

Complete Signal Modeling and Score Normalization for Function-Based Dynamic Signature Verification

J. Ortega-Garcia, J. Fierrez-Aguilar, J. Martin-Rello, and J. Gonzalez-Rodriguez

Biometrics Research Lab., ATVS, Universidad Politécnica de Madrid, Spain
{jortega, jfierrez}@diac.upm.es
<http://www.atvs.diac.upm.es>

Abstract. In this contribution a function-based approach to on-line signature verification is presented. An initial set of 8 time sequences is used; then first and second time derivatives of each function are computed over these, so 24 time sequences are simultaneously considered. A valuable function normalization is applied as a previous stage to a continuous-density HMM-based complete signal modeling scheme of these 24 functions, so no derived statistical features are employed, fully exploiting in this manner the HMM modeling capabilities of the inherent time structure of the dynamic process. In the verification stage, scores are considered not as absolute but rather as relative values with respect to a reference population, permitting the use of a best-reference score-normalization technique. Results using MCYT_Signature sub-corpus on 50 clients are presented, attaining an outstanding best figure of 0.35% EER for skilled forgeries, when signer-dependent thresholds are considered.

1 Introduction

Automatic signature verification has been an intense research field because of the social and legal acceptance and the widespread use of the written signature as a personal authentication method. Biometric recognition techniques have made possible notable improvements in the objective assessment of quantitative similarities between handwritten samples, leading to the development of automatic on-line signature verification systems [1], [2]. Nevertheless, in the last years, almost minor improvements in kind of analysis, characteristic selection or performance evaluation have been reported [3].

The inherent behavioral-based nature of the on-line signing process, makes the input information well adjusted to be considered as a random process rather than as a deterministic signal. This dynamic input information, acquired through a time sampling procedure, must be consequently considered as discrete time random sequences. Many feature-based approaches make use of these sequences in order to derive statistical parameters, but the use of complete sequences have so far yielded better re-

sults [4], as reducing time sequences just to statistical features should affect in diminishing our ability to make a precise characterization of this dynamic process.

In any case, this time-based sequence characterization process is strongly related to the way in which a reference model is established, as a competitive modeling process to cope with this complete random sequences is needed. Hidden Markov Models (HMMs) [5] have shown this capability regarding other behavioral-based biometric traits, like speech, outperforming other classical approaches like distance measure, (weighted) cross correlation or dynamic time warping (dynamic string matching). With respect to on-line signature recognition, HMMs have been also used [6–8], but not in all cases taking advantage of the complete sequences involved.

Our recent work in the field [9] has been oriented to exploit dynamic signature information as complete time sequences [10] by means of continuous density HMMs, in order to derive function-based on-line signature verification systems. In the present contribution, the effect of: *i*) considering complete input sequences, *ii*) computing first and second time sequence derivatives [11], *iii*) statistically normalizing the complete sequence set, and *iv*) considering HMM outputs as relative scores with respect to a reference population through a best-reference score normalization technique [12], are analyzed. Results using MCYT_Signature database [13] are presented, yielding remarkably performance in both common and user-specific threshold settings [14].

2 MCYT_Signature Database

The number of existing large public databases oriented to the performance evaluation of recognition systems based specifically on signature is quite limited. In this context, the MCYT project, oriented to the acquisition of multiple biometric traits (namely, fingerprints and signatures), was launched. The expected number of individuals considered in the database is roughly 450; about 350 of them are currently being acquired following a single-session procedure, (although by the time this contribution was being realized, less than 100 were supervised and fully available). And about 100 more individuals are planned to be acquired by mid 2003, in a multi-session procedure, in order to incorporate intrinsic short-term signature variability, signature size variability, and over-the-shoulder and time constrained forgeries.

In order to acquire the dynamic signature sequences, a WACOM™ graphics tablet, model INTUOS A6 USB has been employed. The graphic tablet resolution is 2,540 lines per inch (100 lines/mm), and the precision is ± 0.25 mm. The maximum detection height is 10 mm (so also pen-up movements are considered), and the capture area is 127×97 mm. This tablet provides the following discrete-time dynamic sequences (dynamic range of each sequence is specified): *i*) Position in x -axis, x_t : [0–12,700], corresponding to 0–127 mm, *ii*) position in y -axis, y_t : [0–9,700], corresponding to 0–97 mm, *iii*) pressure p_t applied by the pen: [0–1,024], *iv*) azimuth angle γ_t of the pen with respect to the tablet: [0–3,600], corresponding to 0°–360°, and *v*) altitude angle ϕ_t of the pen with respect to the tablet: [300–900], corresponding to 30°–90°.

