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Rapid and brief communication

Discriminative multimodal biometric authentication based on quality measures

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Abstract

A novel score-level fusion strategy based on quality measures for multimodal biometric authentication is presented. In the proposed method, the fusion function is adapted every time an authentication claim is performed based on the estimated quality of the sensed biometric signals at this time. Experimental results combining written signatures and quality-labelled fingerprints are reported. The proposed scheme is shown to outperform significantly the fusion approach without considering quality signals. In particular, a relative improvement of approximately 20% is obtained on the publicly available MCYT bimodal database.

Keywords: Biometrics; Multimodal; Authentication; Verification; Quality; Support vector machine; Fingerprint; Signature

1. Introduction

A number of works have been focused on information fusion for multimodal biometrics [1,2]. Nevertheless, none of them have explicitly explored the effect of using quality measures into the problem (with the exception of a few cases in specialized events, see Ref. [3] and references therein). In this work, an operational procedure for dealing with degraded data in multimodal biometric authentication is presented and evaluated on real data from the MCYT bimodal corpus [4].

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2. Proposed quality-based fusion strategy

The proposed scheme is based on user-independent adaptive score-level fusion (see Fig. 1 for the system model), and support vector machine (SVM) classifiers for training the fusion function. With adaptive, we mean that the score-level fusion function is adapted every time biometric data are sensed depending on the estimated quality at this time.

Let $\mathbf{q} = [q_1, \ldots, q_R]'$ denote the quality vector of the multimodal similarity score $\mathbf{x} = [x_1, \ldots, x_R]'$, where q_r is a scalar quality measure corresponding to similarity score x_r with $r = 1, \ldots, R$ and R is the number of modalities. In this work, the quality values q_r are computed as follows:

$$q_r = \sqrt{Q_r \cdot Q_{r,\mathrm{claim}}}, \tag{1}$$

where Q_r and $Q_{r,\mathrm{claim}}$ are the quality measure of the sensed signal for biometric trait r, and the average signal quality of the biometric samples used by unimodal system r for

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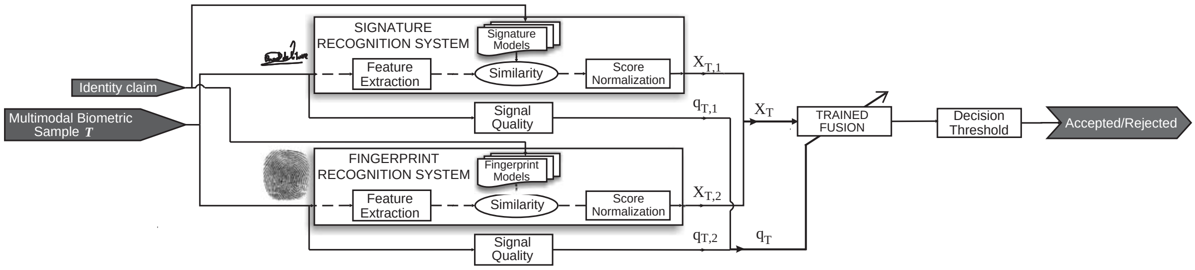

Fig. 1. System model of multimodal biometric authentication based on score-level fusion and quality measures.

modelling the claimed identity, respectively. The two quality labels Q_r and $Q_{r,\text{claim}}$ are supposed to be in the range $[0, Q_{\max}]$ with $Q_{\max} > 1$, where 0 corresponds to the poorest quality, 1 corresponds to standard quality, and $Q_{\max}$ corresponds to the highest quality.

The proposed score-level fusion scheme based on SVM classifiers and quality measures is as follows:

(1) (*Training phase*) An initial fusion function ($f_{\text{SVM}} : \mathbb{R}^R \to \mathbb{R}$, $f_{\text{SVM}}(\mathbf{x}_T) = \langle \mathbf{w}, \Phi(\mathbf{x}_T)\rangle + w_0$) is trained by solving the problem

$$\min_{\mathbf{w}, w_0, \xi_1, \ldots, \xi_N} \left(\frac{1}{2}\|\mathbf{w}\|^2 + \sum_{i=1}^{N} C_i \xi_i \right) \tag{2}$$

$$\text{s.t.} \quad y_i(\langle \mathbf{w}, \Phi(\mathbf{x}_i)\rangle + w_0) \geqslant 1 - \xi_i, \quad i = 1, \ldots, N, \tag{3}$$

$$\xi_i \geqslant 0, \quad i = 1, \ldots, N \tag{4}$$

in its dual representation and exploiting the kernel trick, as usual [3], using as cost weights

$$C_i = C \left(\frac{\prod_{r=1}^{R} q_{i,r}}{Q_{\max}^R} \right)^{\alpha_1}, \tag{5}$$

where $q_{i,r}$, $r = 1, \ldots, R$ are the components of the quality vector $\mathbf{q}_i$ associated with training sample $(\mathbf{x}_i, y_i)$, $y_i \in \{-1, 1\} = \{\text{Impostor}, \text{Client}\}$, and C is a positive constant. As a result, the higher the overall quality of a multimodal training score the higher its contribution to the computation of the initial fusion function. Additionally, R SVMs of dimension $R-1$ (SVM_1 to SVM_R) are trained leaving out traits 1 to R, respectively. Similarly to Eq. (5), $C_i = C(\prod_{j \neq r} q_{i,j} / Q_{\max}^{(R-1)})^{\alpha_1}$ for SVM_r.

