Pattern Recognition 45 (2012) 993–1003

Contents lists available at ScienceDirect

Pattern Recognition

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

BioSecure signature evaluation campaign (BSEC'2009): Evaluating online signature algorithms depending on the quality of signatures

N. Houmani [a,*], A. Mayoue [a], S. Garcia-Salicetti [a], B. Dorizzi [a], M.I. Khalil [b], M.N. Moustafa [b], H. Abbas [b], D. Muramatsu [c], B. Yanikoglu [d], A. Kholmatov [e], M. Martinez-Diaz [f], J. Fierrez [f], J. Ortega-Garcia [f], J. Roure Alcobé [g], J. Fabregas [g], M. Faundez-Zanuy [g], J.M. Pascual-Gaspar [h], V. Cardeñoso-Payo [h], C. Vivaracho-Pascual [h]

[a] *Institut Telecom; Telecom SudParis, Department of Electronics and Physics, Evry, France*
[b] *Ain Shams University, Department of Computer and Systems Engineering, Cairo, Egypt*
[c] *Seikei University, Department of Electrical and Mechanical Engineering, Tokyo, Japan*
[d] *Sabanci University, Faculty of Engineering and Natural Sciences, Istanbul, Turkey*
[e] *TUBITAK-UEKAE, Sceintific and Technological Research Council of Turkey*
[f] *Universidad Autonoma de Madrid, Biometric Recognition Group-ATVS, Madrid, Spain*
[g] *Escola Universitaria Politecnica de Mataro, Spain*
[h] *Universidad de Valladolid, Department of Computer Science, Valladolid, Spain*

ARTICLE INFO

Article history:
Received 8 April 2011
Received in revised form
24 June 2011
Accepted 4 August 2011
Available online 11 August 2011

Keywords:
On-line signature verification
Evaluations
Signature Categorization
Quality
Entropy

ABSTRACT

In this paper, we present the main results of the BioSecure Signature Evaluation Campaign (BSEC'2009). The objective of BSEC'2009 was to evaluate different online signature algorithms on two tasks: the first one aims at studying the influence of acquisition conditions (digitizing tablet or PDA) on systems' performance; the second one aims at studying the impact of information content in signatures on systems' performance. In BSEC'2009, the two BioSecure Data Sets DS2 and DS3 are used for tests, both containing data of the same 382 people, acquired respectively on a digitizing tablet and on a PDA. The results of the 12 systems involved in this evaluation campaign are reported and analyzed in detail in this paper. Experimental results reveal a 2.2% EER for skilled forgeries and a 0.51% EER for random forgeries on DS2; and a 4.97% EER for skilled forgeries and a 0.55% EER for random forgeries on DS3.

1. Introduction

For the last twenty years, most of the works carried out in the framework of handwritten signature verification are focused on the development and the implementation of new algorithms for online signature recognition. Such works aim at improving the performance of automatic identity verification systems based on the online handwritten signature modality.

However, even though verification systems in the literature are evaluated using publicly available databases in recent years, it is still difficult to compare the performance of such verification systems because of the differences in experimental conditions. To overcome this issue, it is important for the scientific community to conduct signature evaluation campaigns allowing an objective comparison of the algorithms with respect to each other and to standard approaches of the state-of-the-art, using the same databases and evaluation protocols.

In the past, only a few public evaluations have been organized for comparing advances in online signature verification. These include the first Signature Verification Competition (SVC) held on 2004 [18], the Signature Competition of the BioSecure Multimodal Evaluation Campaign (BMEC), held on 2007 [19], and more recently the ICDAR Signature Verification Competition, held in 2009 [20].

SVC'2004 [18] was carried out on a database of very limited size (60 people, only one session), mixing signatures of different cultural origins, captured on a digitizing tablet. The signatures in this database were not "true" signatures; indeed, the subjects were advised not to use their real signatures for privacy reasons. SVC'2004 was divided into two tasks, depending on the input features available: in Task 1, only the pen coordinates and the sample time stamps were available; in Task 2, the pen pressure and pen inclination angles (azimuth and altitude) were also available. For both tasks, the Dynamic Time Warping-based system submitted by *Sabanci University* [7] obtained the best Equal Error Rate (EER) when tested on skilled forgeries

* Corresponding author.
E-mail address: nesma.houmani@it-sudparis.eu (N. Houmani).

0031-3203/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.patcog.2011.08.008

(EER=2.84% in Task 1 and EER=2.89% in Task 2). In second position, we distinguished the HMM-based systems with an EER around 6% in Task 1 and 5% in Task 2, when tested on skilled forgeries. On random forgeries, the HMM-based system submitted by *Universidad Autonoma de Madrid* [13] was the best system, with an EER of 2.12% in Task 1 and of 1.70% in Task 2.

The BMEC'2007 Signature Competition [19] was carried out in the framework of the BioSecure Network of Excellence [22,26]. It was the first signature verification evaluation on signatures captured on a mobile platform (Personal Digital Assistant, PDA) [19]. The aim of this competition was to compare the performance of different verification systems in mobile conditions, on the large BioSecure Data Set 3 (DS3) (430 people, 2 sessions) [19,22,26]. In this evaluation, we noticed that the model-based systems outperformed those based on distance approaches [19]. Indeed, the Gaussian Mixture Model-based system submitted by *EPFL* [19] obtained the best performance, when tested on both skilled and random forgeries (EER=13.43% and EER=4.03%, respectively). This winning system was followed by the HMM-based Reference System of *Telecom SudParis* [17,27,30], with an EER of 15.36% for skilled forgeries and of 4.88% for random forgeries.

The ICDAR'2009 Signature Verification Competition [20] was held in 2009, in the framework of the 10th International Conference on Document Analysis and Recognition (ICDAR'2009). This competition was carried out on the Netherlands Forensic Institute (NFI) signature database (100 people), containing both offline dataset and its corresponding online dataset acquired on a digitizing tablet. This competition was the first signature verification evaluation on offline signatures and also the first competition where offline and online signatures were combined [20]. Moreover, the competition aimed at combining expert forensic judgments with the performance of automatic verification systems by testing systems on a forensic-like dataset. For the online task, the best result was obtained by *Parascript, LLC* with an EER of 2.85%. For the offline task, the best result was obtained by *Centre for Mathematical Morphology* with an EER of 9.15%. The only system which combined both offline and online data was that of *Universidad Autonoma de Madrid*, which obtained an EER of 8.17% [20]. No information was given on the classifiers used by the submitted systems.

At the same time as ICDAR'2009 Signature Competition [20], a new evaluation campaign was organized in 2009, namely the BioSecure Signature Evaluation Campaign (BSEC'2009) [23], which was held in conjunction with the International Conference on Biometrics (ICB'2009) [21], and which is the subject of the present paper. This competition was divided into three tasks and was focused on the evaluation of online signature verification systems following new benchmarking frameworks. In the previous signature competitions, signatures were acquired with a single sensor in each competition: a digitizing tablet at SVC'2004 [18] and ICDAR'2009 [20], and a PDA at BMEC'2007 [19]. In contrast, BSEC'2009 was performed on the two existing largest databases containing the same persons, acquired with two different sorts of sensors, namely a digitizer (BioSecure Signature Corpus DS2) and a PDA touch screen (BioSecure Signature Corpus DS3) [22,26]. The DS3 corpus is indeed the first on-line signature multi-session database acquired in a mobile scenario, while the DS2 corpus was collected on a fixed platform, from the same subjects. BSEC'2009 [23] aimed at measuring the real impact of a mobile platform on algorithms' performance on these two databases. This first objective was studied in Task 1 of BSEC'2009.