The sampling frequency of the acquired signals is set to be 100 Hz, taking into account the Nyquist sampling criterion, as the maximum frequencies of the related biomechanical sequences are always under 20–30 Hz. Each target user produces 25 genuine signatures, and 25 skilled forgeries are also captured for each user. These skilled forgeries are produced by the 5 subsequent target users by observing the static images of the signature to imitate, trying to copy them again at least 10 times, and then, producing with a natural dynamic the valid acquired forgeries. In this way, shape-based *high skilled* forgeries are usually obtained, as shown in Fig. 1. Following this procedure, user n (ordinal index) realizes 5 samples of his/her genuine signature, and then 5 skilled forgeries of client $n-1$. Then, again 5 new samples of his/her genuine signature; and then 5 skilled forgeries of user $n-2$; this procedure is iterated by user n , making genuine signatures and imitating previous users $n-3$, $n-4$ and $n-5$. Summarizing, user n produces finally 25 samples of his/her own signature (in groups of 5 samples) and 25 skilled forgeries (5 samples of users $n-1$, $n-2$, $n-3$, $n-4$ and $n-5$). Vice versa, for user n , 25 skilled forgeries will be produced by users $n+1$, $n+2$, $n+3$, $n+4$, and $n+5$ (in groups of 5 samples each).

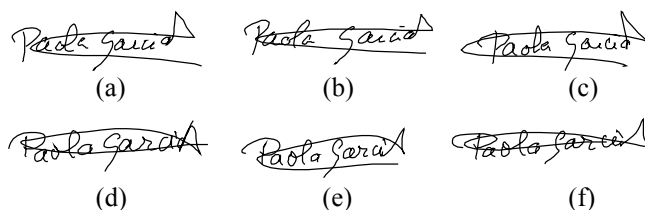


Fig. 1. From (a) to (c), genuine client signature samples; from (d) to (f), skilled forgeries, produced each forgery by one different individual

3 Analysis of Complete Sequences

3.1 Function-Based Approach

Different approaches are considered in the literature in order to extract signature information; they can be divided into [1]: *i*) Function-based approaches, in which signal processing methodology is applied to the dynamically acquired time sequences (i. e., velocity, acceleration, force or pressure), and *ii*) Feature-based approaches, in which statistical parameters are derived from the acquired information; regarding these, one can specify also different levels of classification, so it is possible to use and combine shape-based global static (i. e., aspect ratio, center of mass or horizontal span ratio), global dynamic (i. e., total signature time, time down ratio or average speed) or local (stroke direction, curvature or slope tangent) parameters.

The behavioral nature of handwriting makes dynamic signal information to be considered as random processes rather than as deterministic signals; in order to adapt our processing techniques to this specific nature, and to make a better exploitation of the instantaneous dynamic information that the on-line acquisition process is offering us, the complete time functions sampled as time sequences by the acquisition device are considered in this contribution.

3.2 Basic Functions

The basic function-based representation of each signature consists of five time sequences x_t , y_t , p_t , γ_t and φ_t , where t is the discrete time index, given by the input device and characterizing instantaneous dynamic properties of the signing process. Fig. 2(a) shows a genuine sample signature, and Fig. 2(b), shows the corresponding basic sequences associated to it. The horizontal axis reflects the number of acquired samples so, in this particular case, more than 400 samples (corresponding to more than 4 s) of each sequence are acquired.

