Combining Fingerprint and Voiceprint Biometrics for Identity Verification: an experimental comparison

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Abstract. Combining multiple biometrics may enhance the performance of personal authentication system in accuracy and reliability. In this paper, we compare 13 combination methods in the context of combining the voiceprint and fingerprint recognition system in two different modes: verification and identification. The experimental results show that Support Vector Machine and the Dempster-Shafer method are superior to other schemes.

1. Introduction

The emergency of biometrics helps to solve the problems that the traditional methods such as password and IC cards have faced. But there are many problems such as noisy data, non-universality, which may affect the performance of the biometrics system when using a single biometric feature. Multiple biometrics can help to solve several practical problems.

There has been much work on combining multiple biometrics and multi-classifier combination. Roberto [15] presented a person identification system on acoustic and visual features. Ross [7] combined three biometric features: face, fingerprint and hand geometry and Hong [9] integrated face and fingerprints to meet the accuracy and response time requirements of system. Wang [6] used three methods to combine the iris and face recognition system. Except the research of multi-biometrics system, a comprehensive list of classifier combination strategies can be found [5,12]. And a lot of traditional methods such as fuzzy integral [3], naive Bayes [4], Dempster-Shafer fusion rule [2], neural network [6], Fisher discriminant function [6] and logistic regression [4] have been used in multiple classifier system.

Although there has been a substantial amount of work done on combining different biometrics for a variety of purposes, however, not much work has focused on the combination of fingerprint and voiceprint. With the development of mobile communication, we need verify one's identity more frequently. The fingerprint and voiceprint system can be easily applied to the mobile applications to overcome a number of inherent difficulties of the standalone classifier system without much cost increase. In this paper we will try to construct a multi-biometrics authentication system using 13 different combination methods in the context of combining the voiceprint and fingerprint recognition system and give some theoretical analysis of fusion methods.

The rest of this paper is organized as follows: Section 2 gives a brief overview of multi-biometrics systems as well as the fingerprint and voiceprint recognition system used in our experiment. Section 3 introduces 13 different combination methods and Section 4 presents the experimental results. Finally, Section 5 concludes the paper.

2. Multi-biometrics

2.1 Biometrics and Multi-biometrics

A biometrics system can be deemed as a pattern recognition system, which may work in two different modes: identification and verification. An identification system can be measured by Correct Recognition Rate (CRR) and the performance of a verification system measured by Receiver Operation Characteristic Curve (ROC Curve).

For the reason of noise, non-universality of single biometric feature, multi-biometrics system is proposed. Suppose N biometrics features $\left[F_1, F_2, \cdots\cdots, F_N\right]$ are used to verify the claimed identity. Let $\{1,2,\cdots\cdots,c\}$ be the label set of c classes (c persons in this paper). For each person x, using F_k feature we will get c matching scores from the matching with other $c-1$ persons and himself. So we can get a matrix $H(x)$ for person x [1]:

$$H(x) = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1N} \\ \mu_{21} & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \mu_{(c-1)N} \\ \cdots & \cdots & \mu_{c(N-1)} & \mu_{cN} \end{bmatrix} \qquad \textbf{(1)}$$

Where $\mu_{i,j}$ denotes the matching score of x and the *ith* person given by the *jth* classifier.

2.2 Fingerprint and Voiceprint Authentication

A critical step in fingerprint verification system is to automatically and reliably extract minutiae from the input fingerprint images. We use the minutia extraction algorithm presented in [14]. With these minutia features, an alignment-based elastic matching algorithm is used. For the voiceprint recognition system, at first we divide the input speech into several small segments with a fixed length and for each segment a 39-dimensional MFCC (Mel Frequency Cepstral coefficients) feature vector is extracted. With these MFCCs, we train the Gaussian Mixture Model (GMM) for each speaker [13].

3. Algorithms for Multi-biometrics Combination

In this part, we will outline the methods employed for fusion in two modes: verification and identification.

3.1 Verification Mode

In this mode, the incomer X will be only matched with the template of the person he claims. We treat the fingerprint and voiceprint matchers output x_1 and x_2 as a feature vector $X = (x_1, x_2)$. Then we can use any known classifiers to determine the separation bound between imposter and client. The fusion methods we employed to combine fingerprint and voiceprint are introduced as follows:

T1: Logistic regression (LOG)

This method depends on the assumption that the fingerprint and voiceprint recognition system is independent and that the conditional density of the client and imposter class can be written as the logistic distribution function [4].

