Feature Level Fusion in Biometric Systems

Arun Ross and Rohin Govindarajan

Lane Dept. of Computer Science and Electrical Engg., West Virginia University, Morgantown, West Virginia 26506

ross@csee.wvu.edu, rohin@csee.wvu.edu

Abstract

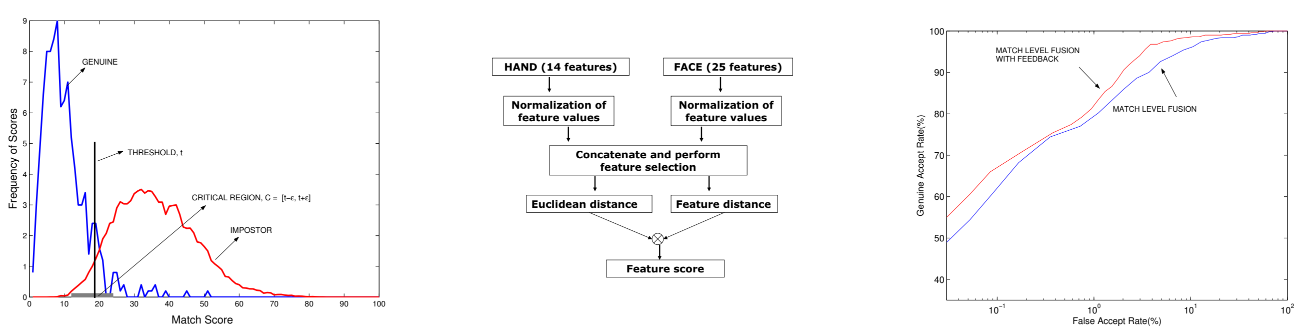
Multimodal biometric systems utilize the evidence presented by multiple biometric sources (e.g., face and fingerprint, multiple fingers of a user, multiple impressions of a single finger, etc.) in order to determine or verify the identity of an individual. Information from multiple sources can be consolidated in three distinct levels [1]: (i) feature extraction level; (ii) match score level; and (iii) 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 we present a novel technique to perform fusion at the feature level by considering two biometric modalities - face and hand geometry. Preliminary results indicate that the proposed technique can lead to substantial improvement in multimodal matching performance.

1. Introduction

Fusion at the feature level involves the integration of feature sets corresponding to multiple modalities. 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 recognition 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; and (iii) concatenating two feature vectors may result in a feature vector with very large dimensionality leading to the 'curse of dimensionality' problem. We describe a technique that utilizes the fused feature vectors of face and hand geometry in order to improve the performance of a multimodal biometric system.

2. Algorithm for Feature Level Fusion

Let $\boldsymbol{F_i} = \{f_{i,1}, f_{i,2}, \ldots f_{i,n}\}$ and $\boldsymbol{H_i} = \{h_{i,1}, h_{i,2}, \ldots h_{i,m}\}$ represent the feature vector of the face (eigen-coefficients [2]) and hand (geometric features [3]) modalities of a user, respectively. The fused feature vector $\boldsymbol{X_i} = \{x_{i,1}, x_{i,2}, \ldots x_{i,d}\}$ can be obtained by augmenting the normalized feature vectors $\boldsymbol{F_i'}$ and $\boldsymbol{H_i'}$, and performing feature selection on the concatenated vector. The normalized vectors $\boldsymbol{F_i'}$ and $\boldsymbol{H_i'}$ are computed by applying a



(a) (b) (c)

Fig. 1: (a) Distribution of genuine and impostor scores (S_{fus}) showing the critical region. (b) Procedure to compute the S_{euc} and S_{feat} scores. (c) Performance gain obtained using the feedback technique.

transformation to the individual feature values (via normalization schemes like min-max, z-score and median absolute deviation (MAD)) in order to ensure that the feature values across the two modalities are compatible. Consider feature vectors $\{\boldsymbol{F_i}, \boldsymbol{H_i}\}$ and $\{\boldsymbol{F_j}, \boldsymbol{H_j}\}$ obtained at two different time instances i and j. The corresponding fused feature vectors may be denoted as $\boldsymbol{X_i}$ and $\boldsymbol{X_j}$, respectively. Let S_F and S_H be the normalized match (distance) scores generated by comparing $\boldsymbol{F_i}$ with $\boldsymbol{F_j}$ and $\boldsymbol{H_i}$ with $\boldsymbol{H_j}$, respectively and let $S_{fus} = (S_F + S_H)/2$ be the fused match score obtained using the simple sum rule.