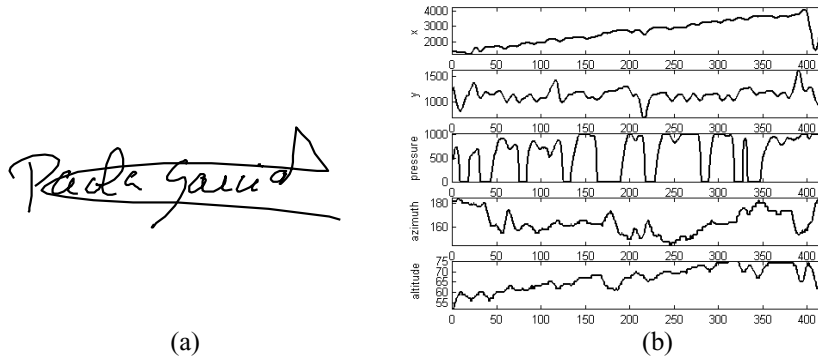


Fig. 2. On-line signature acquisition. (a) Client signature; (b) Basic dynamic signals obtained from the graphics tablet for the client signature in (a) during the handwriting process: position in x -axis, position in y -axis, pressure, azimuth, and altitude (from top to bottom, respectively)

3.3 Extended Functions

From the basic sequence set we have derived some other signal-based sequences. Previous results with other dynamic sequences (i. e., tangential acceleration, normal acceleration, or instantaneous displacement) [9] have shown good levels of performance; in the present contribution, three derived dynamic sequences have been used as extended functions, namely:

- Path-tangent angle: $\theta_t = \tan^{-1}(\dot{y}_t/\dot{x}_t)$
- Path velocity magnitude (speed): $v_t = [\dot{x}_t^2 + \dot{y}_t^2]^{1/2}$
- Log curvature radius: $\rho_t^* = \log \rho_t = \log(v_t/\theta_t)$

in which $\log(\cdot)$ is applied in order to reduce the dynamic range of function values. In all cases, discrete time derivatives have been computed using the second-order regression procedure (described in the next point). Thus, regarding our function-based instantaneous vector set, including 5 basic time sequences, and 3 more extended, we get:

$$\mathbf{u}_t = [x_t, y_t, p_t, \gamma_t, \varphi_t, \theta_t, v_t, \rho_t^*] \quad 1 \leq t \leq T \quad (1)$$

where T is the time duration of the considered signature.

3.4 First and Second Time Derivatives

First and second time derivatives of complete instantaneous function-based vector sets, have shown to be highly effective in order to take into account the velocity and acceleration of change of each instantaneous vector set [11]. Because of the discrete nature of the above-mentioned functions, first time derivatives are calculated using a second order regression, expressed through operator Δ , namely:

$$\dot{f}_t \approx \Delta f_t = \frac{2}{\tau-1} \tau (f_{t+\tau} - f_{t-\tau}) \bigg/ 2 \frac{\tau^2}{\tau-1} \quad (2)$$

where $\Delta\Delta$ is computed applying equation (2), but this time on Δ .

In this way, each signature can be formally described as a global set \mathbf{V} of time vectors, $\mathbf{V} = [\mathbf{v}_1 \mathbf{v}_2 \dots \mathbf{v}_T]$, where \mathbf{v}_t is a column vector including the 24 considered sequences:

$$\mathbf{v}_t = [\mathbf{u}_t, \Delta\mathbf{u}_t, \Delta\Delta\mathbf{u}_t] \quad 1 \leq t \leq T \quad (3)$$

3.5 Statistical Signal Normalization

A final statistical normalization, oriented to obtain zero mean and unit standard deviation function values, which has proved to increase the verification performance [9], is applied to the global set \mathbf{V} :

$$\mathbf{w}_t = \mathbf{v}_t - \frac{1}{T} \sum_{\tau=1}^T \mathbf{v}_\tau, \quad 1 \leq t \leq T \quad (4)$$

so a new global normalized vector function set $\mathbf{O} = [\mathbf{o}_1 \mathbf{o}_2 \dots \mathbf{o}_T]$ is obtained through:

$$\mathbf{o}_t^n = \mathbf{w}_t^n \bigg/ \sqrt{\frac{1}{T-1} \sum_{\tau=1}^T [\mathbf{w}_\tau^n]^2} \quad 1 \leq t \leq T, \quad 1 \leq n \leq 24 \quad (5)$$

where \mathbf{w}_t^n is the n -th component of vector \mathbf{w}_t .

This means that global vector set \mathbf{O} , comprises 24 statistically-normalized complete time sequences; taking into account that sampling rate is 100 samples/s, every dynamic signature is characterized by a parameter rate of 2,400 values/s.

