Information Fusion 44 (2018) 103–112

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Multiple classifiers in biometrics. Part 2: Trends and challenges

Julian Fierrez*, Aythami Morales, Ruben Vera-Rodriguez, David Camacho

School of Engineering, Universidad Autonoma de Madrid, Madrid, Spain

ARTICLE INFO

Keywords:
Classifier
Fusion
Biometrics
Multimodal
Adaptive
Context

ABSTRACT

The present paper is Part 2 in this series of two papers. In Part 1 we provided an introduction to Multiple Classifier Systems (MCS) with a focus into the fundamentals: basic nomenclature, key elements, architecture, main methods, and prevalent theory and framework. Part 1 then overviewed the application of MCS to the particular field of multimodal biometric person authentication in the last 25 years, as a prototypical area in which MCS has resulted in important achievements. Here in Part 2 we present in more technical detail recent trends and developments in MCS coming from multimodal biometrics that incorporate context information in an adaptive way. These new MCS architectures exploit input quality measures and pattern-specific particularities that move apart from general population statistics, resulting in robust multimodal biometric systems. Similarly as in Part 1, methods here are described in a general way so they can be applied to other information fusion problems as well. Finally, we also discuss here open challenges in biometrics in which MCS can play a key role.

1. Introduction

The present paper is Part 2 in a series of two papers dedicated to overviewing the field of Multiple Classifier Systems (MCS) in biometrics. In Part 1, we introduced the fundamentals of MCS [1], including: nomenclature, architecture, and a flexible theoretical framework. We then provided a review of MCS applied to multimodal biometric person authentication in the last 25 years [2]. That review was developed using a generic MCS framework and mathematical notation, with the purpose of facilitating the transfer of MCS achievements from biometrics to other pattern recognition applications like video surveillance [3], speech technologies [4], human-computer interaction [5], data analytics [6], behavioural modelling [7], or recommender systems [8].

Here in Part 2 we build from Part 1 to overview more recent trends in MCS applied to biometrics, with a focus in context-based information fusion [9]. In particular, the main MCS architectures in biometrics that have successfully exploited context information are based on quality measures [10], or user-specificities [11]. Similarly as in Part 1, the methods here are described in a general way so they can be applied to other information fusion problems as well. Additionally, particular implementations of the reported context-based MCS architectures are described using two paradigms: 1) statistical based on Bayesian statistics, and 2) discriminative based on Support Vector Machine classifiers.

We end this series of two papers with a discussion of open challenges in biometrics. The challenges exposed largely follow the excellent survey and outlook of the field of biometric person recognition by Jain et al. [2], which we complement with our personal view, and augment with the way MCS developments can advance those key challenges in biometrics. With that, we also hope to provide some light about the future of other pattern recognition and information fusion areas as well.

The present paper is organized as follows. Section 2 overviews current trends in context-based fusion for biometrics, first focusing in user-dependent fusion, and then in quality-based fusion. In both cases, we first discuss general architecture and then describe specific fusion algorithm under two paradigms: statistical (combination approach), and discriminative (classification approach). Section 3 summarizes open challenges in biometrics, and discusses the role of MCS methods in overcoming those challenges. The paper ends in Section 4 with some concluding remarks.

2. Trends in biometrics: Context-based MCS

This section is focused on MCS for multimodal biometric authentication, adapted both to user-specificities and to the input biometric quality. In the following sections we summarize key related works in these areas.

The adaptive MCS schemes for multimodal biometrics are divided into three classes: 1) user-dependent, 2) quality-based, and 3) user-dependent and quality-based. Although the last class includes the first two classes as particular cases, the three classes are introduced sequentially in order to facilitate the description.

For each class of methods, we first sketch the system model and then

* Corresponding author.
E-mail address: julian.fierrez@uam.es (J. Fierrez).

https://doi.org/10.1016/j.inffus.2017.12.005
Received 24 November 2017; Received in revised form 19 December 2017; Accepted 21 December 2017
Available online 22 December 2017
1566-2535/

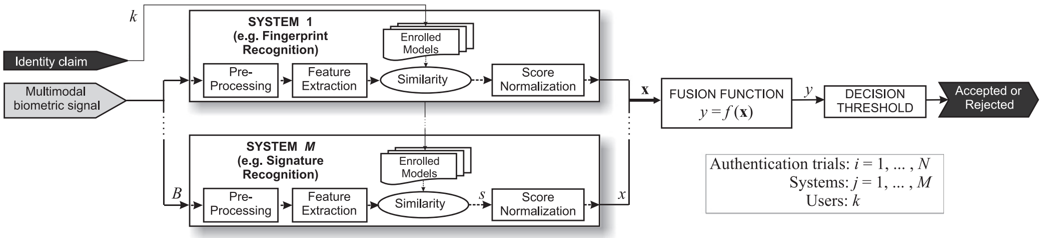

Fig. 1. General system model of multi-modal biometric authentication using score level fusion including name conventions.

we derive particular implementations by using standard pattern recognition methods, either based on generative assumptions following Bayesian theory, or discriminative criteria using Support Vector Machines. These two classes of implementations aim at minimizing the Bayesian error and the Structural Risk of the verification task, respectively.