The second objective of BSEC'2009 [23], studied in Task 2, was to analyze the impact of time variability on systems' performance and to assess the relative pertinence over time of the different time functions captured by the sensor [23]. It is worth noticing that there are very few works in the literature studying the impact of time variability of signatures on systems' performance. The two BioSecure databases DS2 and DS3 [22,26] are well suited to this study as they were collected in two sessions separated in time by several weeks.

Finally, a biometric system's performance is measured, in general, globally on all the available data in a database, in terms of the two types of errors that a biometric system can make, namely False Rejections and False Acceptances. This is the case of all previous signature evaluation campaigns [18,19,20]. However, it is obvious that some persons possess a signature that is easier to recognize than others. This can be related to the complexity and the stability of their signatures. Therefore, to have a better insight on the behavior of a classifier, it is wise to split the database in subsets, according to a criterion related to the difficulty of recognizing an individual. Therefore, the third objective of BSEC'2009 [23], studied in Task 3, was to evaluate the performance of different algorithms depending on the information content in the signatures, thanks to a protocol categorizing the data of both DS2 and DS3 in subsets [23]. To this end, we exploited the notion of Personal Entropy, introduced in [24,25] to categorize people depending on the quality of their signatures. Systems' performance was also measured globally on the complete databases for comparison purposes.

In this paper, we present the BioSecure Signature Evaluation Campaign BSEC'2009. As the participants did not use all combination of features in order to study the impact of time functions on systems' performance, we cannot report the results of Task 2 and we only present in this paper the results of the two major tasks, those relying on the quality of signatures. More precisely, we present the results of Task 1 studying the impact of mobile conditions, and the results of Task 3 studying the impact of information content of signatures on performance assessment. Table 1 provides a summary for BSEC'2009 and highlights the differences of this competition with respect to previous ones (SVC'2004, BMEC'2007 and ICDAR'2009) in terms of datasets used, the different tasks considered, the number of participants, and the best performance achieved.

This paper is organized as follows: Section 2 presents the two BioSecure Signature Data Sets DS2 and DS3 used for this evaluation. Section 3 describes the calculation of the Personal Entropy measure associated to a given person by means of a Writer-HMM, and how it can be used to automatically generate writer categories through a hierarchical clustering procedure. Section 4 describes the evaluation protocol and the two main tasks of BSEC'2009: Task 1 and Task 3. In Section 5, we give a brief description of the 12 submitted systems. Section 6 presents the most pertinent experimental results of Task 1 and Task 3. Finally, conclusions are stated in Section 7.

2. BioSecure signature datasets

Two datasets were used in this competition [22]. These datasets were acquired in several sites in Europe, in the framework of BioSecure Network of Excellence [22,26]: DS2 was acquired on a digitizing tablet, and DS3 was acquired on a mobile platform (PDA).[1]

For this evaluation, two development datasets of 50 people from respectively BioSecure DS2 and DS3 have been distributed to the participants. Note that for such datasets, the donors provided their own genuine signatures (not fake signatures as in SVC'2004 [18]), and the 50 people are the same in the two development datasets [23]. Besides, two other datasets containing signatures of

[1] Part of the BioSecure Signature Data Sets DS2 and DS3 are publicly available on the website of BioSecure Association [22].

Table 1
Summary of the four signature competitions.

Competitions	SVC'2004	BME'C 2007	ICDAR'2009	BSEC'2009
Development dataset	40 people (donors did not use their real signatures)	BioSecure DS3 of 50 people, 2 sessions.	NISDCC dataset of 12 people, containing both offline and online signatures.	BioSecure DS2 and DS3 of 50 people, 2 sessions.
Test dataset	60 people of different cultural origins, one session.	BioSecure DS3 of 430 people, 2 sessions.	Netherlands Forensic Institute dataset of 100 people, containing offline and online signatures.	BioSecure DS2 and DS3 of 382 people, 2 sessions.
Data acquisition	Digitizing tablet	Personal Digital Assistant (PDA)	Digitizing tablet for the online dataset	Digitizing tablet for DS2, and PDA for DS3
Tasks	*Task 1*: performance considering only pen coordinates and the sample time stamps. *Task 2*: performance considering pen coordinates, pen pressure and pen inclination angles.	*Task:* performance depending on the type of forgeries (random, skilled and synthetic imitations).	*Task 1*: performance of online systems on skilled forgeries. *Task 2*: Performance of offline systems on skilled forgeries.	*Task 1*: impact of mobile conditions on systems' performance on both DS2 and DS3, considering only pen coordinates and the sample time stamps. *Task 2*: impact of time variability on systems' performance on DS2 dataset, considering coordinates, pen pressure and pen inclination angles. *Task 3*: impact of signature information content on systems' performance on DS2.
Participants	*Task 1*: 15 teams and 15 systems *Task 2*: 12 teams and 12 systems	6 teams and 11 systems	*Task 1*: 12 teams and 15 online systems *Task 2*: 7 teams and 8 offline systems	*Task 1 and Task 3:* 8 teams and 12 systems *Task 2*: 10 teams and 14 systems
Best performance on skilled forgeries	*Task 1*: EER=2.84% *Task 2*: EER=2.89%	EER=13.43%	*Task 1*: EER=2.85% *Task 2*: EER=9.15%	*Task 1* On DS2: EER=2.20% On DS3: EER=4.97% *Task 2* Without variability: On DS2: EER=1.71% With variability: On DS2: EER=3.48% *Task 3*: EER=1.38%
Best performance on random forgeries	*Task 1*: EER=2.12% *Task 2:* EER=1.70%	EER=4.03%	/	*Task 1* On DS2: EER=0.51% On DS3: EER=0.55% *Task 2* Without variability On DS2: EER=0.42% With variability On DS2: EER=1.37% *Task 3:* EER=0.27%

382 people from respectively BioSecure DS2 and DS3 were used by the organizer to test the submitted systems, and they were being kept sequestered.

The two test sets contain the same 382 people in order to measure the real impact of mobility acquisition conditions on algorithms performance [23]. In the following, these two test sets are denoted as DS2-382 and DS3-382.

2.1. BioSecure signature data set 2 DS2

BioSecure Data Set 2 (DS2) [22,26] contains signatures acquired in a PC-based, offline, supervised scenario with a digitizing tablet WACOM INTUOS 3 A6. The pen tablet resolution is 5080 lines per inch and the precision is 0.25 mm. The maximum detection height is 13 mm and the capture area is 270 mm (width) $\times$ 216 mm (height). Signatures are captured on paper using an inking pen. At each sampled point of the signature, the digitizer captures, at 100 Hz sampling rate, the pen coordinates, pen pressure (1024 pressure levels) and pen inclination angles (azimuth and altitude angles of the pen with respect to the tablet) [22,26].

Two sessions were acquired spaced off around two weeks, each containing 15 genuine signatures and 10 skilled forgeries acquired by each donor as follows: the donor was asked to perform, alternatively, three times 5 genuine signatures and 10 forgeries. More precisely, at each session, each subject is asked to imitate 5 times, the signature of two other persons. No special interface has been provided to the subject for helping him/her recovering the dynamic of the signature that he/she has to forge.

2.2. BioSecure signature data set 3 DS3

BioSecure Data Set 3 (DS3) [22,26] contains signatures acquired on the PDA HP iPAQ hx2790, at the frequency of 100 Hz and with a touch screen resolution of 1280$*$960 pixels. Three time functions are captured from the PDA: x and y coordinates and the time elapsed between the acquisition of two successive points. The user signed while standing and had to keep the PDA in his or her hand.

Two sessions were acquired spaced by around 5 weeks, each containing 15 genuine signatures. The subject was asked to perform, in each session, 15 genuine signatures and 10 forgeries (5 imitations for each of two other persons). In order to imitate the dynamics of the signature, the forger visualized on the PDA screen the writing sequence of the signature he/she had to forge and could sign on the image of such signature in order to obtain a better quality forgery, both from the point of view of the dynamics and of the shape of the signature. Due to the low resolution of the PDA, some coordinates are missing. To overcome this problem, the organizer performed a spatial interpolation between consecutive points.