4 Signature Modeling through Hidden Markov Models

In order to derive real recognition benefits in terms of enhanced verification performance, this complete function-based signature characterization process is strongly related to the way in which a reference model is established: a competitive modeling scheme, capable of coping with this global set of random sequences, with a strong underlying time-basis, is required. Hidden Markov Models (HMMs) [5] were introduced in the pattern recognition field as a robust method to model the variability of discrete time random signals, where time or context information is available.

HMMs have shown this capability regarding other behavioral-based biometric traits, like speech, outperforming other classical pattern recognition approaches: distance measure, (weighted) cross correlation or dynamic time warping (dynamic string matching). With respect to on-line signature recognition, HMMs have been also used [6–8], although not always clear performance improvements have been documented; mainly due to different reasons like, e.g., making use of incomplete sets of time sequences or employing discrete- instead of continuous-density models.

4.1 HMM Modeling of Time Sequences

Basically, the HMM models a doubly stochastic process governed by an underlying Markov chain with finite number of states and a set of random functions each of which is associated to the output observation of one state. At discrete instants of time t , the process is in one of the states and generates an observation symbol according to the random function corresponding to that current state. The model is hidden in the sense that the underlying state which generated each symbol cannot be deduced from symbol observation. An example of a left-to-right state transition topology considering a continuous-density random output function for each state is depicted in Fig. 3.

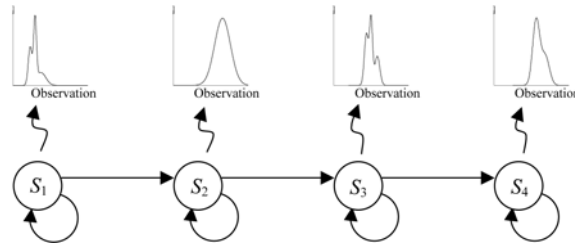


Fig. 3. HMM with left-to-right topology. The model has 4 states, with no transition skip between them; the associated continuous probability density functions to each state are also shown

Formally, a HMM is described as following:

- N , number of hidden states $\{S_1, S_2, \dots, S_N\}$. The state at t will be denoted as q_t .
- A state transition matrix $A = \{a_{ij}\}$ where $a_{ij} = \Pr[q_{t+1} = S_j | q_t = S_i]$, $1 \leq i, j \leq N$
- The observation symbol probability density function in state j , $b_j(\mathbf{o})$, $1 \leq j \leq N$
- The initial state distribution $\pi = \{\pi_i\}$ where $\pi_i = \Pr[q_1 = S_i]$, $1 \leq i \leq N$

In this contribution, $b_j(\mathbf{o})$ has been modeled as a mixture of M multi-variate Gaussian densities:

$$b_j(\mathbf{o}) = \sum_{m=1}^M \epsilon_{jm} \mathcal{N}(\mathbf{o}, \boldsymbol{\mu}_{jm}, \mathbf{U}_{jm}), \quad 1 \leq j \leq N \quad (6)$$

where $N(\mathbf{o}, \boldsymbol{\mu}_{jm}, \mathbf{U}_{jm})$ is a normal distribution, with mean $\boldsymbol{\mu}_{jm}$ and diagonal covariance matrix \mathbf{U}_{jm} . Thus, the observation symbol density functions can be parameterized with the set $B = \{c_{jm}, \boldsymbol{\mu}_{jm}, \mathbf{U}_{jm}\}, 1 \leq j \leq N, 1 \leq m \leq M$.

A particular HMM is described by the set $\lambda = (\pi, A, B)$, which is the set that will represent the K modeling reference signature samples of a determined target user. The score of an input signature $\mathbf{O} = [\mathbf{o}_1 \mathbf{o}_2 \dots \mathbf{o}_T]$ claiming the identity λ is calculated as $(1/T) \cdot \log(\Pr[\mathbf{O} | \lambda])$ using the Viterbi algorithm, that considers just the locally-optimal state sequence.

4.2 Score Normalization

If the verification problem is considered as a form of hypothesis test, it would be reasonable for the signature verification system to score for an input signature \mathbf{O} and a given identity λ_i not an absolute quantity related with $\Pr[\mathbf{O} | \lambda_i]$, but rather a (relative) measure of $\Pr(\lambda_i | \mathbf{O}) / \Pr(\bar{\lambda}_i | \mathbf{O})$, where $\bar{\lambda}_i$ stands for “an antithetical identity with respect to λ_i ”. The underlying idea is related to the normalization ability to separate even more client and impostor scores, and to group together what is more similar to non-client or impostor scores.