The algorithm first determines if S_{fus} falls in the critical region, C, of the match score distribution (Fig. 1(a)). The critical region is defined as a range of scores, $[t - \epsilon, t + \epsilon]$, where the probability distributions of the genuine and impostor scores have substantial overlap. Note that match scores which occur below (above) C can be (almost) definitively stated to be genuine (impostor) scores. However, $S_{fus} \in C$ presents an ambiguous situation. Thus, the fused vectors $\boldsymbol{X_i}$ and $\boldsymbol{X_j}$ are also used in the decision process. We observe that in the case of genuine pairs, a high match score is typically the effect of a *few* feature values constituting the vector while a similar score for an impostor pair is typically the cumulative effect of *all* feature values. Thus, two distance measures are considered to distinguish genuine and impostor pairs (Fig. 1(b)): (i) the euclidean distance, $S_{euc} = \sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2$, and (ii) the feature distance, $S_{feat} = \sum_{k=1}^{d} I(|x_{i,k} - x_{j,k}|)$, where $I(.)$ is the indicator function such that $I(y) = 1$, if $y > t_1$ (and 0 otherwise). Now S_{feat} and S_{euc} along with S_{fus} is used to arrive at the final decision. This technique is termed as the *feedback technique* since a feedback routine is implemented between the feature extraction and the matching modules of the biometric system.

3. Experimental Results

A set of 5 face images and hand images were acquired from 50 users. Two different experiments were conducted to evaluate the performance of the proposed technique. In the first experiment the efficacy of the feedback technique was studied. Fig. 1(c) presents the ROC curve that summarizes the matching performance by plotting the Genuine Accept Rate (GAR) against the False Accept Rate (FAR) at various thresholds. It can be seen that the feedback technique results in improved matching performance. The Equal Error Rate (EER) using match score level fusion alone is 6.35%; the EER drops to 3.58% when the feedback technique is used. In the second experiment, the evidence at the match score level was integrated with the evidence at the feature level. Fig. 2 indicates the performance gain obtained when such type of an integration is performed. The EER, in this case, is observed to be 1.58%. Also, there has been a substantial improvement in GAR at very low FAR values thus underscoring the importance of feature level fusion. For example, at a FAR close to 0.01%, the GAR is seen to improve from 50% to 65%.

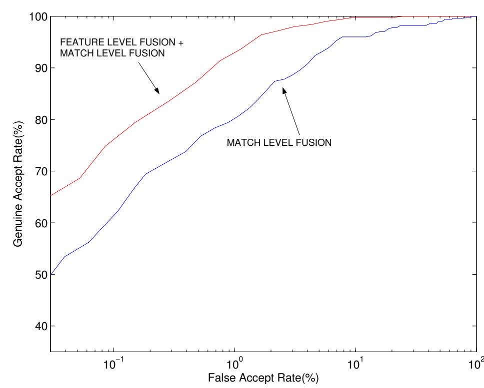


Fig. 2: Performance gain observed after merging information at the feature level and the match score level.

4. Future Work

A feature level fusion scheme to improve multimodal matching performance has been proposed. The scheme has been tested on two relatively weak biometric systems, face and hand geometry. The performance gain observed has been substantial thereby indicating the importance of pursuing research in this direction. Future work will include studying the effect of noisy data on the performance of the technique and the adoption of other biometric traits in this work (viz., fingerprint and iris).

5. References

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