3. Entropy-based quality measure

In this section, we will briefly recall the main steps of our novel entropy computation presented in detail in [24,25].

3.1. Measuring Personal Entropy with a Hidden Markov Model

The entropy of a random variable depends on its probability density function [28]. Thus, a good estimation of this probability density is important. As there are local dependencies in the dynamics of the hand-drawn signature, a local paradigm for density estimation seems to be natural. To this end, we model each writer' signature thanks to a Hidden Markov Model (HMM) [29] trained on a set of K genuine signatures of such a writer. Then, we consider each signature as a succession of portions, generated by its segmentation via the Viterbi Algorithm [29], according to the Writer-HMM. Then we consider each point (x,y) in a given stationary portion S_i of the signature as the outcome of one random variable Z_i, which follows a given probability mass function $p(z)=\Pr(Z_i=z)$ where z belongs to the Alphabet A of ordered pairs (x,y). The entropy [28] of such a portion is then computed as follows:

$$H_{S_i}(Z_i) = -\sum_{z \in S_i} p(z)\log_2(p(z)) \quad (1)$$

The estimation of the local probability distribution functions is carried out by considering all sample points belonging to each portion across the K instances of the writer's signatures [25]. Then, the entropy of a genuine signature sample "*sig*" is computed by averaging the local entropy values $H_{S_i}(Z_i)$ on all of its portions S_i, normalized by the signing time of such signature sample:

$$H_{sig}(Z) = \frac{1}{N{*}T}\sum_{i=1}^{N} H_{S_i}(Z_i) \quad (2)$$

where T is the length of the signature sample and N the number of portions generated by the Writer-HMM. We thus retrieve an entropy measure expressed in bits per second [25]. Note that the signing time normalization allows comparing users between them in terms of entropy; indeed, without such normalization, due to the great difference in length between signatures of different persons, entropy tends to be higher on longer signatures.

Finally, averaging this measure across the K genuine signatures being considered allows the Personal Entropy [25] to be computed:

$$\overline{H} = \frac{1}{K}\sum_{sig=1}^{K} H_{sig}(Z) \quad (3)$$

Note that Personal Entropy, quantified for each writer, measures on a set of genuine signatures the "uncertainty" or "degree of disorder" of the writer's signature. Indeed, the local probability density functions are estimated by an HMM on a set of genuine signatures [25]. Therefore, our entropy measure quantifies disorder or uncertainty locally and thus, inversely, information content: high information content means low entropy and thus a low degree of disorder.

3.2. Personal Entropy-based writer categories

We performed on the two BioSecure evaluation datasets DS2 and DS3 containing the same 382 people, a hierarchical clustering procedure on their writer's Personal Entropy values. Three writer categories were this way automatically generated. Fig. 1 shows examples of some signatures from DS2 in the three Entropy-based categories. Note that we displayed signatures whose owners authorized their publication.

We notice visually that the first category of signatures (Fig. 1a), those having the Highest Personal Entropy values, contains short, simply drawn and not legible signatures, often with the shape of a simple flourish. At the opposite, signatures in the third category (Fig. 1c), those of Lowest Personal Entropy values, are the longest and their appearance is rather that of handwriting, some are even legible. In between, we notice that signatures with Medium Personal Entropy (second category, Fig. 1b) are longer and sometimes become legible, often showing the aspect of a complex flourish.

4. Description of the main tasks of BSEC'2009

As mentioned at the end of Section 1, we remind that, in this paper, we present only the two tasks related to the evaluation of algorithms depending on the quality of signatures: Task 1 and Task 3, which are described in detail in this section.

*TASK 1***:** goal is to study the impact of mobility acquisition conditions on algorithms' performance.

Only pen coordinates are considered in this task. Participants used the Development Data Set DS2, containing data of 50 people.

Evaluation protocol: The submitted systems in this task are tested by the organizer on the whole DS2-382 and DS3-382 datasets to study the impact of the mobile platform on systems' performance.

Fig. 1. Examples of signatures from DS2 database of (a) High, (b) Medium and (c) Low Personal Entropy (with authorization of the writers).

TASK 3: goal is to study the impact of information content in signatures on algorithms' performance.

Evaluation protocol: All the submitted systems in Task 1 are now tested on DS2-382, on different writer categories depending on the quality of their signatures. Writer categories are generated on DS2-382 using a hierarchical clustering on the 382 Personal Entropy values. Note that this quality measure was not available to participants; it was only used by the organizer, *Telecom SudParis,* in the test phase.

For both tasks, performance assessment was carried out on DS2-382 and DS3-382 according to the following Generic Protocol: for each enrolled person, 5 genuine signatures of Session 1 are used as reference signatures. Tests are carried out on the remaining 10 genuine signatures of Session 1, on 10 skilled forgeries of Session 1, and on 15 random forgeries.

5. Description of the submitted systems

This evaluation campaign involves 11 submissions from 8 sites. A Reference System, which was developed by Telecom SudParis, is also considered for comparison purpose [17,27,30]. A complete list of the systems is shown in Table 2. We also give in Table 3 a brief description of the systems submitted for Task 1 and Task 3.

6. Experimental results

Performance assessment was evaluated in terms of the two types of errors, namely False Acceptance Rate (FAR) and False Rejection Rate (FRR). The results are reported in terms of the DET-Curves [31] and the Equal Error Rate functioning point (EER).

To get an idea about the confidence interval (CI) at 95% at the Equal Error Rate functioning point (EER), we used a parametric function [32] in order to calculate the error rate FRR (t) (or FAR (t)), at the threshold t_{EER}, at which the EER occurs. The confidence interval is thus computed as follows:

$$CI = 1.96\sqrt{\frac{FRR(t_{EER})(1-FRR(t_{EER}))}{\text{Number of authentic matching scores}}} \quad (4)$$

We found that for all experiments the confidence interval is lower than 0.01.

6.1. Results of task 1: impact of mobile acquisition conditions on systems' performance

In order to study the impact of mobile acquisition conditions on systems' performance, the 11 submitted systems and the Reference System were tuned using the Development Data Set DS2, which contains data of 50 people, then tested on DS2-382 and DS3-382 datasets containing the same 382 people, following the Generic Protocol (see Section 4).

The experimental results of each system obtained on DS2-382 and DS3-382 are shown respectively by the DET-Curves in Figs. 2 and 3, with both skilled and random forgeries. Equal Error Rate functioning point values associated to the submitted systems are reported in Table 4.

When we compare the obtained results on DS2-382 and DS3-382, we observe that systems' performance on DS2-382 is globally better than on DS3-382, which is acquired on a mobile platform. Indeed, we notice in Table 4 that with skilled forgeries, the performance on DS3-382 is degraded roughly by a factor 2 at the EER. With random forgeries, the degradation is less significant.

It is also observed, as expected, that all the submitted systems, except the "*UAM-HMM system*", detect more easily random forgeries than skilled forgeries. This is also observed on the DET-Curves in Figs. 2 and 3: indeed, with random forgeries, at a False Rejection Rate (FRR) equals to 0%, the False Acceptance Rate (FAR) of the majority of systems is lower than 30%; while on skilled forgeries the FAR is higher than 40%.