T2: Fisher discriminant classifier

Fisher rule is a well-known linear discriminant, which has been widely used in the field of pattern recognition. It designs the discriminant bound by performing dimensionality reduction using linear projection and still preserve linear separability [6].

T3: User-specific weighted sum rule

This method is proposed by Jain [9]. The so-called 'user-specific weight' means that the weights of the matching scores of different classifier when summing are selected specifically for each person. In our experiment, we estimate the user-specific weights by exhaustive search in the space $\{(W_1, W_2) \mid W_1 + W_2 = 1\}$ to find the weights corresponding to the minimum error rate on the train set.

T4: ENN (Nearest-Neighbor with Class Exemplars)

Suppose the norm of x, $y = \sqrt{x_1^2 + x_2^2}$, and we find the within class scatter of y is 0.3372 while that of X is 0.665. So we use y as the classification feature. We deem the mean value of y of imposter and client as their exemplar value and compare the norm of an unclassified x with the two-exemplar values and make decision.

T5: Support vector machine

The standard SVM produces a non-linear classification boundary in the original input space by constructing a linear boundary in a transformed version of the original input space. The classification result is showed in Figure 1.

3.2 Identification Mode

T6: Minimum, maximum, average and product Rule

According to Section 2, for a given input pattern x we will get a matrix $H(x)$. Find the minimum (or maximum, or average, or product) values of every row, which are the similarity measure between x and pre-stored templates. The output of these rules simply consists in assigning x to class i if the *ith* value is the maximum of them. A tie will be broken by choosing one randomly.

T7: Naive Bayes rule

This method can be found in many published papers. In this method, the independence of fingerprint and voiceprint recognition system must be satisfied [4].

T8: Fuzzy integral rule

Fuzzy integral has been used for classifier fusion in several applications. Each classifier produces a confidence value for every class, which represents the worth of the corresponding classifier for the class. The overall confidence for the class is the fuzzy integral value. The input will be assigned to the class with the largest integral value [3].

T9: Decision templates

This method is proposed by Kuncheva [1]. Suppose $Z = \{z_1, \cdots\cdots, z_n\}, z_j \in \Re^N$ be the training set. In this method, at first the decision template (DT_i) is trained for each class, which is in fact the average of the matrix $H(x)$ of the elements whose label is i in the training set Z . For an unclassified input x , we deem DT_i and $H(x)$ as a fuzzy set, compute the similarity between them. Here we use four kinds of similarity measures in our experiment. The first measure is the Euclide distance of the two sets and the other three is denoted as following:

$$S_1(A,B) = \frac{\|A \cap B\|}{\|A \cup B\|} \qquad S_2(A,B) = 1 - \|A \nabla B\| \qquad S_3(A,B) = 1 - \|A \Delta B\|$$

T10: Dempster-Shafer rule

In this frame of the evidence theory, the best representation of support is a belief function rather than a Bayesian mass distribution. The theory embraces the familiar idea of assigning numbers between 0 and 1 to indicate the degree of support but, instead of focusing on how this numbers are determined, it concerns the combination of degrees of belief. Here, we use the algorithm proposed by [1].

4. Experimental Results and Discussions

4.1 Experimental Results

The experiment is conducted on the database that contains 44 persons and for each person 24 fingerprint samples and 24 voiceprint samples have been collected. The collection course is divided into two sessions, which have an interval of one month. For each person, 12 samples are captured in each session. We can get the matching scores of each sample with the 44 pre-stored templates by the designed fingerprint and voiceprint recognition system. For the fusion methods that need training, we use the first four samples of each person to constitute the training set and the rest to constitute the testing set.

All of the results of these methods including those introduced in verification mode are presented in Table 1. Here we did not give the CRR of SVM because it is computing costly for SVM to achieve a multi-classification.

Table 1. The Correct Recognition Rate of different methods.

Methods	CRR	Methods	CRR	Methods	CRR
Fingerprint only	98.2%	Voiceprint only	93.7%	Max Rule	99.6%
				Min Rule	98.6%
Naïve Bayes	98.2%	Fuzzy Integral	98.2%	Average Rule	99.1%
Fisher	98.8%			Product Rule	98.9%
Dempster-Shafer	99.9%	Decision template	S1 99.4%	User-specific	99.8%
			S2 99.1%	Logistic	99.1%
ENN	99.3%		S3 97.1%		
			Eu 99.1%		

And we present the ROC curve of different techniques in Figure 2. In the mode of verification, we use the leave-one-out strategy to compute the ROC curve.

