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Multimodal Biometric Identification System with One Training Sample Based on Face and Palmprint

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Abstract: *Multimodal biometric identification systems alleviates many problems in unimodal biometric systems, which use a single biometric trait for recognition. We demonstrate that multimodal biometric can play a very important role in one training sample problem. This paper proposed a user-dependent fusion approach, which is based on the investigations that most users have some traits of better class separability than other traits they have. A new user-dependent fusion algorithm is proposed based on imposter score distribution and fusion binary tree. We then observed that our fusion algorithm improved mean recognition rate by 5.4% on a multimodal biometric database with 120 individuals. It also presents better robustness than other existed fusion methods in all experiments.*

Keywords: *Multimodal, Biometric, User-dependent, One training sample.*

1. INTRODUCTION

Unimodal biometric systems use a single source of biometric information for personal identification, which include many problems: noisy sensor data, lack of individuality and non-universality [1]. The purpose of multimodal biometric is to overcome the limitations of the unimodal, while a better performance can be obtained by combining the evidences presented by multiple traits of fingerprint, face, hand and so on.

To deal with the problem that how multibiometrics systems outperform the traditional unimodal biometric system, many fusion solution have been discussed in the literature. Noticing that most users have some traits of better class separability than other traits they have, a user-independent fusion approach is proposed for multimodal biometric identification. Jain and Ross [2] proposed the method of exploiting user-specific parameters at the decision-level, but it is based on exhaustive search which costs too much time. Fierrez-Aguilar [3] introduced a fusion technique based on Support Vector Machines (SVM). Kumar and Zhang [4] presented a feed-forward neural network to integrate palmprint with face for identification. Subsequently,

One training sample problem has been an active research area in respect that it is a realistic problem existing in many applications. Almost all of the proposed fusion methods can not perform properly when only one training sample is provided. This study attempts to propose a novel user-dependent fusion approach, combining one palmprint training sample and one face training sample for identification.

The remainder of this paper is organized as follows: In section 2, we briefly review the face and palmprint recognition based on eigenface and eigenpalm. A novel user-dependent fusion approach is proposed in Section 3. How to deal with the problem of system template generation is described in Section 4. Experimental results are presented in Section 5 followed by a conclusion drawn in Section 6.

2. EIGENFACE AND EIGENPALM

Principal components analysis (PCA) [15], which maximizes the scatter of all projected samples by choosing a dimensionality reducing linear projection, is commonly used for face recognition [16]. Lu [17] proposed a palmprint recognition method named eigenpalm based on Karhunen–Loeve transform.

2.1 Feature Extraction Based on Eigenface

Suppose that each one of a set of N sample images $\{x_1, x_2, \ldots, x_N\}$ belongs to one of C classes $\{X_1, X_2, \ldots, X_C\}$. After reducing dimensionality, a new feature vector is

$$y_k = W^T x_k \tag{1}$$

where k = 1,2,…,N. Scatter matrix S_T is defined as

$$S_T = \sum_{k=1}^{N} (x_k - \mu)(x_k - \mu)^T \qquad (2)$$

The total scatter matrix of the projected samples is maximized by computing W_{OPT} as follows.

$$W_{OPT} = \arg\max_{W} |W^T S_T W| \qquad (3)$$

Thus we obtain a set of n-dimensional eigenvectors of S_T, i.e., $[w_1, w_2, \ldots, w_m]$, which corresponds to the m largest eigenvalues.

2.2 Feature Extraction Based on Eigenpalm

The training samples of the palmprint images are $x_1, x_2, \ldots, x_M$, where M is the number of images in the training set. The average palmprint image is

$$\mu = \frac{1}{M} \sum_{i=1}^{M} x_i \qquad (4)$$

The covariance matrix of $\{x_i\}$ is

$$C = \frac{1}{M} \sum_{i=1}^{M} (x_i - \mu)(x_i - \mu)^T = \frac{1}{M} XX^T \qquad (5)$$

where matrix C is satisfied $Cu_k = \lambda_k u_k$.

Palmprint images are transformed into eigenpalm by applying

$$f_i = U'(x_i - \mu), \text{ i=1,2,...,M} \qquad (6)$$

where U' is the set of significant eigenvectors with the largest associated eigenvalues.

2.3 Classification Method

After a transformation based on eigenspace technology, a feature vector is obtained for each image. In both of face recognition and palmprint recognition, a nearest neighbor classifier is then used for classification. The matching score is represented by the Euclidean distance between the two feature vectors.

