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On-Line Signature Verification

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10.1 Introduction

Automatic signature verification is an important research area because of the social and legal acceptance and widespread use of the handwritten signature as a personal authentication method [66, 45, 67]. Another advantage of the handwritten signature as a biometric modality is that it is easily acquired either with an inking pen over a sheet of paper or by electronic means with a number of existing pointer-based devices (e.g., pen tablets, PDAs, Tablet PCs, touch screens, etc.)

In spite of the advantages of the handwritten signature modality, the practical deployment of this technology is very slow and signature biometrics still remains a challenging research problem. This is mainly due to the large intra-class variations and, when considering forgeries, small inter-class variations as well. Figs. 10.5 and 10.6 show some examples of Chinese and European signatures where this effect is evident. Other challenges of signature biometrics include low universality, as not everyone may be able to sign, low permanence, as the handwritten signature tends to vary along time, and vulnerability to direct attacks using forgeries.

Similar to some other biometric modalities (e.g., PIN-based voice biometrics), impostors may know some information about the client that degrades signature verification performance when it is exploited, for example, signature shape. As a result, two kinds of impostors are usually considered in signature verification, namely: *casual impostors* (producing *random forgeries*), when no information about the target signature is known, and *real impostors* (producing *skilled forgeries*), when some information regarding the signature being forged is used. Different kinds of information available to the impostors produce different types of forgeries (e.g., statically skilled forgeries, over-the-shoulder forgeries, professional forgeries, etc.)

Signature verification methods can be classified according to the input signature information into two classes: *on-line* and *off-line*. On-line refers to the use of the time functions of the dynamic signing process (e.g., position

trajectories, or pressure versus time), which are obtained using acquisition devices like touch screens or digitizing tablets. Off-line refers to the use of the static image of the signature. This chapter deals with on-line signature verification. Signature verification based on the static image of the signature can be found in [67, 21, 76]. Note also that some off-line problems can be solved using on-line methods [36], as some dynamic information can be estimated from the static images [55], and viceversa, as static images can be easily generated from the dynamic information.

The chapter is organized as follows: The introduction is completed with an overview of the history of signature recognition, some practical applications and commercial systems, and standardization efforts related to on-line signature biometrics. Sect. 10.2 outlines the system architecture of on-line signature verification systems, and presents some of the key concepts related to each of the modules. In Sect. 10.3 we summarize the existing reference systems and publicly available on-line signature databases. Sect. 10.4 describes a case study of signature verification combining feature- and function-based approaches on a widely available signature corpus. Sect. 10.5 summarizes the chapter and outlines some open problems in on-line signature verification.

10.1.1 History

Osborn [62] was one of the first published works studying the problem of signature verification. In this pioneer work the problem of signature verification was studied from the forensic examiner point of view, including recommendations for practitioners and some real-world case studies. Fig. 10.1 shows two sets of signatures from a celebrated case of a contested will in New York in the year 1900, involving an estate worth more than six million dollars. The court accepted that the five signatures on the left were genuine and the five on the right were forgeries, which led to the establishment of Rice University in Houston. Modern approaches for the forensic examination of signatures are summarized in Hilton [31].

The first published work on automatic signature verification seems to be Mauceri [50]. This work was followed by the popular development of Herbst and Liu in 1977 [30], which also summarized the state-of-the-art up to that date. This was followed by an increasing number of approaches, summarized in the state-of-the-art survey in 1989 by Plamondon and Lorette [66]. This survey of existing methods was updated in 1994 [45] and subsequently in 2000 [67]. In the meantime, the popular methods of Dynamic Time Warping [53], and Hidden Markov Models [80] were successfully applied to on-line signature verification, and the search for good global features was significantly advanced [47].

Some recent milestones in the history of signature verification are the availability of benchmark databases [60], and the organization of the First International Signature Verification Competition (SVC) in 2004 [81].

Fig. 10.1. Genuine (left) and forged signatures (right) in a celebrated court case [62].

10.1.2 Applications

The most important applications of on-line signature biometrics are in the legal (document authentication), medical (record protection), and banking sectors (cheque and credit card processing). The main applications include:

- Signature forensics. This is the oldest application of the handwritten signature [31], commonly applied to the off-line image of the written signature. Forensic approaches for the evaluation of on-line signature evidence are now under development [28].
- Signature authentication. This type of application includes system login based on signature, document encryption, web access, etc. One example for Tablet PC can be found in [2].
- Signature surveillance. The automatic comparison of on-line signatures can be used to track and detect signers (e.g., blacklists of individuals), or can be used to warn the human operator at points of sales or other credit card-based services.
- Digital Rights Management based on signature [59].
- Biometric cryptosystems based on signature. New developments have demonstrated the feasibility of generating cryptographic keys based on the time functions of the on-line signatures [25].

