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Information Fusion and Person Authentication Using Face and Fingerprint Data

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Abstract: - This paper describes the integration of face and fingerprint data to improve the performance of a person identity verification system. In the conetxt of multi-modal person authentication, a set of experts give their opinion as a scalar number, called score, about the identity of an individual. A fusion module receiving as input the scores has to take a binary decision: accept or reject the claimed identity. The performance of several fusion methods have been evaluated and compared on a multi-modal database, containing face and fingerprint modalities.

Key-Words: - Multi-modal identity verification, Biometrics, Score-level fusion

1 Introduction

As biometrics attracts more and more attention from many areas, the demand of high accuracy and reliability is also increasing. Although various biometric systems have been developed and improved, there are still limitations which have to be overcome to meet stringent performance requirements from many applications. For example, face recognition is fast but not extremely reliable, while fingerprint verification is reliable but inefficient in database retrieval. Multimodal biometrics may be therefore, the only way to construct a robust identification system.

Multi-modal biometric systems can be implemented by fusing more than two biometric systems[1-4]. There are three possible levels of fusion when combining multiple biometric systems [5]: (a) fusion at the feature extraction level, where features extracted using multiple sensors are concatenated, (b) fusion at the confidence level, where matching scores reported by multiple matchers are combined, and (c) fusion at the abstract level, where the accept/reject decisions of multiple systems are consolidated.

In this paper, we use fusion at the confidence level and investigate three fusion methods, LDA, SVM, Sum rule. One fingerprint and two face verification systems are used as fusion sources. The organization of the paper is as follows. The three unimodal identification systems and fusion methods will be described in Section 2 and Section 3, respectively. And experimental results for fusion are shown in Section 4. Finally, we present our conclusion in Section 5.

2 Person Authentication

2.1 Face Verification

For face recognition, feature extraction is required to represent high dimensional image data into low dimensional feature vectors. Among various methods, we use PCA(Principal Component Analysis), which is known as eigenfaces in face recognition field [6-7]. The main idea of the PCA is to find the vectors which best account for the distribution of the face images within the entire image space. PCA generates a new orthonormal basis vectors for the image space, where each component is not correlated with any other component. These vectors define the subspace of face images, which we call “face space” By projecting a face image onto the eigenfaces, the linear combination weights for eigenfaces are calculated. These weights are used as representations of the face. In this paper, comparisons between feature vectors of a probe and a galley set are performed using Euclidean distance and SVM(Support Vector Machine) [8]. While Euclidean distance gives distance values as dissimilarity scores, SVM gives classification results as similarity scores.

2.2 Fingerprint Verification

It is widely known that a professional fingerprint examiner relies on details of ridge structures to make fingerprint identification. It implies that fingerprint authentication can be based on the matching of structural patterns. Generally structural features used in fingerprint identification are composed of the point where ridge ends and that ridge bifurcates, which are called minutiae.

(a) bifercation (b) ending

Fig. 1 A fingerprint image and minutiae features

Our representation is minutiae based, and each minutia is described by its position in x, y coordinates, the direction it flows and the type i.e., ridge ending or bifurcation. After refinement and alignment of fingerprint images, two minutiae from a probe and a gallery set are compared based on their position, direction, and type. Then a matching score is computed. A detailed method can be found in [9].

3 Fusion Method

A fusion module receives the scores which are extras input and takes a binary decision: accept or reject the claimed identity. which are extracted from several biometric systems. In this section, we describe three fusion approaches at score level.

3.1 LDA(Linear Discriminant Analysis)

Linear discriminant analysis[10] searches for those vectors in the underlying space that best discriminate among classes. More formally, given a number of independent features relative to which the data is described, LDA creates a linear combination of these which yields the largest mean differences between the desired classes. Mathmatically speaking, for all the samples of all classes, we define two measures: 1) one is called *within-class* scatter matrix, as given by

$$S_w = \sum_{j=1}^{c}\sum_{i=1}^{N_j}(\mathbf{x}_i^j - m_j)(\mathbf{x}_i^j - m_j)^T \qquad (1)$$

where x_i^j is the ith sample of class j, m_j is the mean of class j, c is the number of classes, and N_j is the number of samples in class j; and 2) the other is called *between-class* scatter matrix

$$S_b = \sum_{j=1}^{c}(m_j - j)(m_j - m)^T \qquad (2)$$

where m represents the means of classes.

The goal is to maximize the ration of between class scatter to within class scatter|.