3. A NOVEL USER-DEPENDENT FUSION APPROACH

3.1 Fusion Based on Imposter Matching Score Distribution

More attention should be paid to imposter score distribution in biometric identification. Both of genuine and imposter score distribution [12] are regarded as normal distribution (Figure 1). Both of the genuine and the impostor matching score distribution are computed and graphically reported to explain how well the classifier "separates" the two classes. Generally speaking, higher scores are associated with more closely matching trait. The traditional user-dependent fusion approach is unable to solve one training sample problem, because it has to rely on both of imposter score distribution and genuine score distribution. In fact, genuine score distribution provides much less class separability information, using limited genuine training samples, than impostor score distribution does. When it comes to one training sample scenario, we even can not obtain genuine score distribution while we have plenty of imposters to obtain imposter score distribution.

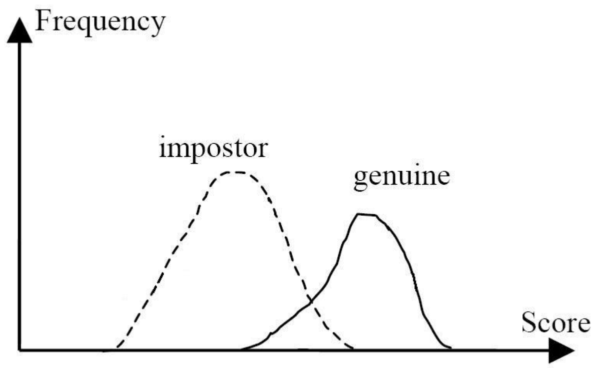

Figure 1: Genuine and Imposter Score Distribution

If one's trait can be imitated easily by other users, who are also called lambs [8], the class separability of this trait is not good. For a certain user, her or his traits have different performance on class separability. In this stage of fusion, a method based on imposter score distribution is proposed to evaluate class separability for all traits, which is the foundation of generating a user-dependent fusion tree in Section 3.2.

Previously, A variety of methods have been proposed to exploit the class separability information of distribution based on the class mean and class covariance, including the approximate pairwise accuracy criterion (aPAC) [9] and the common-mean feature extraction (CMFE). Note that aPAC incorporates a weighting function into the criterion of the proposed linear discriminant analysis feature extraction. Recently, a spanning-tree is designed based on the class mean and class covariance for multiclass classification by P. Hsieh, D. Wang, and C. Hsu [10].

Suppose that the imposter score distribution is Gaussian, with mean $\mu_u(t)$ and standard deviation $\sigma_u^2(t)$, i.e. $N(\mu_u(t), \sigma_u^2(t))$, where *t* denotes for a random trait and *u* denotes for a random user. Instead of using d-prime metric [11] [12], we use a distance [10] that resembles the Bhattacharyya distance as measure of the separation of two normal distributions:

$$d_{pq} = [\frac{2}{3}(\mu_p - \mu_q)^2 (\frac{F}{2})^{-1}]^{2/3} + [\ln \frac{|\frac{F}{2}|}{\sqrt{F}}]^{2/3} \qquad (7)$$

where $F = \sigma_p^2 + \sigma_q^2$

By applying (7), we obtain the distance between user m and user n for a certain trait *t*:

$$\forall m, \forall n, d_{mn}(t) = [\frac{2}{3}(\mu_m(t)-\mu_n(t))^2(\frac{F_{mn}}{2})^{-1}]^{2/3} + [\ln\frac{|\frac{F_{mn}}{2}|}{\sqrt{F_{mn}}}]^{2/3} \quad (8)$$

where $F_{mn} = \sigma_m^2(t) + \sigma_n^2(t)$

If one classifier is used for one kind of trait recognition, approximated classification error of classifier t for user m is:

$$\begin{cases} \varepsilon_m(t) = 0.5(1+e^{-\frac{d_{mn}}{2d_{MAX}(t)}}), if\ \mu_n(t) > \mu_m(t) \\ \varepsilon_m(t) = 0.5(1-e^{-\frac{d_{mn}}{2d_{MAX}(i)}}), if\ \mu_n(t) < \mu_m(t) \end{cases}$$

where $d_{mn}(t) = d_{MAX}(t) = Max\{d_{pq}(t) \mid p,q = 1,2,...,U\}$

3.2 User-dependent Fusion Using Binary Tree

To describe the user-dependent fusion algorithm more clearly, this algorithm is divided into following two sub-algorithms. Algorithm 1 is "Generate User-dependent Tree" and Algorithm 2 is "Vote Fusion".