10.1.3 Commercial Systems

From the IBG's Biometrics Market and Industry Report 2006-2010 [37], it can be observed that the signature modality is the second behavioral trait in commercial importance just after voice biometrics, with approximately 1.7% of the current market share. Although the market for signature systems is growing at a faster rate than other biometric modalities, especially due to the advent of touch-screen portable devices, signature biometrics is only a small
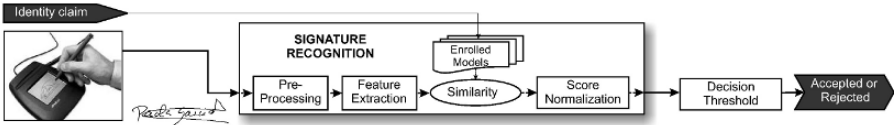
Fig. 10.2. Architecture adopted by most on-line signature verification systems.

fraction of the biometrics market, which is mainly dominated by modalities like fingerprint (43.6% of the market share) and face (19.0%).

A number of companies are currently distributing handwritten signature verification products on different platforms. Some examples are included in the following list, which is not exhaustive:

- Communication Intelligence Corporation has a number of signature verification products [9], including SignatureOne®and Sign-it®, which enable signature-based system login using dynamic signature information.
- SOFTPRO distributes a number of signature verification modules enabling both static and on-line signature verification [73].
- Cyber-SIGN sells various plug-ins and applications for on-line signature verification [10].

10.1.4 Standardization

The ISO/IEC JTC1 SC37 committee is addressing the interoperability issues in various biometric systems [72]. One point of particular importance subject to standardization, in order to enable the interoperability of signature systems, is the interchange formats for storage and transfer of signature data. The signature modality is represented by two parts of the standard ISO/IEC 19795.

Part 7 of the standard defines a time series format that allows the transmission and storage of a series of time-stamped pen-based standard channels (e.g., x position, y position, time, velocity, etc.). Along with these channels, the storage of proprietary data is also permitted. A set of recommendations and best practices are also given with the standard. Part 11, now in consideration, defines a set of common statistical features extracted from the raw data, which can be extended by another set of proprietary features. The whole feature set must allow interoperability at a feature level between samples collected on different types of devices.

10.2 On-Line Signature Verification Systems

The common architecture of on-line signature verification systems is depicted in Fig. 10.2. In the following sections we will summarize the main techniques and related issues for each of the system modules.

One major research trend in biometric verification is the successful exploitation of the different information levels embodied in the biometric signal at hand. This is usually done by combining the confidences provided by a number of different machine experts [5, 44], each one working at a specific information level. Multilevel approaches for on-line signature verification are described in [41, 23].

10.2.1 Data Acquisition and Preprocessing

The on-line acquisition of the time functions of the handwritten signature is usually carried out by using devices such as digitizing tablets [79, 34] or touch screens, such as those included in Tablet PCs and PDAs. These acquisition devices provide coordinate information (e.g., horizontal x and vertical y pen position) and, in some cases, pen pressure and pen angle versus time [71]. Other on-line signature acquisition devices are dedicated pens with specialized hardware attached to provide some on-line signature data such as coordinate or velocity information [33].

On-line signature capture devices usually operate at between 100 and 200 samples per second. Taking into account the Nyquist sampling criterion and the fact that the maximum frequencies of the related biomechanical sequences are always under 20-30 Hz [4], this sampling frequency leads to a precise discrete-time signature representation.

Some preprocessing steps before feature extraction are noise filtering (for example with Gaussian windows [38]) and resampling. Resampling is carried out in some systems in order to obtain a shape-based representation consisting of equidistant points [38]. Other systems avoid the resampling step as some discriminative speed characteristics are lost in the process [43].

10.2.2 Feature Extraction

Many different approaches have been considered in order to extract discriminative information from on-line signature data [66]. The existing methods can broadly be divided into two classes: *feature-based*, in which a holistic vector representation consisting of a set of global features is derived from the signature trajectories [47, 42], and *function-based*, in which time sequences describing local properties of the signature are used for recognition [53, 15, 38, 49], e.g., position trajectory, velocity, acceleration, force, or pressure [48]. A case study of feature- and function-based approaches is given in Sect. 10.4. Although recent works show that feature-based approaches are competitive with respect to function-based methods in some situations [23], the latter approach has traditionally yielded better results.

The set of features used can be a result of a feature selection process [40] during a development phase [47, 48, 23], or can be adapted during the enrollment phase to the specificities of the user at hand. The latter approach is believed to be better suited to the problem of signature verification [46, 13],

mainly because of the large differences in information content and complexity between signers [7, 14]. However, the user-specific approach encounters challenges of training data scarcity.

10.2.3 Enrollment

Depending on the matching strategy, enrollment can be divided into two classes: *reference-based*, and *model-based*.

In reference-based enrollment [38, 43], the features extracted from the set of training signatures are stored as a set of template signatures, each one in the template set corresponding to one training signature. The matching process is then performed by comparing the input signature to each one of the reference templates and then combining the resulting matching scores with a score-level fusion technique [20, 70].

In model-based enrollment [41, 23], the set of training signatures of a given subject is used to estimate a statistical model which describes the behavior of that particular signer. As in the feature extraction process, the model complexity can also be adjusted to be user-dependent [78, 64].