This idea has shown to be effective regarding several biometric recognition systems [12]. The selection of the reference set representing the background population (representing an opposite identity with respect to the client), or *cohort*, is very important in practice, and better results are obtained if the cohort set for user λ_i is based on models similar to it.

In our case, the implementation of the score normalization idea is based on:

$$\log \Pr(\mathbf{O} | \lambda_i) - \max_{\lambda \in Ref, \lambda \neq \lambda_i} \log \Pr(\mathbf{O} | \lambda) \quad (7)$$

which, as it has been stated, improves the separation of client and impostor score distributions. The left term in (7) is directly related with the score provided by the HMM, and will be referred to as *raw score*. The right term in (7) is the normalization factor, where the cohort set is reduced in this case to just the maximum score of the input signature \mathbf{O} against a reference set of signature-based identity models (or *best reference*) different from the claimed one.

This *best reference* score normalization stage has been considered in the implemented on-line signature verification system and a comparison of no score normalization, best reference with a *casual cohort* (models of a separate population) and best reference with a *skilled cohort* (models of forgers of λ_i) will be performed.

5 System Performance

A HMM configuration with $N=4$ states, $M=8$ mixture densities per state and $K=6$ training reference samples has been used for the evaluation. This configuration provides, as demonstrated in [9], good generalization performance.

A testing sub-corpus of the MCYT database has been selected consisting of 50 client signers, providing 15 signatures each and 15 skilled forgeries for each of them (from 3 forgers out of 5); as 6 genuine samples are used to train each client model, a total of 450 client and 750 skilled impostor attempts are considered for global evaluation. Best reference score normalization has been tested on the described sub-corpus with two different types of normalization cohorts: casual and skilled. The casual cohort is composed of 50 external (separate set, common to all users) signers from MCYT_Signature subcorpus. The skilled cohort comprises samples from the 2 remaining forgers for each user not previously included in the impostor attempts.

Verification results for the above-mentioned sub-corpus, considering always skilled forgeries as impostor samples, are shown for no score normalization, best reference score normalization with casual normalization cohort and best reference score normalization with skilled normalization cohort, in all cases considering global decision thresholds, are shown in Fig. 4 in form of DET plots (type I vs. type II errors on normal deviation scale); this representation clearly improves, in terms of separation between similar curves and precision near the origin, the traditional ROC curves.

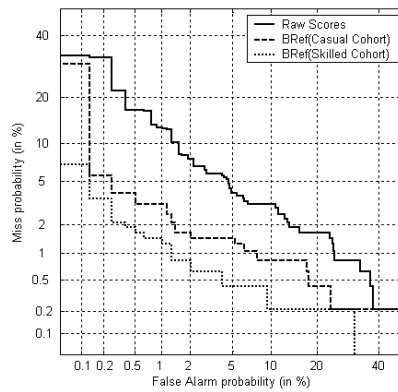


Fig. 4. DET plot showing verification results: for raw scores (no normalization) (solid line); for best reference normalization (BRef) using casual cohort (dashed line); and for (BRef) using skilled cohort (dotted line)

Global EER verification results in case of global decision threshold (common to all users) and average EER in case of user-dependent threshold [14], are shown with and without score normalization in Table I.

Table 1 Signature Verification Results (Skilled Forgeries)

EER	Raw scores	Best Reference (Casual Cohort)	Best Reference (Skilled Cohort)
Global Threshold	4.83 %	1.75 %	1.21 %
User-Specific Threshold	0.98 %	0.56 %	0.35 %

6 Conclusions and Future Work

The use of a complete function-based sequence set, considering Δ and $\Delta\Delta$ time derived sequences, with statistical normalization of function values, modeling through continuous density HMMs, and employing score normalization techniques, have shown to produce notable performance improvements regarding on-line signature verification systems; in our case, from a 4.83% EER, obtained by using a global threshold on the described database, we decrease down to 1.75% when best reference normalization is used for a casual cohort set. In the case we use a skill cohort normalization, global EER goes down to just 1.21%, due to a good adaptation of the reference cohort to the skilled forgeries' attempts.