We define set $U = \{u_1, u_2, \ldots, u_p\}$ and set $T = \{t_1, t_2, \ldots, t_k\}$, p is the number of different users in the system's database and k is the number of different traits to identification.

Algorithm 1 Generate user-dependent Tree

Input: $\forall t_j \in$ T, $\forall u_i \in$ U, training samples

Output: a binary tree $b_{i,j}$, where i = 1,2,…,p, j = 1,2,..,k// $b_{i,j}$ has and only has p nodes: $u_1, u_2, \ldots, u_p$

Step 1: We can obtain $D_{t_i} = \{ d_{ij} \mid \forall i, j \in U$, apply to calculate d_{ij} using training samples};

Step 2: u_i is the root node of $b_{i,j}$;

Step 3: //Locate other nodes
{ u_m = root node of $b_{i,j}$;
For all $u_n \in U$, n=1,2,…,m-1,m+1,…,p
{The less d_{mn} is, the closer u_n is to root node }
}

Suppose that we use one classifier for one trait recognition. Thus we define set $C = \{c_1, c_2, \ldots, c_k \mid \forall i$, *$c_i$ is the classifier for recognition t_i* }.

Algorithm 2: Vote Fusion

Input: B, C, U', testing samples, L=1.

Output: output of fusion u_f

Step 1: We can obtain U' = {$u_1, u_2, \ldots, u_k \mid \forall i$, u_i is the output of classifier c_i };

Step 2: For all $u_i \in U$ {Generate a user-dependent tree using Algorithm 1 for u_i based on trait t_i;}

Step 3: //vote using k binary trees All nodes on the level L vote before any of the nodes vote on the next level;

Step 4: If (time of u_f votes >=2)
{Stop;
Output u_f;}
Else
{L = L+1;
Go to Step3;}

4. TEMPLATE GENERATION

4.1 Palmprint and Face Image Acquisitions

In our multimodal system, the palmprint capture device includes ring source, CCD camera, lens, frame grabber, and A/D (analogue-to-digital) converter. We use a case and a cover to form a semiclosed environment for a stable palmprint image, and the ring source provides uniform lighting conditions during palmprint image capturing. Besides, six pegs on the platform are control points to locate the user's hands. The A/D converter directly transmits the images captured by the CCD camera to a computer. Fig. 2 shows a schematic diagram of our palmprint capture device. Palmprint images can be obtained in sizes of 768×568 presented in Fig. 3. Face images, which can be easily captured using digital cameras, is obtained in sizes of 640×480 presented in Fig. 4.

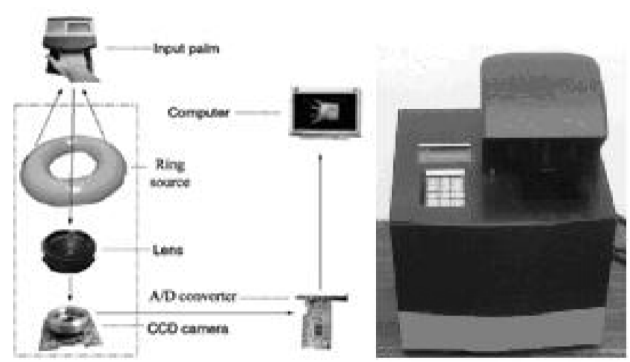

Figure 2: Palmprint Capture Device

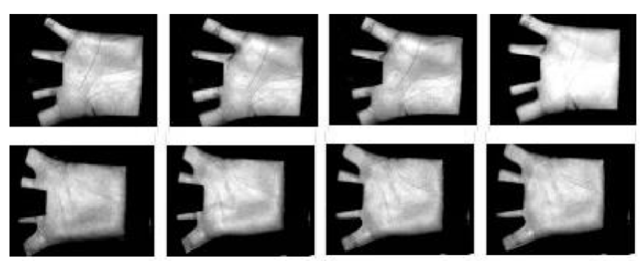

Figure 3: Captured Palmprint Pictures

Figure 4: Captured Face Pictures

4.2 Palmprint Template Generate

In the palmprint recognition, we regard only the central part of a palmprint as the template for recognition purpose. In this section, we will describe how to extract the central part of a palmprint, for reliable feature measurements, we use the gaps between the fingers as reference points to determine a coordinate system. The five major steps (see Fig. 5) in processing the image are:

Step 1: A lowpass filter, $L(u,v)$, such as Gaussian smoothing, is applied to the captured image, $O(x,y)$. A threshold, T_P, is used to convert the convolved image to a binary image, $B(x,y)$, as shown in Fig. 5b.