(2) (*Authentication phase*) Let the sensed multimodal biometric sample generate a quality vector $\mathbf{q}_T = [q_{T,1}, \ldots, q_{T,R}]'$. Re-index the individual traits in order to have $q_{T,1} \leqslant q_{T,2} \leqslant \cdots \leqslant q_{T,R}$. A multimodal similarity score $\mathbf{x}_T = [x_{T,1}, \ldots, x_{T,R}]'$ is then generated. The combined quality-based similarity score is computed as follows:

$$f_{\text{SVM}_Q}(\mathbf{x}_T) = \beta_1 \sum_{r=1}^{R-1} \frac{\beta_r}{\sum_{j=1}^{R-1} \beta_j} f_{\text{SVM}_r}(\mathbf{x}_T^{(r)}) + (1 - \beta_1) f_{\text{SVM}}(\mathbf{x}_T), \tag{6}$$

where $\mathbf{x}_T^{(r)} = [x_{T,1}, \ldots, x_{T,r-1}, x_{T,r+1}, \ldots, x_{T,R}]'$ and

$$\beta_r = \left(\frac{q_{T,R} - q_{T,r}}{Q_{\max}} \right)^{\alpha_2}, \quad r = 1, \ldots, R-1. \tag{7}$$

As a result, the adapted fusion function in Eq. (6) is a quality-based trade-off between not using and using low-quality traits.

3. Experiments

Experiments are carried out by using both the minutiae-based fingerprint verification system used in Ref. [3] and the function-based on-line signature verification system used in Ref. [4] on real bimodal data from MCYT corpus [4]. 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). All fingerprint images have been supervised and labelled (between 0 and 2) according to the image quality by a human expert [3] and these labels are used as quality measures for fingerprints. In case of signatures, uniform quality $q = 1$ is used for all signatures.

In the following, the proposed quality-based multimodal approach ($\alpha_1 = 0.5$, $\alpha_2 = 1$ and $C = 100$) is compared to multimodal fusion without quality ($q = 1$ for all signals), as well as multi-probe results using individual traits but various sensed signals (in order to reveal the benefits of incorporating various traits) by using a variant of bootstrap resampling for training/testing the different methods [3]. Comparative performance results are given in Figs. 2 (a) and (b). Remarkable performance improvement is obtained with the quality-based approach in both cases. As compared to the fusion approach not using quality measures, approximately 20% relative performance improvement around the EER is obtained when considering fingerprint quality measures.

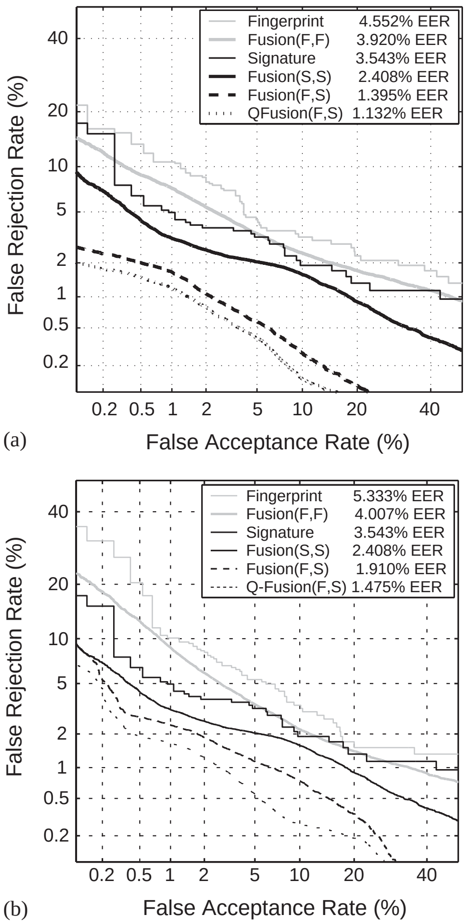

Fig. 2. Verification performance results considering (a) index fingers, and (b) highest quality finger for 95% of users and poorest quality finger for the remaining 5% users.

4. Conclusion

An operational procedure for adapting score-level fusion functions based on quality measures for multimodal biometrics has been presented and evaluated on publicly available real bimodal biometric data. Using a novel experimental protocol that mitigates some of the problems commonly encountered in other works (e.g., data scarcity, lack of understanding of the correlation effects within and between biometric traits) based on a worst case scenario, bootstrap error estimation, and multi-modal versus multi-probe comparative experiments, the benefits of exploiting quality information have been revealed.

Acknowledgements

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