Performance degradation on DS3-382 can be explained by two factors. The first factor is related to the quality degradation of signatures acquired on a mobile platform: signature realizations in mobile conditions always display distortions and alterations compared to their realizations on a stable writing surface (digitizing tablet) with an inking pen. Actually, in the mobile acquisition of DS3, the writer signed while standing and holding the PDA (see Section 2.2). The second factor is related to the forgery acquisition protocol of DS3, which is better suited to capture good quality forgeries. Indeed, a specific acquisition interface was exploited providing to the impostor both static and dynamic information about the target signature (as mentioned in Section 2.2). This clearly appears on the FAR's behavior in Fig. 2 (on DS2) compared to Fig. 3 (on DS3): the FAR reach much higher values on DS3 compared to DS2 (at FRR=0%). Nevertheless, in case of random forgeries, performance degradation is due exclusively to the quality degradation of genuine signatures: indeed, random forgeries are very "far" from the target genuine signatures for both DS2 and DS3 datasets. This explains what we previously observed: performance degradation on DS3-382 with random forgeries is less important compared to that with skilled forgeries.

Now, when we compare the submitted systems between them, we notice that on skilled forgeries, the best performance on DS2 is obtained with the "*VDU system*", with an EER of 2.20%, closely followed by the "*UAM-FUS system*" with an EER of 2.22%; while on DS3 (mobile platform), the best performance is obtained with the "*SU system*", with an EER of 4.97%. When comparing these three systems between them, we observe that although the "SU system" comes in the 4th position with an EER of 2.97% when tested on DS2 with skilled forgeries (see Table 4), it appears as the most resistant to the changes of the acquisition conditions, as its associated EER degrades on skilled forgeries by a factor 1.67 from DS2 to DS3; while for the "*UAM-FUS system*" and the "*VDU*

Table 2
List of participants.

ID	Affiliation	Participants
Ref	Telecom SudParis, France	Reference System
ASU	Ain Shams University, Egypt	M.I. Khalil, M. Mostafa, H. Abbas
SKU	Seikei University, Japan	D. Muramatsu
SU	Sabanci University, Turkey	B. Yanikoglu
	Scientific and Technological Research Council of Turkey (TUBITAK-UEKAE)	A. Kholmatov
UAM-DTWr DTWs,HMM, GLO, FUS	Universidad Autonoma de Madrid, Spain	M. Martinez-Diaz, J. Fierrez, J. Ortega-Garcia
UPM1	Escola Universitaria Politecnica de Mataro, Spain	J. Roure Alcobé
UPM2		J. Fabregas, M. Faundez-Zany
VDU	Universidad de Valladolid, Spain	J. M. Pascual-Gaspar, V. Cardeñoso-Payo, C. Vivaracho-Pascual

Table 3
Description of the systems.

Approach	classifier	ID	System description
Distance-based systems	**DTW distance**	**SU**	– Local features: relative offsets of pen coordinates. – Score computation: distance to template signature (most central reference signature) normalized by the corresponding mean value of the reference set [7].
		UAM-DTWr	– 27 local features [14]. – Feature selection via Sequential Forward Floating Selection (SFFS). Optimization criterion: EER against random forgeries. – Score computation: min and mean distance of the test to the reference signatures for DS3 and DS2 respectively [7].
		UAM-DTWs	– 27 local features [14]. – Feature selection via SFFS. Optimization criterion: EER against skilled forgeries. – Score computation: as for SU system [7,15].
		VDU	– Local features: time derivative of pen coordinates. – DTW normalization requiring 2 score distributions [8,9]: one obtained from the training signatures, the other derived from a cohort of casual impostors, selected from MCYT-100 [10].
		ASU	– Local features: speed and curvature changes. – Score based on the average min and the average max distances computed on the reference set. Final binarized score obtained by score comparison to a fixed threshold (get on DS2) [5,6].
		SKU	– Local features: coordinates, pen direction and velocity. – Score computation based on a fusion model generated by combining many perceptrons, relying on the reference set, using Adaboost algorithm [4].
	Mahalanobis distance	**UAM-GLO**	– 100 global features. - Score computation: Mahalanobis distance [11,12].
	Euclidean distance	**UPM1**	– 16 local features extracted from pen coordinates. – Comparison of signatures on portion level. - Score computation based on ratio of mean and standard deviation of features [1].
Statistical-based systems	**HMM**	**UAM-HMM**	– 27 local features [14]. – Feature selection via SFFS. Optimization criterion: EER against skilled forgeries. – Likelihood score computation [13].
		Ref	– 25 local features. – Score computation based on the fusion of likelihood score and segmentation score generated by Viterbi algorithm [17,27,30].
	Biometric dispersion match	**UPM2**	– Features: one dimensional discrete cosine transform [2,3]. – Feature selection via LDA.
Fusion-based systems	**Fusion of the 4 UAM systems: GLO, HMM, DTWs, DTWr**	**UAM-FUS**	– Weighted sum of the 4 UAM systems [16]. – Optimal sum coefficients computed using logistic regression.

system", the EER degrades on DS3 respectively by a factor 2.46 and 3.

On random forgeries, the "*UAM-DTWr system*" is the best in terms of performance on both datasets and its performance remains stable independently of the acquisition sensor (PDA or digitizing tablet). Indeed, for both DS2 and DS3, the "*UAM-DTWr system*" obtained an EER of 0.5% on random forgeries. However, we should note that this system has been specially tuned for random forgeries, as mentioned on Table 3 in Section 5; and hence it is biased. Close to this winning system, we distinguish the "*UAM-FUS system*" that is based on the score weighted sum fusion of the four UAM systems (*UAM-DTWs, UAM-DTWr, UAM-HMM, UAM-GLO*), and which reached an EER of 0.6% on random forgeries.

Furthermore, regarding the system based on a distance approach with global features, namely "*UAM-GLO*", the results show that it gives worse performance in comparison to the other distance-based systems using local feature extraction, and even though it exploits 100 global features.

Finally, we notice that on DS2 for both types of forgeries, the worst performance is obtained with the "*UAM-HMM system*". This result is a priory surprising and unexpected, because HMM-based systems have always shown good results in the literature [18,19,30], as also observed in this evaluation by the results of the *Reference System* based on Hidden Markov Models. This surprising result may be due to an implementation error or to the fact that this system has not been well tuned. On the other hand, we observe that the worst performance on DS3 is obtained by the "*ASU system*". Indeed, the performance of the "*ASU system*" is degraded significantly when tested on DS3, roughly by a factor 10 (see Table 4). This can be explained by the fact that this system uses the same decision threshold for DS2 and DS3 in order to get the final binarized score (refer to Table 3). This threshold obtained experimentally on DS2 is

Table 4
Equal Error Rates (EERs) of the submitted systems of Task 1, on DS2-382 and DS3-382 datasets, with skilled and random forgeries.

12 Systems	DS2-382		DS3-382	
	EER on skilled forgeries (%)	EER on random forgeries (%)	EER on skilled forgeries (%)	EER on random forgeries (%)
UMP1	4.89	2.32	7.38	1.86
UPM2	4.39	1.86	8.19	2.04
SKU	2.88	1.57	7.87	1.29
ASU	3.82	2.66	31.57	30.64
VDU	**2.20**	0.97	6.59	1.67
SU	2.97	2.22	**4.97**	4.31
UAM-DTWr[a]	4.15	**0.51**	12.17	**0.55**
UAM-DTWs	2.88	1.46	5.77	1.54
UAM-HMM	19.17	24.24	25.81	21.34
UAM-GLO	6.70	3.34	13.16	4.73
UAM-FUS	2.22	0.62	5.47	0.66
Ref	4.47	1.74	11.27	4.8

[a] We recall that the "*UAM-DTWr*" *system* was especially tuned on random forgeries.

