while removing few more keypoints from the paired clusters. Further iterative relaxation algorithm is used for searching the best possible pair of isomorphic graphs from all possible graphs.

Improved version of PAM clustering using Silhouette approximations. Silhouette technique can be used to verify the quality of a cluster of data points. After applying the PAM clustering technique to the sets of SIFT keypoints for face and palmprint images, each cluster can be verified by Silhouette technique. Let, for each keypoint  $i$ ,  $x(i)$  be the average distance of  $i$  with all the keypoints in cluster  $c_m$ . Consider  $x(i+1)$  as an additional average distance next to  $x(i)$ . These two successive distances  $x(i)$  and  $x(i+1)$  are considered to verify the matching of these keypoints  $i$  and  $(i+1)$  to the cluster where these points are assigned. Then the average distances of  $i$  and  $(i+1)$  with the keypoints of another single cluster are found. Repeat this process for every cluster in which  $i$  and  $(i+1)$  are not a member. If the cluster with lowest average.

### 3.4 Establishing Methodology

The existing algorithm has been extended by taking another average distances  $x(i+1)$  and  $y(i+1)$  for a pair of clusters and it has been determined that a better approximation could be arise while PAM algorithm is used for partition the keypoints set. The precision level of each cluster is increased by this improved approximation method where more relevant keypoints are taken instead of taking restricted number of keypoints for fusion. points in the cluster for face is less than that of the cluster for palmprint, many points of interest from the palmprint cluster needs to be

### 3.3 Isomorphic Graph Representations of Partitioned Clusters

To interpret each pair of clusters for face and palmprint, isomorphic graph representation has been used. Each cluster contains a set of SIFT keypoints and each keypoint is considered as a vertex of the proposed isomorphic graph. A one-to-one mapping function is used to map the keypoints of the isomorphic graph constructed on a face cluster to a palmprint cluster while these two clusters have been made correspondence to each other. When two isomorphic graphs are constructed on a pair of face and palmprint clusters with equal number of keypoints, two feature vectors of keypoints are constructed for fusion.

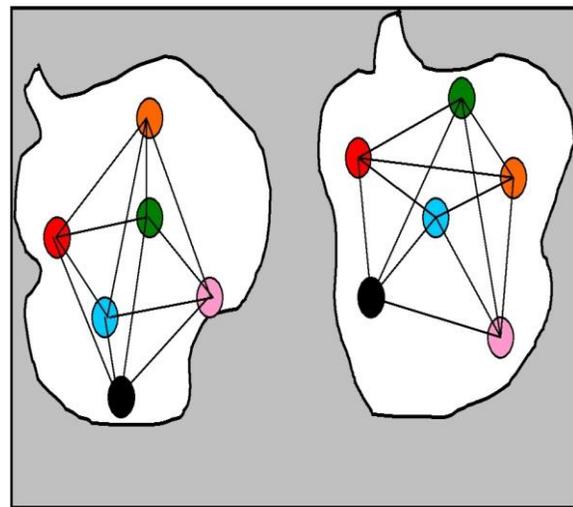
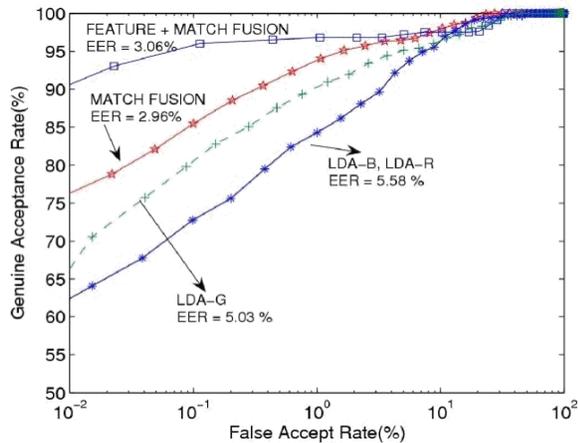
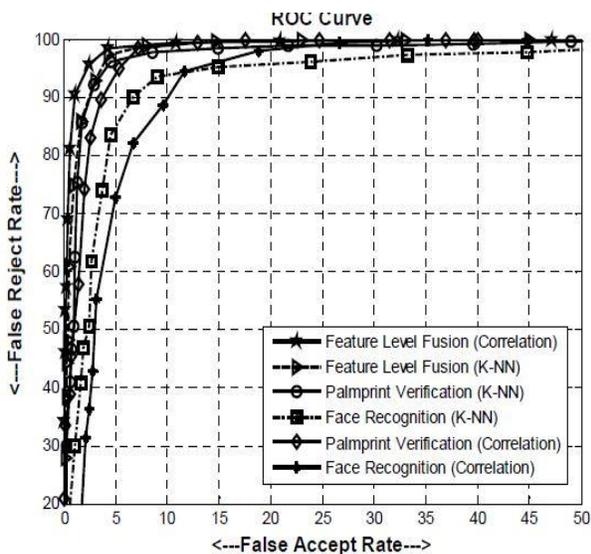


Figure 4. Isometric Graph Representation of FACE and PALM



**Figure 5. The results of fusion when combining the LDA coefficients corresponding to the R, G, B channels of a face image.**



**Figure 6. ROC Curve**

## IV CONCLUSION

A feature level fusion scheme to improve multimodal matching performance has been proposed. In this formulation, information at the feature level and match level are consolidated. The technique has been tested on inter-modal and intra-modal fusion scenarios consisting of both strong and weak biometric classifiers. It offers high percentage of GAR and increase in accuracy when compared with existing unimodal system. It has been found that the technique exhibits increase in accuracy and significant improvement over the existing methodologies. In certain scenarios (viz., combining R, G, B channels) the performance gain has been substantial, thereby indicating the importance of

pursuing the work in this direction.

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