3.2 SVM(Support Vector Machines)

SVM is binary classification method that finds the optimal linear decision surface based on the concept of structural risk minimization. The decision surface is a weighted combination of elements of the training set. These elements are called *support vectors* and characterize the boundary between the two classes.

Given a set of N examples

$$(\mathbf{x}_1, y_1), \cdots (\mathbf{x}_i, y_i), \cdots (\mathbf{x}_N, y_N) \quad \mathbf{x}_i \in R^N,\ y_i \in \{-1,1\} \qquad (3)$$

In case of linear separable data, maximum margin classification aims to separate two classes with hyperplane that maximizes distance of supports vectors. This hyperplane is called OSH(Optimal Separating Hyperplane). OSH can be expressed as in Eq. (2).

$$f(\mathbf{x}) = \sum_{i=1}^{N}\alpha_i y_i(\mathbf{x}_i^T\mathbf{x}) + b \qquad (4)$$

This solution is defined in terms of subset of training samples (supports vectors) whose α_i is non- zero.

In the case of linearly non-separable patterns, SVM is to perform non-linear mapping of input vector into high dimensional dot product space F. This is called the *feature space*. In this feature space, we can exploit the linear algorithm mentioned in the previous part, but with a difference. The separating hyperplane is now defined as a linear function of vectors drawn from the feature space rather than the original input space. In general, however, the dimension of the feature space is very large, so we have the technical problem of computing high dimensional spaces. Kernel method gives the solution to this problem.

The formula for non-linear SVM with kernel is

$$f(\mathbf{x}) = \sum_{i=1}^{N} \alpha_i y_i k(\mathbf{x}_i, \mathbf{x}) + b \quad (5)$$

3.3 Sum Rule

This is a simple and unsupervised method at score level. The sum rule method of integration takes the weighted average of the individual scores. We assigned equal weights to each modality. After transforming all scores into a similarity measure, it sums all the scores. The fused score for candidate *i* is given as

$$f_i = \sum_{m=1}^{M} s_{i,m} \quad (6)$$

Where $s_{i,m}$ is a similarity score for candidate *i* given by system *m*.

4 Experimental Results

4.1 Database

The database for fusion experiments consists of verification results of one fingerprint and two face systems. Because fingerprint and face are supposed to be independent of each other, we construct a multimodal database from two distinct fingerprint and face database. The fingerprint database is provided by KISIS [11] and the face database is XM2VTS. The database was divided into two sets: training set, test set. Each set consists of 500 genuine scores and 500 imposter scores.

An important aspect that has to be dealt with is the normalization of the scores obtained from the different domain experts [12]. Normalization typically involves mapping the scores obtained from multiple domains into a common framework before combining them. For score level fusion, we transformed a dissimilarity measure, which is based on distance, into a similarity measure by multiplying -1. Then all scores were normalized between -1 and 1 by subtracting the minimum value and dividing the maximum value.

The scatter plot of the normalized scores for training is shown in Fig. 3. In case of fingerprint system, scores of genuine and impostor are separated clearly, but not the face systems.

4.2 Experimental Results

We combined face(Euclidian Distance, SVM) and fingerprint scores using three fusion methods. Table 1. shows the performance of each unimodal system. The rates presented here are the false rejection rate(FRR), the false acceptance rate(FAR), and total error rate(TER) TER = FAR+FRR.

Table 1. Results of unimodal biometric systems

	FAR	FRR	TER
Face(Euc)	12.4%	22.2%	34.6%
Face(SVM)	28.8%	8.0%	36.8%
Fingerprint	1.8%	6.2%	8.0%

In table 2 we present the minimum total error rates of multimodal biometric systems. Among various fusion methods and different combinations of sources, SVM fusion with three sources gave the best result. Also to be noted is the simple Sum Rule, which is an unsupervised fusion method, achieved a better performance improvement than LDA and SVM fusion when face(SVM) and fingerprint are combined.