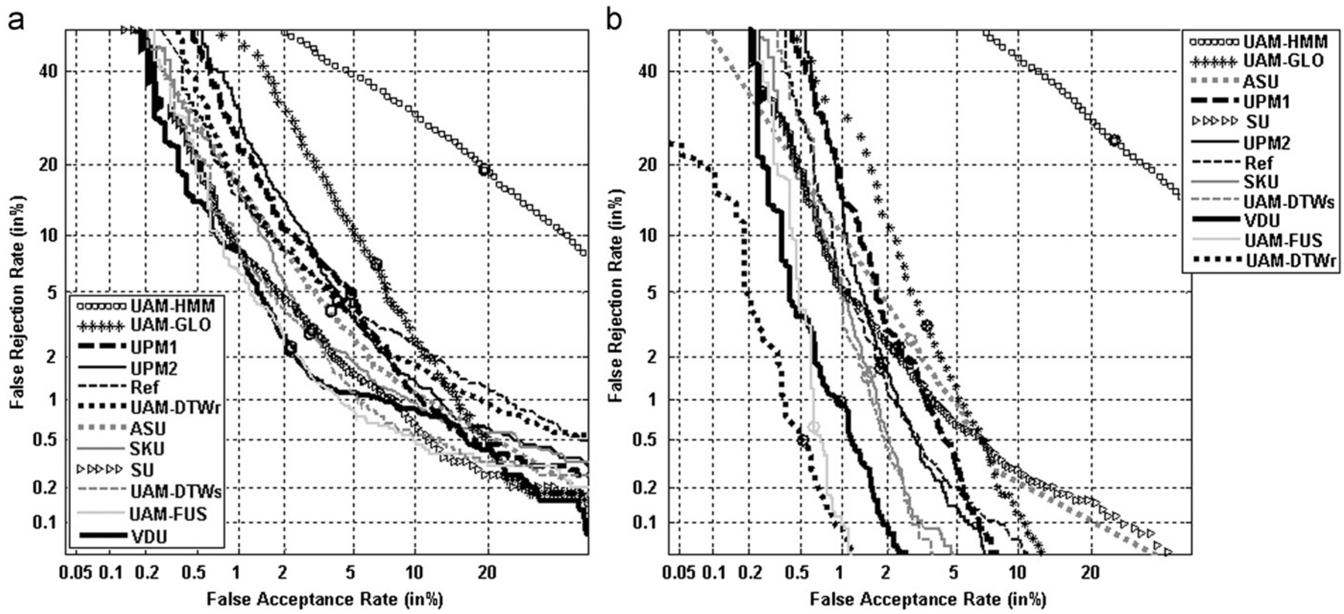

Fig. 2. DET-Curves on DS2-382 with: (a) skilled forgeries and (b) random forgeries.

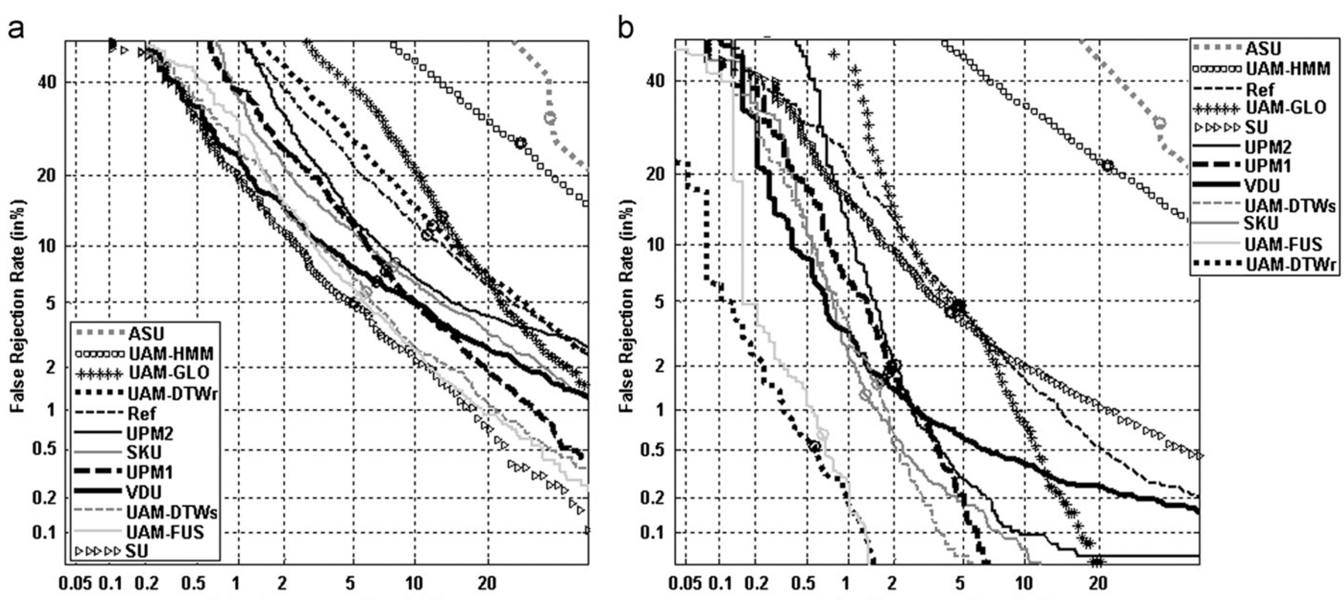

Fig. 3. DET-Curves on DS3-382 with: (a) skilled forgeries and (b) random forgeries.

not adequate for DS3, as signatures of DS2 and DS3 have different characteristics as they are acquired on different sensors.

6.2. Results of task 3: impact of information content of signatures on performance

In order to study the impact of information content of signatures on algorithms' performance, all systems submitted in Task 1 are now tested on DS2-382 on different categories of writers depending on the quality of their signatures, which is measured using our Personal Entropy measure [24,25], defined in Section 3.

For this evaluation campaign, we consider only the two extreme Entropy-based categories, namely the High Personal Entropy category and the Low Personal Entropy category. The first one corresponds to signatures of low quality in terms of verification purposes, and contains signatures of 60 people (among the 382 people). The second category corresponds to signatures of high quality and contains signatures of 161 people (among the 382 people).

The experimental results obtained on DS2-382 on these two extreme categories, are shown by the DET-Curves in Fig. 4 considering in this task skilled forgeries. We report in Table 5 the Equal Error Rate (EER) values and the EER ratio values of the two extreme categories. Note that the confidence interval at 95% at the Equal Error Rate functioning point is lower than 0.01.

We first observe that there is a significant difference in classifiers' performance between the two extreme categories: except for "*UAM-HMM*", all systems give the best performance on writers belonging to the category of Low Personal Entropy, containing the longest, most complex and most stable signatures (see Table 5). These results are coherent with those presented in [24,25], where two basic classifiers were evaluated on each Entropy-based category, namely a Hidden Markov Model and a Dynamic Time Warping classifiers.

Moreover, when we compare the DET-Curves in Fig. 4a to those in Fig. 4b, we notice that for nearly all the submitted systems, at FRR=0%, FARs are much lower considering the Lowest Entropy category (Fig. 4b): indeed, for the majority of the submitted systems, FAR does not exceed 30% when considering the Lowest Entropy category (Fig. 4b), while it is always more than 40% when considering the Highest Entropy category (Fig. 4a). In the same way, we observe that the FRRs are low for the Lowest Entropy category: for FAR=1%, the FRR of the majority of systems does not exceed 20% for the Lowest Entropy category (Fig. 4b), while it reaches 40% for the Highest Entropy category (Fig. 4a).

When we compare the submitted systems between them, we first notice that the systems' ranking changes according to the category of Personal Entropy used for test. Table 5 shows that the best system in terms of performance on High Entropy category is the "*VDU system*" with an EER=3.58%, followed by the "*SU system*" with an EER of 4%. On the Lowest Entropy category, the best performance are obtained by the "*UAM-FUS system*" with an EER=1.48%, closely followed by the "*VDU system*" with an EER=1.69%. Note that these two systems are those leading to the best performance on the whole DS2-382 dataset with skilled forgeries in Task 1 (see Table 4).