Reference-based enrollment is more appropriate than model-based enrollment when the set of training signatures is small. This is because the statistical models used for signature verification (typically HMMs [80]) require at least 4 to 6 training signatures to perform reasonably well [19]. An experimental comparison of reference- versus training-based enrollment for different training set sizes can be found in [22]. As a rule of thumb, although reference-based enrollment can provide satisfactory performance results with fewer than 5 training signatures in some scenarios (e.g., 3 training signatures in [38]), it is generally accepted that a training set of around 5 signatures is the best cost-performance operating point for automatic on-line signature verification [29, 53, 22, 19]. The same observation was noticed as early as 80 years ago when considering static signatures for human verification [62].

A big challenge related to the enrollment stage is the time variation of signatures [24]. This problem can be alleviated by using training signatures from different sessions [19]. An alternative approach is template or model adaptation [77], which may be more appropriate for practical deployments.

10.2.4 Similarity Computation

Pre-Alignment

The matching stage is generally preceded by a *pre-alignment* between the input signature and the enrolled template/model. In the case of reference-based enrollment, the pre-alignment is usually conducted before feature extraction based only on the signature shape. Techniques following this approach include basic position and rotation alignment, or more sophisticated approaches based
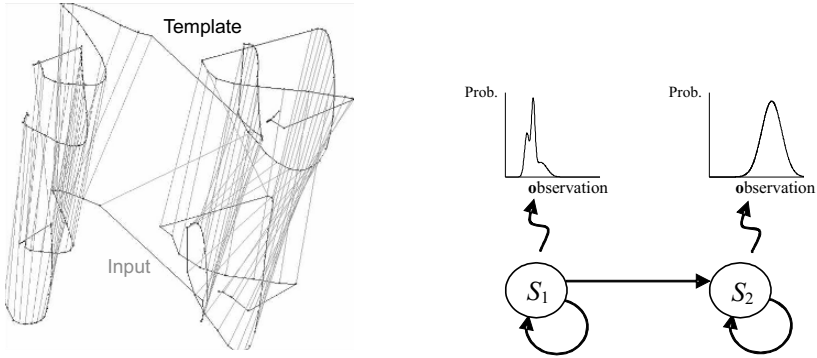
Fig. 10.3. Example of local elastic matching of signatures based on DTW (left, Chinese signature from SVC 2004) and regional modeling based on HMM (right).

on boundary warping [65]. In the case of model-based enrollment, the pre-alignment usually consists in the application of a common reference system [35], for example: position trajectories with respect to the initial point or to the center of mass, scaling to a fixed size frame, etc.

When no pre-alignment is used, the alignment is either embedded in the matching procedure [43] or a fixed frame is used during acquisition in order to have pre-aligned signatures [23].

Matching

In feature-based approaches with reference-based enrollment, the matching scores are usually obtained by using some kind of distance measure between the feature vectors of input and template signatures [57, 47], or a trained classifier. Distance measures used for signature verification include Euclidean distance, weighted Euclidean distance, and Mahalanobis distance. Trained classifiers include approaches like Neural Networks [63]. In the case of feature-based approaches with model-based enrollment, statistical models such as non-parametric density estimation based on Parzen Windows have been used [23]. This latter case is discussed in Sect. 10.4.

Function-based approaches can be classified into *local* and *regional* depending on the matching strategy.

In local approaches, the time functions of the different signatures (or some elaboration of the signatures, based on extended features of the time functions at each sampling point) are directly matched by using elastic distance measures such as Dynamic Time Warping [51, 43, 16]. An example of this elastic matching process is shown in the left part of Fig. 10.3, which is obtained by using the DTW approach described by Fierrez-Aguilar et al. [22].

In regional methods, the time functions are converted into a sequence of vectors, each one describing regional properties of a segment of the signature
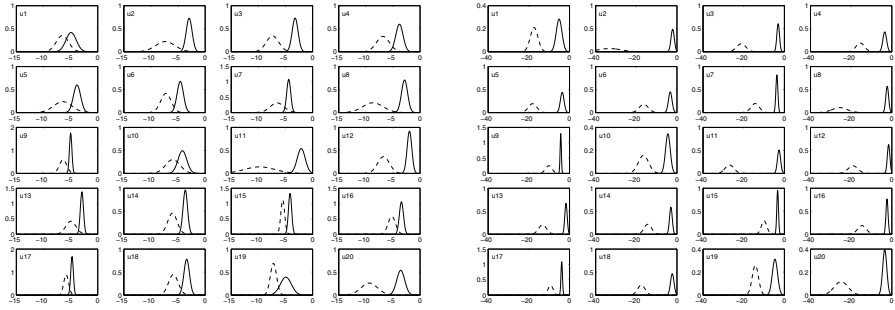
Fig. 10.4. Gaussian fit of client (solid) and impostor (dashed) score distributions of SVC 2004 development corpus for a HMM-based system for skilled (4 left columns) and random forgeries (4 right columns).

