Bayesian Adaptation for User-Dependent Multimodal Biometric Authentication

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Abstract

A novel score-level fusion strategy based on Bayesian adaptation for user-dependent multimodal biometric authentication is presented. In the proposed method, the fusion function is adapted for each user based on prior information extracted from a pool of users. Experimental results are reported using on-line signature and fingerprint verification subsystems on the MCYT real bimodal database. The proposed scheme outperforms both user-independent and user-dependent standard approaches. As compared to non-adapted user-dependent fusion, relative improvements of 80% and 55% are obtained for small and large training set sizes respectively.

Key words: Biometrics, multimodal, authentication, verification, Bayes, adaptation, fingerprint, signature

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1 Introduction

A number of works have focused on information fusion for multimodal biometrics in the last decade [1]. The prevalent approach is to combine the scores provided by the different biometric systems using a user-independent fusion function (also referred to as global approaches hereafter). Motivated by the enhanced universality and performance that can be achieved by exploiting user-dependencies at the decision level, user-dependent score-level fusion methods have been recently proposed (also referred to as local approaches hereafter) [2]. In this case, one of the main problems encountered is the training data scarcity. This can be partially overcome by considering both global and local training data and trading-off both sources of information [3].

In the present work, an operational procedure for dealing with small training set sizes in user-dependent multimodal biometric authentication is presented. The new approach is based on Bayesian adaptation [4] of the localized fusion functions from the prior knowledge provided by pooling user-independent data. The new method is evaluated on real biometric data from the MCYT bimodal corpus [5], outperforming significantly the non-adapted approach.

2 Adapted score fusion based on Quadratic Discriminants

Given R different unimodal authentication systems, each one computes a similarity score between an input biometric pattern and the enrolled pattern of the given claimant. Let the similarity scores be combined into a multimodal score $\mathbf{x} = [x_1, \ldots, x_R]'$. Let the training set for estimating the fusion function be $X = (\mathbf{x}_i, y_i)_{i=1}^{N}$, where $y_i \in \{\omega_0 = \text{Impostor}, \omega_1 = \text{Client}\}$. Score distributions are modelled as multivariate Gaussians $p(\mathbf{x}|\omega_0) = N(\mathbf{x}|\boldsymbol{\mu}_0, \boldsymbol{\sigma}_0^2)$ and $p(\mathbf{x}|\omega_1) = N(\mathbf{x}|\boldsymbol{\mu}_1, \boldsymbol{\sigma}_1^2)$, respectively [1]. The fused score s_T of a multimodal test pattern $\mathbf{x}_T$ is defined as follows

$$s_T = f(\mathbf{x}_T) = \log p(\mathbf{x}_T|\omega_1) - \log p(\mathbf{x}_T|\omega_0) \tag{1}$$

which is known to be a Quadratic Discriminant (QD) function consistent with Bayes estimate in case of equal impostor and client prior probabilities. The score distributions are estimated using the available training data as follows:

Global The training set X_{G} consists of multimodal scores from a pool of users, and $(\{\boldsymbol{\mu}_{\mathrm{G},0}, \boldsymbol{\sigma}^2_{\mathrm{G},0}\}, \{\boldsymbol{\mu}_{\mathrm{G},1}, \boldsymbol{\sigma}^2_{\mathrm{G},1}\})$ are estimated by using the Maximum Likelihood criterion [4]. The resulting fusion function $f_{\mathrm{G}}(\mathbf{x})$ is applied at the operational stage regardless of the claimed identity.

Local A different fusion function $f_{j,\mathrm{L}}(\mathbf{x})$ is obtained for each client by using Maximum Likelihood density estimates $(\{\boldsymbol{\mu}_{j,\mathrm{L},0}, \boldsymbol{\sigma}^2_{j,\mathrm{L},0}\}, \{\boldsymbol{\mu}_{j,\mathrm{L},1}, \boldsymbol{\sigma}^2_{j,\mathrm{L},1}\})$ computed from a set of development scores X_j of the specific client $j = 1, \ldots, M$.