Step 2: Obtain the boundaries of the gaps, $(F_i x_i, F_i y_j)$ (i = 1,2), between the fingers using a boundary tracking algorithm (see Fig. 5c). The boundary of the gap between the ring and middle fingers is not extracted since it is not useful for the following processing.

Step 3: Compute the tangent of the two gaps. Let (x_1, y_1) and (x_2, y_2) be any points on $(F_1 x_i, F_1 y_j)$ and $(F_2 x_i, F_2 y_j)$, respectively. If the line $(y = mx + c)$ passing though these two points satisfies the inequality, $(F_i y_j \le mF_i x_i + c)$, for all i and j (see Fig. 5d), then the line $(y = mx + c)$ is considered to be the tangent of the two gaps.

Step 4: Line up (x_1, y_1) and (x_2, y_2) to get the Y-axis of the palmprint coordinate system, and use a line passing through the midpoint of these two points, which is perpendicular to the Y-axis, to determine the origin of the coordinate system (see Fig. 5d).

Step 5: Extract a subimage of a fixed size based on the coordinate system. The subimage is located at a certain area of the palmprint image for feature extraction (see Figs. 5e and 5f).

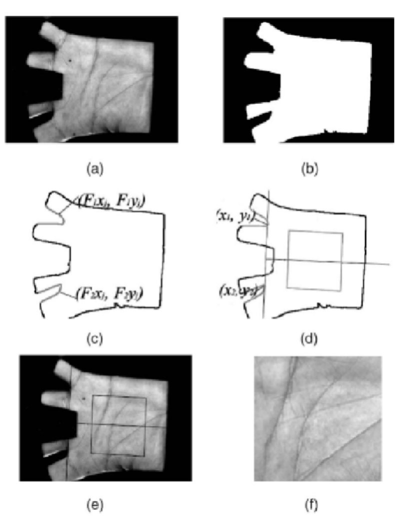

Figure 5: The Steps to Generate Palmprint Templates

5. EXPERIMENT AND RESULTS

5.1 Experiment Setup

In this work, we do not make experiment based on our own biometric database. Instead we use PolyU palmprint database [13] and AR face database [14]. Because they are public database, experiment results can be compared with the earlier republished results. Each of the subjects for palmprint and face were randomly paired to obtain a multimodal database for experiment.

AR face database contains over 4,000 color face images of 126 people (70 men and 56 women, see Fig. 7). 120 individuals took these pictures in 2 sessions (separated by two weeks). The images of these 120 individuals were selected and used in our experiment. Every people has 7 images in session 1 and 7 images in session 2, including frontal views of lighting conditions, faces with different facial expressions and occlusions.

We randomly choose 120 people from the PolyU palmprint database and 14 images per individual for the experiment. The palmprint pictures were also taken in two sessions (separated by few weeks). Then we generate the template of all these pictures. The face template samples are shown in Figure 8. The palmprint template samples are shown in Figure 8.

Figure 7: Template Samples of AR Face Database.

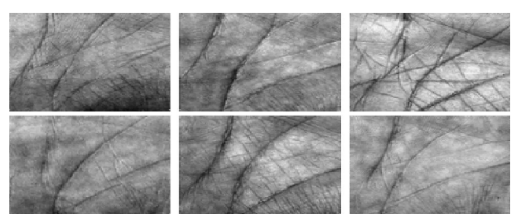

Figure 8: Template Samples of PolyU Palmprint Database.

Thus we made up a challenging multimodal database for one training sample recognition. At one time, we take one pair of face and palmprint images for training while other 13 pairs of images for testing. Therefore 1560 paired test samples are used in our experiment.

5.2 Results and Analysis

At first, both the traditional unimodal biometric solution based on eigenface [16] and eigenpalm [17] is performed in one training sample scenario. The best found correct recognition rate (BstCRR) is shown in Table 1. It is clear that our multimodal recognition algorithm easily outperforms unimodal recognition algorithm.