[11]. One of the most popular regional approaches is the method based on Hidden Markov Models [80, 41, 11]. In most of the cases, the HMMs model stroke-based sequences. Direct modeling of the time functions with HMMs has also been studied [19]. This latter case is developed as a case study in Sect. 10.4 by using the topology shown in the right part of Fig. 10.3.

10.2.5 Score Normalization

The matching scores obtained by comparing the input signature with the template or the enrolled model are usually normalized to a common range such as $[0, 1]$ before comparing them to a decision threshold, using different mapping functions [39]. This score normalization step is crucial when combining different matchers in a multibiometric approach [70].

As in the other modules of the system, the score normalization step can be also user-dependent. A simple experiment helps to visualize the rationale behind user-dependent score normalization. In Fig. 10.4 we show Gaussian fits of the user-dependent matching scores obtained with the function-based system described in Sect. 10.4, on different users in the development set of the Signature Verification Competition (SVC) described in Sect. 10.3.2. We can observe large differences both in the individual verification performance, and in the client-impostor scoring regions. The main objective of user-dependent score normalization techniques [24] is to prevent such misalignments, which are also compensated with user-dependent thresholds [13, 38].

The substantial differences across subjects of the user-dependent score distributions observed in signature verification are related to the complexity of signatures [7, 14] and their robustness against forgery attacks, but this relationship is not fully understood.

10.3 Resources for On-Line Signature Verification

10.3.1 Reference Systems

The availability of open source reference systems in biometrics research is an important milestone, as they provide a baseline to which results obtained with the new systems can be compared. This is the case, for example, of the NIST Fingerprint Image Software [58], which is used as a reference system in many studies [1].

Although there is no widely available reference system for signature verification to date, new efforts are being directed to the development of an open source framework within the Biosecure Network of Excellence [27]. The proposed framework will enable the efficient implementation and evaluation of various techniques (including feature-based and function-based approaches) and system components (including data parsing, pre-processing, feature extraction/selection, and reference template/model storage) related to on-line signature verification [8].

10.3.2 On-Line Signature Databases

One key element for performance evaluation of biometric systems is the availability of biometric databases. The availability of on-line signature databases corresponding to a large population of individuals, together with the desirable presence of biometric variability (i.e., multi-session, multiple acquisition sensors, different signal quality, etc.), and the availability of different kinds of forgeries, make signature database collection a time-consuming and complicated process. Additionally, the legal issues regarding data protection are controversial [68]. For these reasons, the number of available on-line signature biometric databases is quite limited.

The available on-line signature databases are normally obtained as a result of collaborative efforts in joint research projects (e.g., BIOMET [26], MCYT [60], or MYIDEA [12]; all of them are multimodal databases that include the signature modality [17]), or international benchmarks such as SVC 2004 [81]. In a few cases, on-line signature databases are available through the authors of research publications [11, 51].

In the following list we outline some public domain signature databases.

BIOMET. Five different modalities are present in the BIOMET database [26]: audio, face, hand, fingerprint and signature. Three different sessions were realized, with three and five months spacing between them. The number of persons participating in the collection of the database was 130 for the first campaign, 106 for the second, and 91 for the last, with 15 genuine and 17 impostor signatures per user. The signature acquisition device was a WACOM Intuos2 set at 200 Hz. The first session was acquired by using a Grip Pen (without visual feedback) and the remaining sessions were captured with an Ink Pen over a sheet of paper.

MCYT. The MCYT bimodal biometric database consists of fingerprint and on-line signature modalities [60]. In order to acquire the dynamic signature sequences, a WACOM Intuos pen tablet was employed. The sampling frequency was set to 100 Hz. The capture area was further divided into 37.5 mm (width) × 17.5 mm (height) blocks which were used as frames for acquisition [21]. Signature corpus comprises genuine (25 per user in groups of 5) and shape-based skilled forgeries (25 per user from 5 different impostors). The forgeries were generated by contributors to the database imitating other contributors. For this task they were given the printed signature to imitate and were asked not only to imitate the shape but also to generate the imitation without artifacts such as time breaks or slowdowns. Fig. 10.6 shows some example signatures. The MCYT signature corpus was released in 2003 by the Biometric Recognition Group–ATVS [3] and it has been used in more than 30 research groups worldwide [69, 32, 36, 54, 52]. Paper templates of 75 signers (and their associated skilled forgeries) were also selected and digitized with a scanner at 600 dpi [21]. The resulting subcorpus is comprised of 2250 signature images, with 15 genuine signatures and 15 forgeries per user (contributed by 3 different user-specific forgers). This subcorpus is also available [3].