Moreover, similarly to what we observed in Task 1, "*UAM-HMM*" system is still the worst system in terms of performance in each category, and its relative behavior between the two writer

Table 5
Equal Error Rates (EERs) of the submitted systems on each category of writers of DS2-382 with skilled forgeries.

12 Systems	DS2-382—Skilled forgeries		
	EER on High Entropy category (%)	EER on Low Entropy category (%)	EER ratio
UMP1	6.58	4.57	1.44
UPM2	6.50	3.98	1.63
SKU	4.08	2.90	1.41
ASU	5.67	3.11	1.82
VDU	**3.58**	1.69	2.12
SU	4.00	2.90	1.38
UAM-DTWr	7.83	2.90	2.70
UAM-DTWs	4.17	2.43	1.71
UAM-HMM	9.91	21.32	N/A
UAM-GLO	9.00	6.76	1.33
UAM-FUS	4.17	**1.48**	2.81
Ref	6.00	3.81	1.57

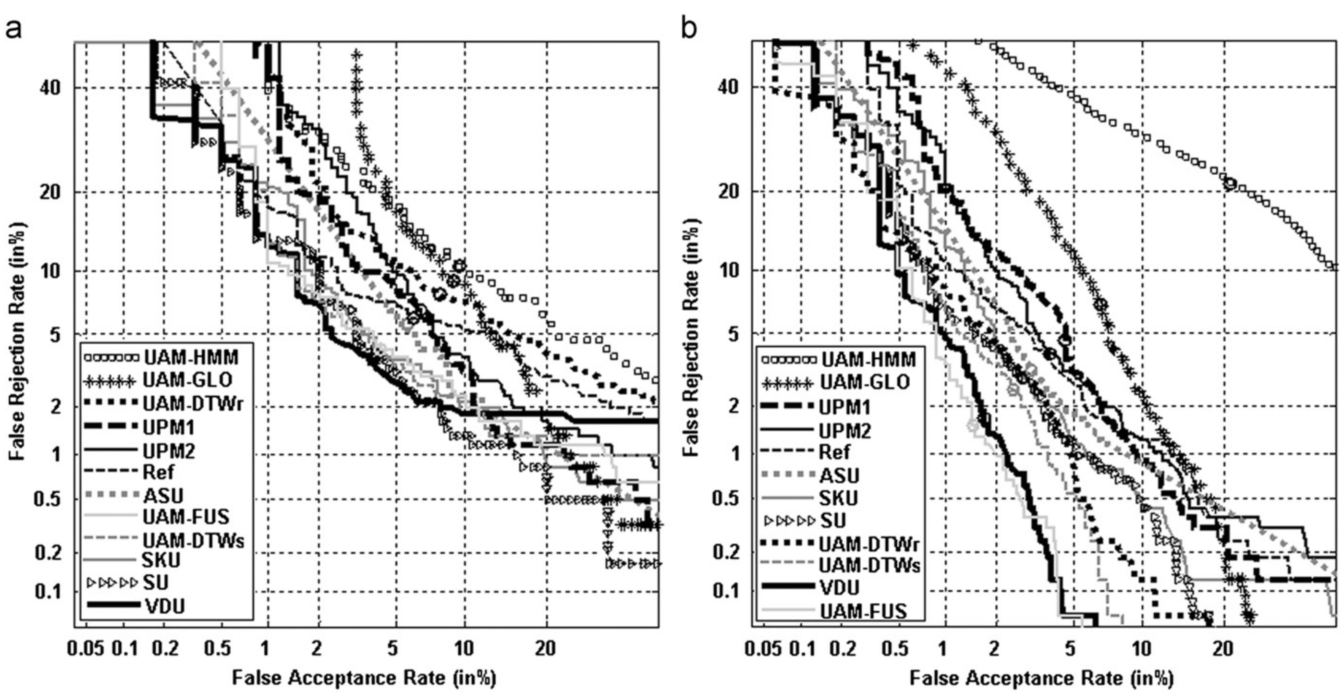

Fig. 4. DET-Curves with skilled forgeries on each writer category of DS2-382: (a) High Entropy category and (b) Low Entropy category.

categories is conflicting with what we found with the other systems and with the previous results of [24,25].

In regard to the EER ratio values reported in Table 5, we notice that some systems are more robust than others to the quality degradation of signatures. Note that the EER ratio value cannot be used alone and should be related to the performance values on each entropy category. Indeed, in spite of the high EER ratio between the two extreme categories with the ''*VDU system*'', this system is considered a good one in terms of performance when tested on each writer category separately.

Finally, in comparison to global performance obtained on skilled forgeries in Task 1, we notice that the ranking of the systems changes when performance are measured globally on the whole database or on each writer category. These interesting results are an essential point for further evaluations: some systems may indeed be more robust than other on one given type of signature, or more robust to quality degradation. At last, in comparison to the obtained results in Task 1 (see Table 4), we notice that the performance obtained on the whole DS2-382 is generally in between those obtained on the Lowest and the Highest Entropy categories in Task 3 (see Table 5).

7. Conclusion

In this paper, we presented the most recent online signature competition, namely the BioSecure Signature Evaluation Campaign BSEC'2009. This competition was focused on the evaluation of online signature algorithms depending on the quality of signatures available on the two BioSecure Data Sets DS2 and DS3 containing the same 382 writers, acquired respectively on a fixed platform and on a mobile one. In this paper, two tasks defined in BSEC'2009 were presented: Task 1, which aims at studying the impact of acquisition conditions on algorithms' performance; and Task 3, which aims at studying the impact of information content in signatures on algorithms' performance.

The results of Task 1 point out the importance of the acquisition conditions to improve systems' performance. Indeed, evaluation of algorithms on BioSecure DS2 and DS3 shows a clear performance degradation on DS3 due first, to the forgery acquisition protocol of DS3, which is better suited to capture good quality forgeries; and secondly, to the quality degradation of signatures acquired in mobile conditions.

The results of Task 3 show the dependence of systems' performance on the quality of the signatures of a person. Indeed, the obtained results point out the interest of evaluating performance of the systems not only globally on the whole database, but also on different categories of writers linked to a specific criterion related to the intrinsic quality of the signatures, based on Personal Entropy measure previously introduced in [24,25]. The results show on one hand that some systems are more robust than others, when dealing with signatures of different qualities; and on the other hand, that the performance of a given classifier can significantly vary when considering good quality signature or bad quality ones in the evaluation.

Finally, in comparison to the previous competitions, BSEC'2009 has shown an important progress in the state-of-the-art in signature recognition. While the best results of SVC'2004 were around 2.84% and 2.12% on skilled and random forgeries, respectively, and those of BMEC'2007 were around 13.43% on skilled forgeries and 4.03% on random forgeries in mobile conditions, the current competition provides an important reduction: 2.2% and 0.51% on skilled and random forgeries, respectively, on DS2; 4.97% and 0.55% on skilled and random forgeries respectively on DS3 (mobile conditions).

To conclude, in BSEC'2009, online signature verification systems were evaluated in terms of quality of the genuine signatures. However, recent research in the field of biometrics has shown an increased interest on systems' resistance to attacks, which can be of different qualities. Therefore, in the future, we intend to conduct a new evaluation campaign, which will aim at assessing the resistance of online signature verification systems to different quality-based categories of skilled forgeries, generated using Personal Entropy measure.

Acknowledgments

We would like to thank the anonymous reviewers for their remarks which helped improving the quality of this paper. We also would like to thank the BioSecure Association for putting at our disposal both DS2-382 and DS3-382 Signature Data Sets.

