

Discriminative Multimodal Biometric Authentication Based on Quality Measures

Julian Fierrez-Aguilar^{a,*}, Javier Ortega-Garcia^a,

Joaquin Gonzalez-Rodriguez^a, Josef Bigun^b

^a*Escuela Politecnica Superior, Universidad Autonoma de Madrid, Ctra. Colmenar
km. 15, E-28049 Madrid, Spain*

^b*Halmstad University, Box 823, S-301 18 Halmstad, Sweden*

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.

Key words: Biometrics, multimodal, authentication, verification, quality, support vector machine, fingerprint, signature

* Corresponding author. Tel.: +34-91-4972269; fax: +34-91-4972235
Email address: Julian.Fierrez@uam.es (Julian Fierrez-Aguilar).

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 [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].

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 is sensed depending on the estimated quality at this time.

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

$$q_r = \sqrt{Q_r \cdot Q_{r,\text{claim}}}, \quad (1)$$

where Q_r and $Q_{r,\text{claim}}$ 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 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 ($f_{\text{SVM}} : \mathbb{R}^R \rightarrow \mathbb{R}$, $f_{\text{SVM}}(\mathbf{x}_T) = \langle \mathbf{w}, \Phi(\mathbf{x}_T) \rangle + w_0$) is trained by solving the problem

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

subject to

$$y_i (\langle \mathbf{w}, \Phi(\mathbf{x}_i) \rangle + w_0) \geq 1 - \xi_i, \quad i = 1, \dots, N \quad (3)$$

$$\xi_i \geq 0, \quad i = 1, \dots, N \quad (4)$$

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

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

where $q_{i,r}$, $r = 1, \dots, R$ 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 $R-1$ (SVM₁ 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 $\mathbf{q}_T = [q_{T,1}, \dots, q_{T,R}]'$. Re-index the individual traits in order to have $q_{T,1} \leq q_{T,2} \leq \dots \leq q_{T,R}$. A multimodal similarity score $\mathbf{x}_T = [x_{T,1}, \dots, x_{T,R}]'$ is then generated. The combined quality-based similarity score is computed as follows:

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

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

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

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 [3] and the function-based on-line signature verification system used in [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.

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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Figure captions:

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

Figure 1:

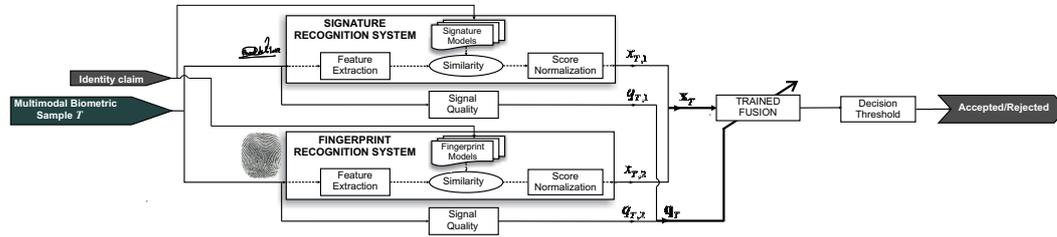
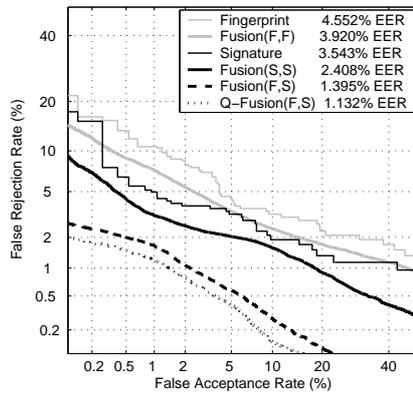
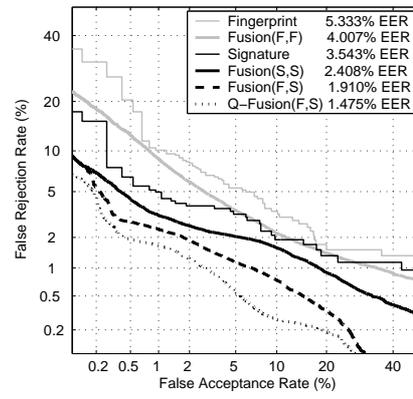


Figure 2:



(a)



(b)

JULIAN FIERREZ-AGUILAR received the M.S. degree in electrical engineering in 2001, from Universidad Politecnica de Madrid. Since 2004 he is with Universidad Autonoma de Madrid, where he is currently working towards the Ph.D. degree on multimodal biometrics. His research interests are focused on signal and image processing, pattern recognition and biometrics. He was the recipient of the Best Poster Award at AVBPA 2003 and led the development of the UPM signature verification system ranked 2nd in SVC 2004.

JAVIER ORTEGA-GARCIA received the Ph.D. degree in electrical engineering in 1996 from Universidad Politecnica de Madrid. He is currently an Associate Professor at Universidad Autonoma de Madrid. His research interests are focused on forensic acoustics and biometrics signal processing. He has participated in several scientific and technical committees, and has chaired “Odyssey-04, The ISCA Speaker Recognition Workshop”.

JOAQUIN GONZALEZ-RODRIGUEZ received the Ph.D. degree in electrical engineering in 1999 from Universidad Politecnica de Madrid. He is currently and Associate Professor at Universidad Autonoma de Madrid. His research interests are focused on signal processing, biometrics and forensics. He is an invited member of ENFSI and has been vice-chairman for “Odyssey-04, The ISCA Speaker Recognition Workshop”.

JOSEF BIGUN obtained his Ph.D. degree from Linkoeping University in 1988. He was elected professor to the signal analysis chair, his current position, at Halmstad University and Chalmers Institute of Technology in 1998. He is a Fellow of the IEEE and IAPR. His interests include biometrics, texture analysis, and understanding of the biological processing of audio-visual signals.