SVC. The First International Signature Verification Competition (SVC) was organized in 2004 providing a common reference for system comparison on the same data and evaluation protocol [81]. The development corpus of the extended task (including coordinate and timing information, pen orientation and pressure) is available through the competition website [74]. This corpus consists of 40 sets of signatures. Each set contains 20 genuine signatures from one contributor (acquired in two separate sessions) and 20 skilled forgeries from five other contributors. The SVC database is especially challenging due to several factors, including: i) no visual feedback when writing (acquisition was conducted by using a WACOM tablet with a Grip Pen), ii) subjects used invented signatures different to the ones used in daily life in order to protect their personal data, iii) skilled forgers imitated not only the shape but also the dynamics, and iv) time span between training and testing signatures was at least one week. The signatures are in either English or Chinese (see Fig. 10.5).

Other ongoing efforts in on-line signature database collection include the Biosecure multimodal database [6], which will include the signature modality acquired with different devices (WACOM Intuos3 digitizing tablet, Samsung Q1 Tablet PC, and HP iPAQ hx2790 PDA) for the same subjects (around 1000) in order to enable interoperability experiments [18].
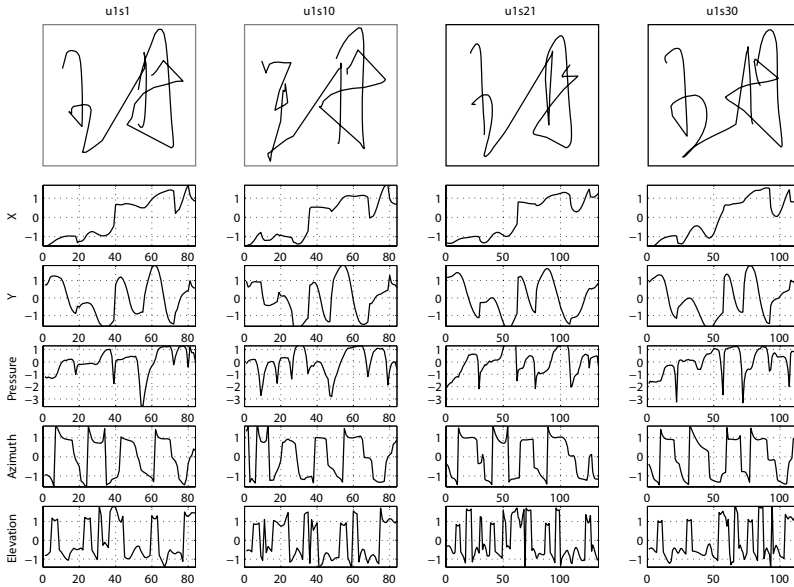
Fig. 10.5. Signature examples from SVC 2004 corpus. For a particular subject, two genuine signatures (left columns) and two skilled forgeries (right columns) are given. Plots of the coordinate trajectories, pressure signal and pen orientation functions are also given.

10.4 Case Study: Combining Feature- and Function-Based Approaches

Feature-Based Approach

This subsystem is based on previous approaches [56, 57, 47] and is further detailed by Fierrez-Aguilar et al. [23].

Feature extraction and selection. The complete set of global features is given in Table 10.1. Note that an on-line signature acquisition process capturing position trajectories and pressure signals both at pen-down and pen-up intervals is assumed. Otherwise, the feature set should be reduced, discarding features based on trajectory signals during pen-ups (e.g., features 32 and 41). Even though the given set has been demonstrated to be robust to the common distortions encountered in the handwritten scenario, not all the parameters are fully rotation/scale invariant, so either a controlled signature acquisition is assumed (as in MCYT database) or some kind of pre-alignment should be performed before computing them. Although pen inclination signals (i.e., azimuth and altitude) have shown discriminative power in some studies [71], no features based on them are introduced in the proposed set. The features in Table 10.1 are sorted by individual

Table 10.1. Set of global features sorted by individual discriminative power (T denotes time interval, t denotes time instant, N denotes number of events, θ denotes angle, **bold** denotes novel feature, *italic* denotes adapted from [56, 57, 47], roman denotes extracted from [56, 57, 47]).