In the rest of the paper we use the following nomenclature and conventions. Given a multimodal biometric verification system consisting of M different unimodal systems $j = 1, \ldots, M$, each one computes a similarity score s between an input biometric pattern and the enrolled pattern or model of the given claimant k. The similarity scores s are normalized to x. Let the normalized similarity scores provided by the different unimodal systems be combined into a multimodal score $\mathbf{x} = [x_1, \ldots, x_M]^T$. The design of a fusion scheme consists in the definition of a function $f: \mathbb{R}^M \to \mathbb{R}$, so as to maximize the separability of client $\{f(\mathbf{x})|\text{client attempt}\}$ and impostor $\{f(\mathbf{x})|\text{impostor attempt}\}$ fused score distributions. This function may be trained by using labelled training scores $(\mathbf{x}_i, z_i)$, where $z_i = \{0 = \text{impostor attempt}, 1 = \text{client attempt}\}$.

In Fig. 1 we depict the general system model including all the notations defined above.

2.1. User-dependent multimodal biometrics

The idea of exploiting user-specific parameters at the score level in multimodal biometrics was introduced, to the best of our knowledge, by [12]. In this work, user-independent weighted linear combination of similarity scores was demonstrated to be improved by using either user-dependent weights or user-dependent decision thresholds, both of them computed by exhaustive search on the testing data. The idea of user-dependent fusion parameters was also explored by [13] using non-biased error estimation procedures. Other attempts to personalized multimodal biometrics include the use of the claimed identity index as a feature for a global trained fusion scheme based on Neural Networks [14], computing user-dependent weights using lambness metrics [15], and using personalized Fisher ratios [16].

Toh et al. [17] proposed a taxonomy of score-level fusion approaches for multi-biometrics. Multimodal fusion approaches were classified as global or local depending firstly on the fusion function (i.e., user-independent or user-dependent fusion strategies) and secondly depending on the decision making process (i.e., user-independent or user-dependent decision thresholds): global-learning and global-decision (GG), local-learning and global-decision LG, and similarly GL and LL. Some example works of each group are listed in Table 1.

These local methods (user-dependent fusion or decision) are confronted with a big challenge: training data scarcity, as the amount of available training data in localized learning is usually not sufficient and representative enough to guarantee good MCS parameter estimation and generalization capabilities. To cope with this lack of robustness derived from partial knowledge, the use of robust adaptive learning strategies based on background information was proposed in related research areas [23]. The idea of exploiting background information and adapt from there the fusion functions of MCS based on context information was introduced in biometrics by Fierrez-Aguilar et al. [11,24], and was soon followed by others [25]. In brief, in these context-based MCS methods, the relative balance between the background information (from a pool of background users) and the local data (a given user) is performed as a tradeoff between both kinds of information.

The system model of user-dependent score fusion including the mentioned adaptation from background information is shown in Fig. 2.

Two selected algorithms implementing the discussed adapted user-dependent fusion are summarized in the following sections.

2.1.1. User-dependent MCS: Combination approach

Here we outline this algorithm, representative of context-based MCS by adapting the score fusion function to each user from general background information. For a more detailed description and experimental evaluation see [24].

Impostor and 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 y_T of a multimodal test score $\mathbf{x}_T$ is defined then as follows

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

which is known to be a Quadratic Discriminant (QD) function consistent with Bayes estimate in case of equal impostor and client prior probabilities [26]. The score distributions are estimated using the available training data as follows:

Global. The training set $X_G = (\mathbf{x}_i, z_i)_{i=1}^{N_G}$ includes multimodal scores from a number of different clients, and $(\{\boldsymbol{\mu}_{G,0}, \boldsymbol{\sigma}_{G,0}^2\}, \{\boldsymbol{\mu}_{G,1}, \boldsymbol{\sigma}_{G,1}^2\})$ are estimated by using the standard Maximum Likelihood criterion [27]. The resulting fusion rule $f_G(\mathbf{x})$ is applied globally at the operational stage regardless of the claimed identity.

Local. A different fusion rule $f_{k,\,L}(\mathbf{x})$ is obtained for each client k enrolled in the system by using Maximum Likelihood density estimates $(\{\boldsymbol{\mu}_{k,L,0}, \boldsymbol{\sigma}_{k,L,0}^2\}, \{\boldsymbol{\mu}_{k,L,1}, \boldsymbol{\sigma}_{k,L,1}^2\})$ computed from a set of development scores X_k of the specific client k.

Adapted. The adapted fusion rule $f_{k,\,A}(\mathbf{x})$ of client k trades off the general knowledge provided by the user-independent development data X_G, and the user specificities provided by the user-dependent training set X_k, through Maximum a Posteriori density estimation [27]. This is done by adapting the sufficient statistics as follows

$$\begin{aligned} \boldsymbol{\mu}_{k,A,l} &= \alpha_l \boldsymbol{\mu}_{k,L,l} + (1-\alpha_l)\boldsymbol{\mu}_{G,l}, \\ \boldsymbol{\sigma}_{k,A,l}^2 &= \alpha_l(\boldsymbol{\sigma}_{k,L,l}^2 + \boldsymbol{\mu}_{k,L,l}^2) + (1-\alpha_l)(\boldsymbol{\sigma}_{G,l}^2 + \boldsymbol{\mu}_{G,l}^2) - \boldsymbol{\mu}_{j,A,l}^2. \end{aligned} \tag{2}$$

For each class $l = \{0 = \text{impostor}, 1 = \text{client}\}$, a data-dependent adaptation coefficient

$$\alpha_l = N_l/(N_l + r) \tag{3}$$

is used, where N_l is the number of local training scores in class l, and r is a fixed relevance factor.

Note that other statistical models or other techniques for trading-off the general and local knowledge can be used in a similar way.

[1] We use diagonal covariance matrixes, so $\boldsymbol{\sigma}^2$ is shorthand for diag(Σ). Similarly, $\boldsymbol{\mu}^2$ is shorthand for diag($\boldsymbol{\mu}\boldsymbol{\mu}'$).