Table 1
The BstCRR using Unimodal and Multimodal

	Eigenface	*Eigenpalm*	*User-dependent Fusion*
BstCRR	76.57%	76.29%	90.06%

For comparison purposes, the existed fusion solution [5] based on Simple Sum (SS) method, Min Score (MIS) method, Max Score (MAS) method, Matcher Weighting (MW) method and Dempster-Shafer (DS) method [21] are also performed in one training sample scenario. In Figure 9, the performances are shown for our set up multimodal database. Our user-dependent (UD) algorithm has the best BstCRR 91.03% among other algorithm. Matcher Weighting (MW) method is the closest one to our performance, which is 3 percent lower than user-dependent algorithm.

For comparing Matcher Weighting (MW) method and our algorithm, Figure 10 presents recognition accuracy using a different training sample. This figure indicates that the performance of our user-dependent fusion algorithm is much better than Matcher Weighting method under conditions where training sample is varied.

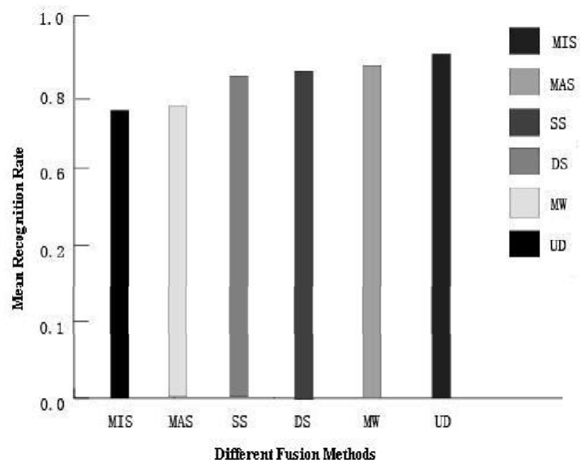

Figure 9: Comparison for Different Fusion Methods.

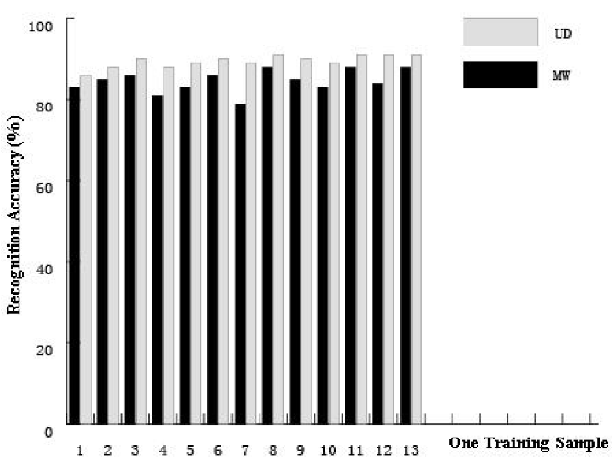

Figure 10: Compare Matcher Weighting (MW) and User-dependent (UD) Algorithm

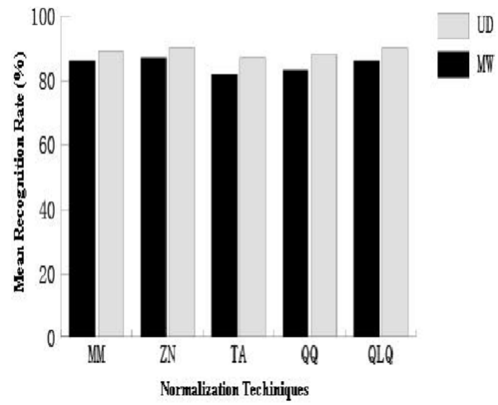

Figure 11: Compare Different Normalization Techniques.

Note that we obtain all the experiment results above using the normalization technique based on Min-Max method. Therefore we also use different normalization techniques [20] to demonstrate the robustness of our algorithm, including Min-Max (MM) method, Z-norm (ZN) method, Tanh (TA) method, Two-Quadrics (QQ) method and Quadric-Line-Quadric (QLQ) method. In Figure 11, performance based on Matcher Weighting (MW) method and our user-dependent (UD) algorithm is given based on normalization techniques above.

6. CONCLUSION

In this paper, a new multimodal biometric identification system is developed. Our algorithm, which is based on the thought that most users have some traits of better class separability than other traits they have, has many advantages over existed fusion methods. First, it improves mean recognition rate by rate 5.4%. Second, it is better in terms of robustness in all experiments using different training samples and normalization techniques.

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