Ranking	Feature Description	Ranking	Feature Description
1	signature total duration T_s	*2*	N(pen-ups)
3	N(sign changes of dx/dt and dy/dt)	**4**	average jerk $\bar{j}$ [56]
5	standard deviation of a_y	**6**	standard deviation of v_y
7	(standard deviation of y)/Δ_y	**8**	N(local maxima in x)
9	standard deviation of a_x	**10**	standard deviation of v_x
11	j_{rms}	**12**	N(local maxima in y)
13	t(2nd pen-down)/T_s	14	(average velocity $\bar{v}$)/$v_{x,\max}$
15	$A_{\min}=(y_{\max}-y_{\min})(x_{\max}-x_{\min})$ $(\Delta_x=\sum_{i=1}^{\text{pen-downs}}(x_{\max\,\lvert i}-x_{\min\,\lvert i}))\Delta_y$	16	$(x_{\text{last pen-up}}-x_{\max})/\Delta_x$
17	$(x_{\text{1st pen-down}}-x_{\min})/\Delta_x$	*18*	$(y_{\text{last pen-up}}-y_{\min})/\Delta_y$
19	$(y_{\text{1st pen-down}}-y_{\min})/\Delta_y$	**20**	$(T_w\bar{v})/(y_{\max}-y_{\min})$
21	$(T_w\bar{v})/(x_{\max}-x_{\min})$	*22*	(pen-down duration T_w)/T_s
23	$\bar{v}/v_{y,\max}$	*24*	$(y_{\text{last pen-up}}-y_{\max})/\Delta_y$
25	$\dfrac{T((dy/dt)/(dx/dt)>0)}{T((dy/dt)/(dx/dt)<0)}$	26	$\bar{v}/v_{\max}$
27	$(y_{\text{1st pen-down}}-y_{\max})/\Delta_y$	28	$(x_{\text{last pen-up}}-x_{\min})/\Delta_x$
29	(velocity rms v)/$v_{\max}$	30	$\dfrac{(x_{\max}-x_{\min})\Delta_y}{(y_{\max}-y_{\min})\Delta_x}$
31	(velocity correlation $v_{x,y}$)/$v_{\max}^2$ [57]	*32*	$T(v_y>0\lvert\text{pen-up})/T_w$
33	$N(v_x=0)$	34	direction histogram s_1 [57]
35	$(y_{\text{2nd local max}}-y_{\text{1st pen-down}})/\Delta_y$	36	$(x_{\max}-x_{\min})/x_{\text{acquisition range}}$
37	$(x_{\text{1st pen-down}}-x_{\max})/\Delta_x$	*38*	$T(\text{curvature}>\text{Threshold}_{\mathrm{curv}})/T_w$
39	(integrated abs. centr. acc. a_{Ic})/$a_{\max}$ [57]	40	$T(v_x>0)/T_w$
41	$T(v_x<0\lvert\text{pen-up})/T_w$	*42*	$T(v_x>0\lvert\text{pen-up})/T_w$
43	$(x_{\text{3rd local max}}-x_{\text{1st pen-down}})/\Delta_x$	44	$N(v_y=0)$
45	(acceleration rms a)/$a_{\max}$	46	(standard deviation of x)/Δ_x
47	$\dfrac{T((dx/dt)(dy/dt)>0)}{T((dx/dt)(dy/dt)<0)}$	48	(tangential acceleration rms a_t)/$a_{\max}$
49	$(x_{\text{2nd local max}}-x_{\text{1st pen-down}})/\Delta_x$	*50*	$T(v_y<0\lvert\text{pen-up})/T_w$
51	direction histogram s_2	**52**	t(3rd pen-down)/T_s
53	(max distance between points)/$A_{\min}$	**54**	$(y_{\text{3rd local max}}-y_{\text{1st pen-down}})/\Delta_y$
55	$(\bar{x}-x_{\min})/\bar{x}$	56	direction histogram s_5
57	direction histogram s_3	58	$T(v_x<0)/T_w$
59	$T(v_y>0)/T_w$	60	$T(v_y<0)/T_w$
61	direction histogram s_8	62	(1st $t(v_{x,\min})$)/T_w
63	direction histogram s_6	**64**	T(1st pen-up)/T_w
65	spatial histogram t_4	66	direction histogram s_4
67	$(y_{\max}-y_{\min})/y_{\text{acquisition range}}$	68	(1st $t(v_{x,\max})$)/T_w
69	(centripetal acceleration rms a_c)/$a_{\max}$	**70**	spatial histogram t_1
71	θ(1st to 2nd pen-down)	*72*	θ(1st pen-down to 2nd pen-up)
73	direction histogram s_7	**74**	$t(j_{x,\max})/T_w$
75	spatial histogram t_2	**76**	$j_{x,\max}$
77	θ(1st pen-down to last pen-up)	**78**	θ(1st pen-down to 1st pen-up)
79	(1st $t(x_{\max})$)/T_w	**80**	$\bar{j}_x$
81	T(2nd pen-up)/T_w	82	(1st $t(v_{\max})$)/T_w
83	$j_{y,\max}$	**84**	θ(2nd pen-down to 2nd pen-up)
85	$j_{\max}$	86	spatial histogram t_3
87	(1st $t(v_{y,\min})$)/T_w	**88**	(2nd $t(x_{\max})$)/T_w
89	(3rd $t(x_{\max})$)/T_w	90	(1st $t(v_{y,\max})$)/T_w
91	$t(j_{\max})/T_w$	**92**	$t(j_{y,\max})/T_w$
93	direction change histogram c_2	**94**	(3rd $t(y_{\max})$)/T_w
95	direction change histogram c_4	**96**	$\bar{j}_y$
97	direction change histogram c_3	*98*	θ(initial direction)
99	θ(before last pen-up)	**100**	(2nd $t(y_{\max})$)/T_w

inter-user discriminative power. For each feature F_k, $k=1,\ldots,100$, we compute the scalar Mahalanobis distance [75] d_{i,F_k}^{M} between the mean of the F_k-parameterized training signatures of client i, $i=1,\ldots,330$, and the F_k-parameterized set of all training signatures from all users. Features are then ranked according to the following inter-user class separability measure $S(F_k)$

$$S(F_k) = \sum_{i=1}^{330} \sum_{j=1}^{330} |d_{i,F_k}^{\mathrm{M}} - d_{j,F_k}^{\mathrm{M}}| \qquad (10.1)$$