Adapted The adapted fusion function $f_{j,\mathrm{A}}(\mathbf{x})$ of client j trades off the general knowledge provided by X_{G}, and the user specificities provided by X_j, through Maximum a Posteriori density estimation [4]. This is done by adapting the sufficient statistics as follows [4]:

$$\begin{aligned}
\boldsymbol{\mu}_{j,\mathrm{A},i} &= \alpha_i \boldsymbol{\mu}_{j,\mathrm{L},i} + (1-\alpha_i)\boldsymbol{\mu}_{\mathrm{G},i} \\
\boldsymbol{\sigma}^2_{j,\mathrm{A},i} &= \alpha_i(\boldsymbol{\sigma}^2_{j,\mathrm{L},i} + \boldsymbol{\mu}^2_{j,\mathrm{L},i}) + (1-\alpha_i)(\boldsymbol{\sigma}^2_{\mathrm{G},i} + \boldsymbol{\mu}^2_{\mathrm{G},i}) - \boldsymbol{\mu}^2_{j,\mathrm{A},i}
\end{aligned} \tag{2}$$

For each class $i = \{0, 1\}$, an adaptation coefficient $\alpha_i = N_i/(N_i + r)$ is used, where N_i is the number of local training scores in class i, and r is a fixed relevance factor.

[1] $\boldsymbol{\sigma}^2$ and $\boldsymbol{\mu}^2$ are shorthand for $\mathrm{diag}(\Sigma)$ and $\mathrm{diag}(\boldsymbol{\mu}\boldsymbol{\mu}')$ respectively.

3 Experiments

Experiments are carried out by using both the minutiae-based fingerprint verification system and the function-based on-line signature verification system used in [3] on real bimodal data from MCYT corpus [5]. In particular, 75×7 client and 75×10 impostor bimodal attempts in a near worst-case scenario are considered (best impostors from a pool of 750 fingers in case of fingerprint, skilled forgers in case of signature). Error rates are computed by using a variant of bootstrap resampling for training/testing the different methods, as done in [3], using the following configuration: 200 global bootstrap data sets of M users with replacement, and 50 local bootstrap data sets of N samples without replacement (half of them in each class, client and impostor).

Comparative performance results are given in Fig. 1. Remarkable performance improvement is obtained with the adapted approach using a relevance factor $r = 2.5$. As compared to the local fusion approach, approximately 80% and 55% relative performance improvements in the EER are obtained for small (6 samples) and large (12 samples) local training set sizes, respectively. In both cases, the global fusion approach is also outperformed (48% and 60% relative improvements, respectively).

4 Conclusion

Bayesian adaptation has been introduced for user-dependent score fusion in multimodal biometric authentication. Experiments have been carried out using fingerprint and signature subsystems on real bimodal data. A non-biased experimental protocol based on a worst case scenario and bootstrap error estimation has been used. Proposed adapted method has been demonstrated to provide remarkable performance improvements with respect to the non-adapted approaches commonly used.

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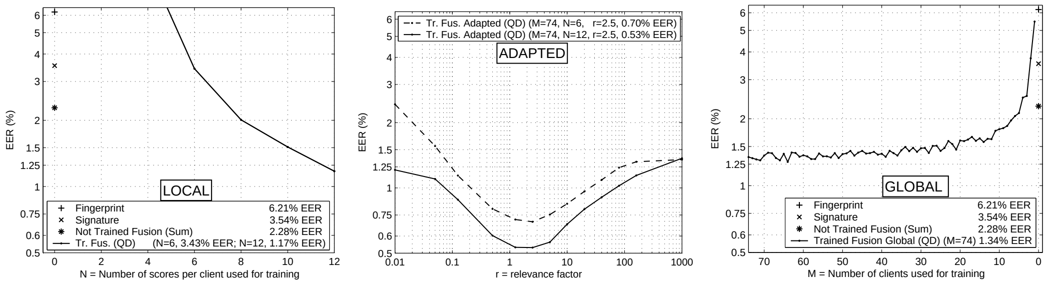

(a) (b) (c)

Fig. 1. Equal error rates of local (a), adapted (b), and global (c) approaches for multimodal fusion based on QDs.