References

[1] E. Keogh, K. Chakrabarti, M. Pazzani, S. Mehrotra, Dimensionality reduction for fast similarity search in large time series databases, Knowledge and Information Systems 3 (3) (2000) 263–286.
[2] J. Fabregas, M. Faundez-Zanuy, On-line signature verification system with failure to enrol management, Pattern Recognition 42 (9) (2009) 2117–2126.
[3] J. Fabregas, M. Faundez-Zanuy, Biometric dispersion matcher, Pattern Recognition 41 (11) (2008) 3412–3426.
[4] D. Muramatsu, Takashi Matsumoto, Online signature verification algorithm with a user-specific global-parameter fusion model, in: Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, 2009, pp. 492–497.
[5] M.I. Khalil, M.N. Moustafa, and H. Abbas, Enhanced DTW-based on-line signature verification, in: Proceedings of ICIP 2009, 2009, pp. 2713–2716.
[6] A.K. Jain, F.D. Griess, S.D. Connell, On-line signature verification, Pattern Recognition 35 (2002) 2963–2972.
[7] A. Kholmatov, B. Yanikoglu, Identity authentication using improved online signature verification method, Pattern Recognition Letters 26 (15) (2005) 2400–2408.
[8] J.M. Pascual-Gaspar, V. Cardeñoso-Payo, C.E. Vivaracho-Pascual, Practical online signature verification, ICB 2009 (2009) 1180–1189.
[9] J.M. Pascual-Gaspar, Uso de la Firma Manuscrita Dinamica para el Reconocimiento Biométrico de Personas en Escenarios Practicos, Ph.D. Thesis, Departamento de Informatica, Universidad de Valladolid, January 2010.
[10] J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, J. Gonzalez, M. Faundez, V. Espinosa, A. Satue, I. Hernarez, J.J. Igarza, C. Vivaracho-Pascual, D. Escudero-Mancebo, Q.I. Moro, MCYT baseline corpus: a bimodal biometric database, IEE Proceedings Vision, Image and Signal Processing 150 (6) (2003) 395401.
[11] M. Martinez-Diaz, J. Fierrez, J. Galbally, J. Ortega-Garcia, Towards mobile authentication using dynamic signature verification: useful features and performance evaluation, In: Proceedings of the International Conference on Pattern Recognition, ICPR, 2008, pp. 1–6.
[12] J. Fierrez-Aguilar, L. Nanni, J. Lopez-Penalba, J. Ortega-Garcia, D. Maltoni, An on-line signature verification system based on fusion of local and global information, in: Proceedings of the of IAPR International Conference on Audio- and Video-Based Biometric Person Authentication, AVBPA, Springer LNCS-3546, 2005, pp. 523–532.
[13] J. Fierrez, D. Ramos-Castro, J. Ortega-Garcia, J. Gonzales-Rodriguez, Hmm-based on-line signature verification: feature extraction and signature modeling, Pattern Recognition Letters 28 (16) (December 2007) 2325–2334.
[14] M. Martinez-Diaz, J. Fierrez, S. Hangai, Signature features, In Encyclopedia of Biometrics, Springer, 2009, pp. 1185–1192.
[15] M. Martinez-Diaz, J. Fierrez, S. Hangai, Signature matching, In Encyclopedia of Biometrics, Springer, 2009, pp. 1192–1196.
[16] F. Alonso-Fernandez, J. Fierrez, D. Ramos, J. Gonzalez-Rodriguez, Quality-based conditional processing in multi-biometrics: application to sensor interoperability, IEEE Transactions on Systems, Man and Cybernetics Part A 40 (6) (2010) 1168–1179.
[17] B. Ly-Van, S. Garcia-Salicetti, B. Dorizzi, On using the viterbi path along with HMM likelihood information for on-line signature verification, IEEE Transactions on Systems, Man and Cybernetics, Part B, Special Issue on Recent Advances in Biometric Systems 37 (5) (October 2007) 1237–1247.
[18] D.Y. Yeung, H. Chang, Y. Xiong, S. George, R. Kashi, T. Matsumoto, G. Rigoll, SVC2004: first international Signature verification competition, in: Proceedings of the International Conference on Biometric Authentication (ICBA), vol. 3072, Springer LNCS, China, pp. 16–22, 2004.
[19] ⟨http://biometrics.it-sudparis.eu/BMEC2007/⟩.
[20] V.L. Blankers, C.E. van den Heuvel, K.Y. Franke, L.G. Vuurpij, The ICDAR 2009 signature verification competition, in: Proceeding of the 10th International Conference on Document Analysis and Recognition, 2009.
[21] B. Dorizzi, R. Cappelli, M. Ferrara, D. Maio, D. Maltoni, N. Houmani, S. Garcia-Salicetti, A. Mayoue, Fingerprint and on-line signature verification competitions at ICB 2009, in: Proceedings of International Conference on Biometrics (ICB 2009), LNCS, vol. 5558, Springer, June 2009, pp. 725–732.
[22] ⟨http://biosecure.it-sudparis.eu/AB/⟩.
[23] ⟨http://biometrics.it-sudparis.eu/BSEC2009/⟩.

[24] S. Garcia-Salicetti, N. Houmani, B. Dorizzi, A novel criterion for writer enrolment based on a time-normalized signature sample entropy measure, EURASIP Journal on Advances in Signal Processing (2009).
[25] N. Houmani, S. Garcia-Salicetti, B. Dorizzi, A novel personal entropy measure confronted with online signature verification systems performance, in: Proceedings of IEEE Second International Conference on Biometrics: Theory, Applications and Systems (BTAS 2008), Washington, September 2008.
[26] J. Ortega-Garcia, J. Fierrez, F. Alonso-Fernandez, J. Galbally, M.R. Freire, J. Gonzalez-Rodriguez, C. Garcia-Mateo, J.L. Alba-Castro, E. Gonzalez-Agulla, E. Otero-Muras, S. Garcia-Salicetti, L. Allano, B. Ly-Van, B. Dorizzi, J. Kittler, T. Bourlai, N. Poh, F. Deravi, M.N.R. Ng, M. Fairhurst, J. Hennebert, A. Humm, M. Tistarelli, L. Brodo, J. Richiardi, A. Drygajlo, H. Ganster, F.M. Sukno, S.K. Pavani, A. Frangi, L. Akarun, A. Savran, The multiscenario multienvironment biosecure multimodal database (BMDB), IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (6) (June 2010).
[27] 〈http://svnext.it-sudparis.eu/svnview2-eph/ref_syst//Signature_GET-INT/〉.
[28] T.M. Cover, J.A. Thomas, Elements of Information Theory, Second ed., John Wiley & Sons, 2006.
[29] L. Rabiner, B.H. Juang, Fundamentals of Speech Recognition, Prentice Hall Signal Processing Series, 1993.
[30] S. Garcia-Salicetti, N. Houmani, B. Ly-Van, B. Dorizzi, F. Alonso-Fernandez, J. Fierrez, J. Ortega-Garcia, C. Vielhauer, T. Scheidat, Online handwritten signature verification, in: D. Petrovska-Delacretaz, G. Chollet, B. Dorizzi (Eds.), Guide to Biometric Reference Systems and Performance Evaluation, Springer-Verlag, London, 2008.
[31] A. Martin, G. Doddington, T. Kamm, M. Ordowski, M. Przybocki, The det curve in assessment of detection task performance, in: Proceedings of EURO-SPEECH'97, vol. 4, Rhodes, Greece, 1997, pp. 1898–1898.
[32] R.M. Bolle, N.K. Ratha, S. Pankanti, Error analysis of pattern recognition systems—the subsets bootstrap, Computer Vision and Image Understanding 93 (1) (2004) 1–33.

Nesma Houmani got her Ph.D. in Biometrics in January 2011 from Institut Telecom; Telecom SudParis. This thesis aims at introducing new measures quantifying the quality of online signatures and thus establishing automatic reliability criteria for verification systems. She is currently taking up a postdoctoral fellowship at the Electronics and Physics Department of Institut Telecom; Telecom SudParis (Intermedia team). Her research interests are focused on biometrics, pattern recognition, signal and image processing.