Similarity computation. Given the feature vectors of the training set of signatures of a client $\mathcal{C}$, a non-parametric estimation $\lambda_{\mathcal{C}}^{\mathrm{PWC}}$ of their multivariate probability density function is obtained by using Parzen Gaussian Windows [75]. On the other hand, given the feature vector $\mathbf{o}_T$ of an input signature and a claimed identity $\mathcal{C}$ modeled as $\lambda_{\mathcal{C}}^{\mathrm{PWC}}$, the following similarity matching score is used

$$s_{\mathrm{PWC}} = p\left(\mathbf{o}_T | \lambda_{\mathcal{C}}^{\mathrm{PWC}}\right) \qquad (10.2)$$

Function-Based Approach

This subsystem is based on earlier approaches [80, 61] and is further detailed in Fierrez and Ortega-Gracia [19].

Feature extraction. Signature trajectories are first preprocessed by subtracting the center of mass followed by a rotation alignment based on the average path tangent angle. The signature is then parameterized as the following set of 7 discrete-time functions $\{x[n], y[n], p[n], \theta[n], v[n], \rho[n], a[n]\}$, $n = 1, \ldots, N_s$, and the first-order time derivatives of all of them, totalling 14 discrete functions. The functions p, θ, v, ρ, and a denote, respectively, pressure, path tangent angle, path velocity magnitude, log curvature radius and total acceleration magnitude. A claim-dependent linear transformation is finally applied to each function so as to obtain zero mean and unit standard deviation values.

Similarity computation. Given the parameterized enrollment set of signatures of a client $\mathcal{C}$, a left-to-right Hidden Markov Model $\lambda_{\mathcal{C}}^{\mathrm{HMM}}$ is estimated [75]. No transition skips between states are allowed and multivariate Gaussian Mixture density observations are used. On the other hand, given the function-based representation $\mathbf{O}_T$ of a test signature (with a duration of N_s time samples) and a claimed identity $\mathcal{C}$ modeled as $\lambda_{\mathcal{C}}^{\mathrm{HMM}}$, the following similarity matching score is used

$$s_{\mathrm{HMM}} = \frac{1}{N_s} \log p\left(\mathbf{O}_T | \lambda_{\mathcal{C}}^{\mathrm{HMM}}\right) \qquad (10.3)$$

The HMM system described above was submitted by the Biometric Recognition Group–ATVS to the First International Signature Verification Competition 2004 with very good results [81]. Considering not only position trajectories but also pressure signals, the proposed system was ranked first for random forgeries and second for skilled forgeries. The proposed system was only outperformed by the winner of the competition, which was based on a DTW approach [43]. Interestingly, it has been recently shown that the HMM approach outperforms an implementation of the DTW approach used by the

winner when enough training signatures are available [22], which is also the case when comparing the HMM method to the feature-based approach described before. More comparative experiments with the function-based system can be found in Garcia-Salicetti et al. [27].

Database and Experimental Protocol

All the signatures of the MCYT database [60] are used for the experiments (330 signers with 25 genuine signatures and 25 skilled forgeries per signer). Two examples of genuine signatures (left and central columns) and one forgery (right column) are given in Fig. 10.6.
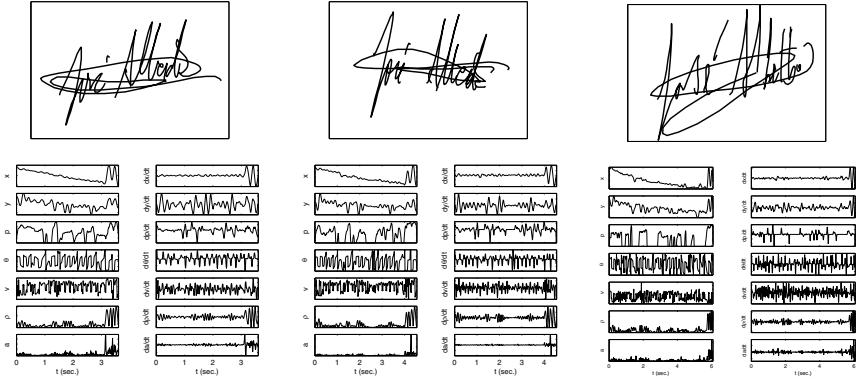
Two genuine signatures (left and central columns) and one skilled forgery (right column). A function-based representation is depicted below each signature.
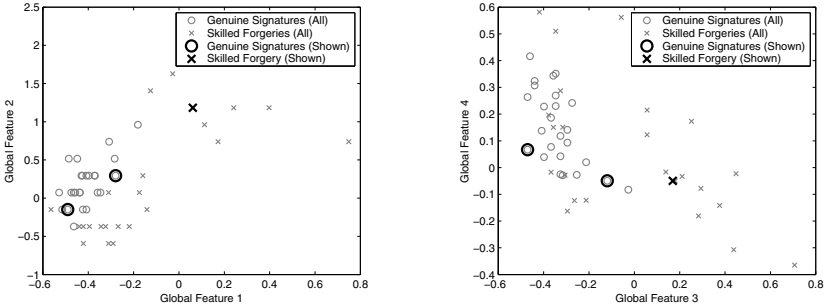
Best individually performing global features, i.e., 1st versus 2nd (left), and 3rd versus 4th (right), are depicted for all the signatures of the above user. Features from the genuine signatures and forgery shown above are highlighted.