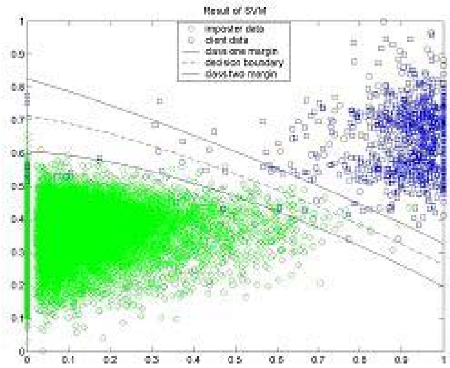

Fig. 1. The distribution of client and imposter. The line in the figure denotes the classification boundary computed by SVM method

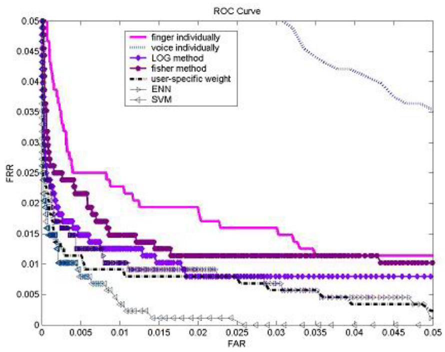

Fig. 2. The ROC curve of different methods

4.2 Discussions

Based on the above results and analysis, we can draw some conclusions and find some issues that need further investigating. The goal of our experiment is to compare the performance of different combination methods in the context of combining fingerprint and voiceprint recognition system. As Table 1 shows, most of the methods are superior to the fingerprint recognition system, which is the best single system. Especially the Dempster-Shafer method and user-specific weighted sum rule both give a very good result with only one and two error classified samples in total 880 samples respectively.

And according to Figure 2, we can find that in the verification mode the SVM method is better than user-specific weighted sum rule and these two methods are the best two methods for verification in our fusion experiment. As shown in Figure 1, the distribution of the imposter and client data cannot be separated by a liner function. And SVM is based on the Structural Risk Minimisation (SRM) principle. So we can see in Figure 2 the decision boundary computed by SVM method is fitted well to the data and SVM give a better performance comparing with Fisher rule that adopts linear discriminant function.

For the simple aggregation methods (Min, Max, Average and Product Rule) that need not train beforehand, they all give a better CRR compare with single biometrics systems. Max and Average rule outperform the other two methods. According to theoretical and experimental results reported in other papers [12], researchers agree that fixed rules usually perform well for the combination of classifiers exhibiting similar performance and methods that need training give a better performance for the combination of classifiers exhibiting different accuracy. In our experiment, the difference of accuracy between fingerprint and voiceprint recognition system is not very large, but it is not very clear that fixed rules outperform those trained rules.

The decision template method has been proved in [1] to get a good performance with both data sets using 10 different similarity measures. But in our experiment, the choice of similarity measure affects the performance of system significantly. We adopted four kinds of measures that give the best performance within the 10 proposals in [1]. However, when using S_3 measure, the system fails to get improvement.

From the experiment results based on combining fingerprint and voiceprint recognition scores, we can find that user-specific weighted sum and SVM get better performance among all the fusion manners. Since the test data are not always as good as the training data, the feature of a specific user may not typical. Such data cannot be divided by a linear function. So the nonlinear classification method: User-specific, DS rule and SVM can give a good solution.

As discussed above, we compared 13 different methods in our experiment. But in our experiment, the test data set is too small and the samples in the data set are mostly "good" samples, which means the samples are collected in the normal condition, so the result of comparison is not very convincing. In the future work, we will investigate these methods in a larger data set and include some "bad" samples. We will also try to add some other biometrics such as gait and face to find out the best method in a more universal context. And with combining more than two biometric features, we can investigate the relationship of the system performance and the characteristics of the combination classifiers.

4. Conclusion

Fusion of multiple biometrics has recently gained more interests with an increasing emphasis on security. In this paper, we have compared 13 different classifier-combination methods based on the fingerprint and voiceprint matching scores in two different modes: identification and verification. Dempster-Shafer combination and

SVM method are proved to get the best performance among all the fusion methods we employed in this paper.

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