Aurélien Mayoue is a Research Engineer in signal and image processing graduated from Institut National Polytechnique of Grenoble (INPG). From 2006, he started to work in biometrics field at TELECOM SudParis before moving to Commissariat à l'Energie Atomique (CEA) in 2009. His main current interest is about sparse coding.

Sonia Garcia-Salicetti got her Ph.D. in Computer Science in December 1996 from the University of Paris 6 (Université Pierre et Marie Curie, France) on a Neuro-Markovian Hybrid Model Applied to On-line Handwriting Recognition. She joined the Intermedia research team at Telecom SudParis as an Associate Professor in March 2001. Her research interests are focused on signal and image processing, pattern recognition and biometric authentication (On-line signature, iris, multialgorithmic and multimodal fusion, particularly in mobility conditions). She has been the leader of French national projects on biometric authentication, and has been actively involved in European projects (e.g., IST-2002 506883 SecurePhone, BioSecure Network of Excellence) dealing with biometrics.

Bernadette Dorizzi got her Ph.D. (Thèse d'état) in Theoretical Physics at the University of Orsay (Paris XIFrance) in 1983, on the study of integrability of dynamical systems. She is a Professor at TELECOM SudParis since September 1989, at the Electronics and Physics department where she is in charge of the Intermedia (Interaction for Multimedia) research team. Her present research activity is related to the biometric domain. She is the coordinator of the Bio-Identity research project at Institut Telecom (http://www.int-evry/biometrics), was the leader of the BioSecure FP6 Network of Excellence (http://biosecure.info) from June 2004 to September 2007, and now acts as a President of BioSecure Association (biosecure.itsudparis.eu/AB/). She is the author of more than 300 research papers and has supervised 15 Ph.D. Thesis.

Mostafa I. Khalil is a student of master degree at Ain Shams University, Egypt. He received his B.Sc. degree from Ain Shams University, Egypt in 2004. His research interests are in the fields of biometrics and pattern recognition.

Mohamed N. Moustafa is an Associate Professor at Ain Shams University, Egypt. He is also a consultant to the biometrics industry including L1 Identity Solutions, USA. He received the Ph.D. degree from the City University of New York, USA in 2001. He is a founding member and chair of educational activities of the IEEE computational intelligence society chapter in Egypt. His research interests include biometrics and pattern recognition.

Hazem Abbas got his B.Sc. (83) and M.Sc. (88) degrees from Ain Shams University, Egypt and Ph.D. (93) from Queens University, Canada, all in Electrical and Computer Engineering. He worked at the Royal Military College in Canada, the IBM Toronto Lab and Queens University. Currently, he is a Professor of Computer Engineering at Ain Shams University. His research interests are in the fields of computational intelligence, pattern recognition and image/signal processing.

Daigo Muramatsu is a specially appointed Associate Professor at the Institute of Scientific and Industrial Research, Osaka University since 2011. He received his B.S., M.E. and Ph.D. degree in Electrical, Electronics and Computer Engineering from Waseda University. From 2007 to 2011, he worked for Seikei University in Japan.

Berrin Yanikoglu got her Ph.D. in Computer Science in 1993 from Dartmouth College, USA. She is currently an Associate Professor at Sabanci University, Computer Science department. Her research interests are biometrics, document analysis and retrieval, machine learning and bioinformatics.

Alisher Kholmatov got his Ph.D. in Computer Science in 2008 from Sabanci University, Turkey. He is a Senior Researcher at Scientific and Technological Research Council of Turkey, working on various aspects of image processing, pattern recognition and machine learning. He focuses on practical application of computer vision for various industrial applications.

Marcos Martinez-Diaz received the Telecommunication Engineering degree from Universidad Autonoma de Madrid. He works in IT project management in a Telecom company. He is also collaborating with the Biometric Recognition Group—ATVS as a pursual for the Ph.D. degree. His research interests include biometrics and pattern recognition primarily focused on signature verification.

Julian Fierrez got his Ph.D. degree in Telecommunications Engineering from Universidad Politecnica de Madrid, Spain, in 2006. Since 2002 he has been affiliated with the Biometric Recognition Group—ATVS, first at Universidad Politecnica de Madrid, and since 2004 at Universidad Autonoma de Madrid, where he is currently an interim Associate Professor. Starting in 2007 he held a 3-year Marie Curie Postdoctoral Fellowship part of which was spent as a Visiting Researcher at Michigan State University in USA. His research interests and areas of expertise include signal and image processing, pattern recognition and biometrics, with emphasis on signature and fingerprint verification, multi-biometrics, biometric databases and system security. He is actively involved in European projects focused on biometrics (e.g., FP6 BioSec IP, FP6 BioSecure NoE and FP7 BBFor2 Marie Curie ITN).

Javier Ortega-Garcia received his Ph.D. degree "cum laude" in Electrical Engineering (Doctor Ingeniero de Telecomunicacion), in 1996 from Universidad Politecnica de Madrid, Spain. He is the founder and co-director of the Biometric Recognition Group—ATVS. He is currently a Full Professor at the Escuela Politecnica Superior, Universidad Autonoma de Madrid, where he teaches Digital Signal Processing and Speech Processing courses. He also holds a Ph.D. degree course in Biometric Signal Processing. His research interests are focused on biometrics signal processing: speaker recognition, fingerprint recognition, on-line signature verification, data fusion and multibiometrics. He chaired "Odyssey-04, The Speaker Recognition Workshop", co-sponsored by IEEE, and co-chaired "ICB-09, the 3rd IAPR International Conference on Biometrics".

Josep Roure Alcobé has worked in Mataró School of Technology (Universitat Politècnica de Catalunya) since 1993. He got his Ph.D. degree in Artificial Intelligence from UPC in 2004. He spent two years, from July 2005 to July 2007, at the Robotics Institutes Auton Lab, Carnegie Mellon University, Pittsburgh (USA) enjoying a Fulbright Grant.

Joan fabregas was born in Barcelona, Spain in 1961. He received his Ph.D. degree in 2008 from the Valladolid University and his interests lie in the field of pattern recognition, neural networks and biometrics. He is now an Associate Professor at EUP Mataro since 1991.

Marcos Faundez-Zanuy got his Ph.D. degree in 1998 from the Polytechnic University of Catalunya (UPC). He is now a Full Professor at EUP Mataro and heads the Signal Processing Group there. Since 2009 he is the Dean of Escola Universitaria Politecnica de Mataró (UPC). Since 2010 he is responsible of the research at tecnocampus. He has the Full Professor Acreditation from AQU Catalunya as well as from ANECA. His research interests lie in the fields of biometrics and speech coding. He was the initiator and Chairman of the European COST action 277 "Nonlinear speech processing", and the secretary of COST action 2102 "Cross-Modal Analysis of Verbal and Non-Verbal Communication".

Juan M. Pascual-Gaspar was born in MÁlaga, Spain. He received his B.Sc. degree in Physics and Electronic Engineer from the University of Granada, and Ph.D. degree from the University of Valladolid. He works in the IT department of the "Hospital ClÍnico Universitario" at Valladolid. His research is on biometric signature verification.

ValentÍn Cardenoso-Payo is an Associate Professor in Computer Science at the University of Valladolid since 1992. In 1988 he got his Ph.D. in Physics from this university and leads the research group on Multimodal Human Computer Interaction at the Department of Computer Science. His current interests include machine learning techniques applied to the characterization of human computer interaction, including biometric identification using static and dynamic features, both for user identification and modelling.

Carlos Vivaracho-Pascual obtained his degree in Physics in 1989 and his Ph.D. degree in 2004, both from the University of Valladolid (Spain). He is currently a university Lecturer in this University. He has published close to 40 technical papers and book chapters. His research interests are focused on biometric and pattern recognition.