On the other hand, if we consider just user-specific (or user-dependent) thresholds, raw scores fall down to 0.98% average EER, as thresholds are specifically adapted to each client's particular score distribution. Applying in this case best reference normalization, we get outstanding results of 0.56% average EER for casual cohort, and 0.35% average EER for skilled cohort. These final results are highly remarkable specially taking into account the state-of-the-art on-line signature verification performance levels [3].

Future work will include unimodal fusion of our function-based approach with feature-based approaches, in order to exploit both perspectives. Also, results on the entire MCYT_Signature subcorpus, considering short-term signature variability, signature size variability, and over-the-shoulder and time constrained forgeries will be explored.

Acknowledgment

Authors wish to thank Spanish Ministry of Science and Technology for supporting this research under project TIC2000-1669-C04-01.

References

- [1] R. Plamondon and G. Lorette, "Automatic Signature Verification and Writer Identification - The State of the Art", *Pattern Recognition*, vol. 22, no. 2, pp. 107-131, 1989.
- [2] F. Leclerc and R. Plamondon, "Automatic Signature Verification: The State of the Art, 1989-1993", *Intl. Jour. of Pattern Rec. and Machine Intell.*, vol. 8, no. 3, pp. 643-660, 1994.
- [3] R. Plamondon and S. N. Srihari. "On-Line and Off-Line Handwriting Recognition: A Comprehensive Survey", *IEEE Trans. Pattern Anal. and Machine Intell.*, vol. 22, no. 1, pp. 63-84, Jan. 2000.

- [4] M. Parizeau and R. Plamondon, "A Comparative Analysis of Regional Correlation, Dynamic Time Warping, and Skeletal Tree Matching for Signature Verification", *IEEE Trans. on Pattern Anal. and Mach. Intell.*, vol. 12, no. 7, pp. 710-717, July 1990.
- [5] L. R. Rabiner. "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition", *Proc. of the IEEE*, vol. 77, no. 2, pp. 257-286, 1989.
- [6] J. G. A. Dolfing, E. H. L. Aarts, and J. J. G. M. van Oosterhout, "On-line Signature Verification with Hidden Markov Models", *Proc. of the IEEE 14th International Conference on Pattern Recognition*, pp. 1309-1312, Brisbane, Australia, August 1998.
- [7] L. Yang, B. K. Widjaja, and R. Prasad, "Application of Hidden Markov Models for Signature Verification", *Pattern Recognition*, vol. 28, no. 2, pp. 161-170, 1995.
- [8] R. S. Kashi, J. Hu, W. L. Nelson, W. Turin, "On-line Handwritten Signature Verification using Hidden Markov Model Features", *Proc. of the 4th Intl. Conf. on Document Analysis and Recognition*, vol. 1, pp. 253-257, 1997.
- [9] J. Ortega-Garcia, J. Gonzalez-Rodriguez, D. Simon-Zorita, and S. Cruz-Llanas, "From Biometrics Technology to Applications regarding Face, Voice, Signature and Fingerprint Recognition Systems", in *Biometrics Solutions for Authentication in an E-World*, (D. Zhang, ed.), pp. 289-337, Kluwer Academic Publishers, July 2002.
- [10] W. Nelson, W. Turin, and T. Hastie: "Statistical Methods for On-Line Signature Verification", *Int. Journ. Pattern Rec. and Mach. Intell.*, vol. 8, no. 3, pp. 749-770, 1994.
- [11] F. K Soong and A.E. Rosenberg, "On the Use of Instantaneous and Transitional Spectral Information in Speaker Recognition", *IEEE Trans. on Acoust., Speech and Signal Proc.*, vol. ASSP-36, no. 6, pages 871-879, 1988.
- [12] S. Furui, "An Overview of Speaker Recognition Technology", *ESCA Workshop on Automatic Speaker Recognition*, Martigny (Switzerland), pages 1-9, April 1994.
- [13] J. Ortega-Garcia, *et al.*, "MCYT: A Multimodal Biometric Database", *Proc. of COST-275 Biometric Recognition Workshop*, Rome (Italy), Nov. 2002. Available at: <http://>
- [14] K. Jain, F. D. Griess, S. D. Connell, "On-Line Signature Verification", *Pattern Recognition*, vol. 35, no. 12, pp. 2963-2972, Dec. 2002.