Table 2. Results of multi-modal biometric systems TER

	LDA	SVM	Sum
Face(Euc),Finger	6.0%	6.0%	6.6%
Face(SVM),Finger	6.0%	6.6%	5.5%
Face(Euc,SVM),Finger	5.8%	5.4%	6.3%

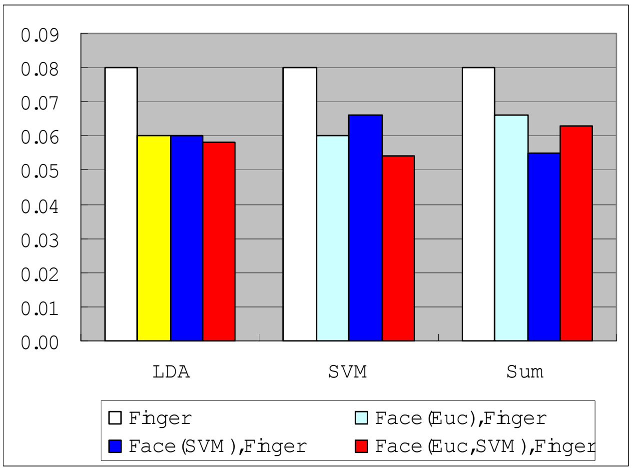

Fig. 2 Comparison of finger and fusion methods

5 Concluding Remarks

This paper provides four schemes to integrate the output scores of tow face systems and one fingerprint systems to improve the performance of verification. The methods used here are LDA, SVM, and Sum rule. Although the verification rate of the fingerprint system was high, all the three fusion methods at the score level provided better verification performance than the individual biometrics. Future experiments will include various fusion level such as feature level fusion and decision level fusion

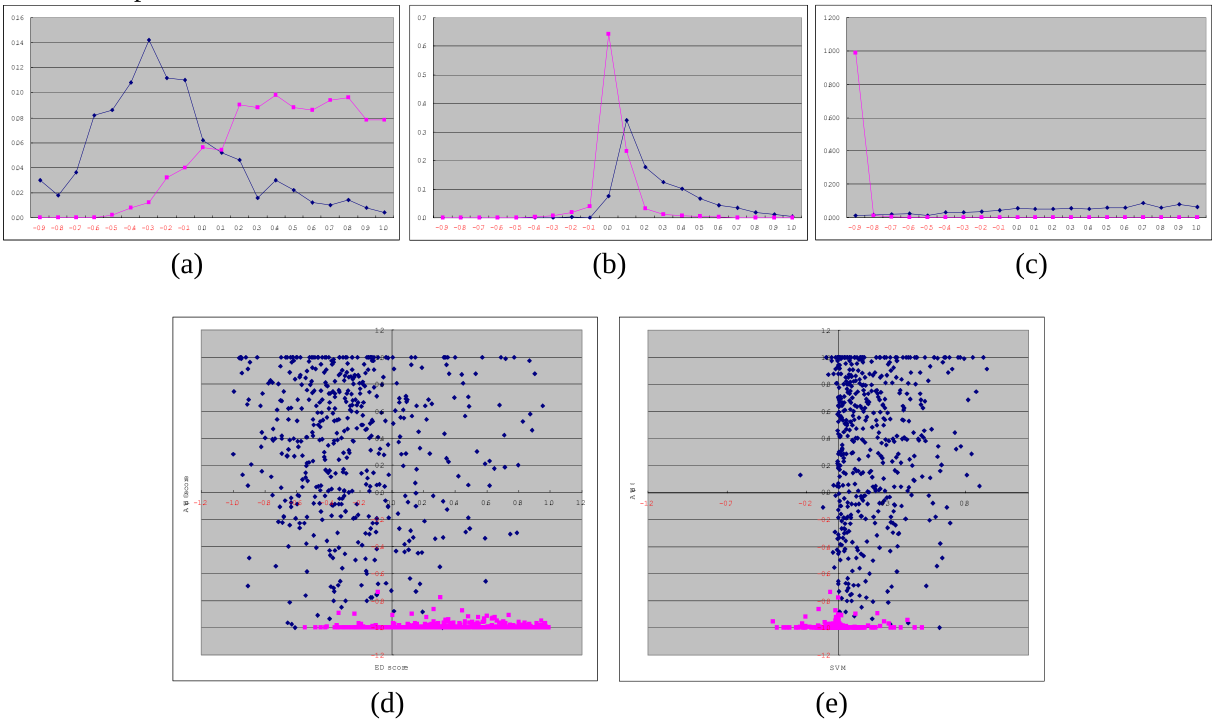

Fig. 3 Scatter plots of normalized scores of training data. ED and SVM represent scores from the face systems using Euclidian distance and SVM, respectively. Finger refers to scores from the fingerprint system. And bule and red stand for genuine and imposter. (a) ED score distribution, (b) SVM score distribution, (c) Finger score distribution, (d) scatter plots of ED and Finger, (e) scatter plots of SVM and Finger

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