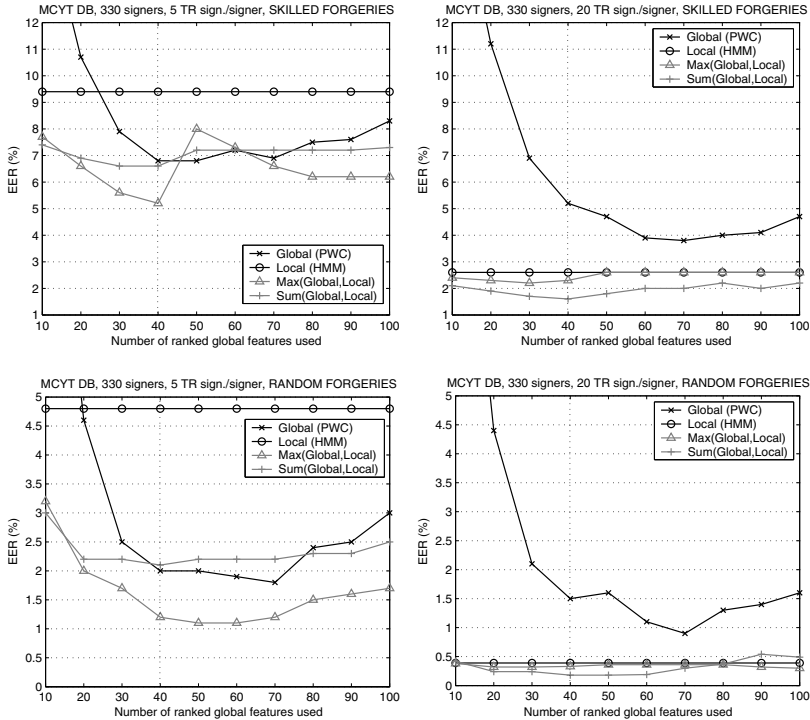**Fig. 10.6.** Signatures from MCYT corpus with extracted functions and features.

Fig. 10.7. Verification performance with user-independent decision thresholds for an increasing number of ranked global features.

The signature corpus is divided into training and test sets. In case of skilled forgeries, the training set comprises either 5 or 20 genuine signatures and the test set consist of the remaining samples (i.e., 330×20 or 330×5 client, respectively, and 330×25 impostor similarity test scores). In case of random forgeries (i.e., impostors are claiming someone else's identity using their own signatures), client similarity scores are as above and we use one signature of each of the remaining users as impostor data so the number of impostor similarity scores is 330×329.

Results

In Fig. 10.7, verification performance results in four common conditions (few/many training signatures and skilled/random forgeries) are given for: *i*) the feature-based system with an increasing number of ranked global features, *ii*) the function-based system, and *iii*) their combination through max and sum fusion rules [44].

The feature-based system outperforms the function-based approach when training with 5 signatures, and the opposite occurs when training with 20

signatures. The two systems are also shown to provide complementary information for the verification task, which is well exploited in the cases of small and large training set sizes using the max and sum rules respectively. Also interestingly, we have found a good working point of the combined system in the four conditions depicted in Fig. 10.7 when using the first 40 ranked features for the global approach. This is highlighted with a vertical dashed line.

10.5 Summary

This chapter started with some historical events related to signature verification, potential applications of this technology, examples of commercial systems, and some notes on the progress of standardization in on-line signature verification.

We then provided a brief review of the state-of-the-art in on-line signature verification, by outlining the main approaches to the following modules: data acquisition and preprocessing, feature extraction (feature- or function-based), enrollment (reference- or model-based), matching with or without pre-alignment, and score normalization. Based on this review, we conclude that the dominant approaches are based on global features with distance measures, or time functions either with statistical modeling (HMM) or elastic matching (DTW). We have also summarized some on-line signature databases such as MCYT or SVC, and we have provided a case study combining feature- and function-based approaches.

Alongside the review of the state-of-the-art, we have also pointed out some open problems in signature verification, such as the large behavioral differences between signers (which make especially appropriate the use of signer-specific features, models, or score mappings), or the signature variations in time (which may be overcome with multi-session training or template adaptation techniques). Other research directions include: multilevel recognition approaches, better understanding of the discriminative features against forgers and between different signers, understanding of the variability and complexity factors in signature, and their relation to verification performance.

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