Online Signature Verification

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Réjean Plamondon, Giuseppe Pirlo, and Donato Impedovo

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Abstract

Along with the exponential rise in the use of the Internet and of mobile devices is a rapidly growing need for personal identity confirmation. As a result, online signature verification is being considered with renewed interest.

This chapter presents an overview of online signature verification and a discussion of the most important theoretical aspects of signature generation and

R. Plamondon (✉)
Département de génie électrique, Ecole Polytechnique de Montréal, Montréal, QC, Canada
e-mail: rejean.plamondon@polymtl.ca

G. Pirlo
Dipartimento di Informatica, Università degli Studi di Bari, Bari, Italy
e-mail: pirlo@di.uniba.it

D. Impedovo
Politecnico di Bari, Bari, Italy
e-mail: impedovo@gmail.com

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modeling. The principal issues related to the development of online signature verification systems are addressed, and the most commonly used approaches proposed in the literature are presented and compared.

Finally, throughout the chapter, based on the state-of-the-art techniques available, current challenges are identified and promising directions for further research are highlighted.

Keywords

Biometrics • Kinematic theory • Logical and physical access control • Log-normal models • Neuromuscular systems • Online signature verification • Personal identification • Security • Signature generation • System evaluation

Introduction

Biometrics is an emerging field of research and technology that involves the recognition of individuals through their physical or behavioral traits. Examples of physical attributes are fingerprints, facial features, the iris, and DNA. Some behavioral characteristics are the signature, the voice, and keystroke dynamics, among others.

Handwritten signatures occupy a very special place in biometrics. A signature is a biometric trait generated by a complex process originating in the signer's brain as a motor control "program," instantiated through the neuromuscular system and left on the writing surface by a handwriting device.

The net result is that automatic signature verification is a multidisciplinary research field involving aspects of disciplines ranging from human anatomy to engineering and from neuroscience to computer and system sciences. The fundamental research issues in biometrics are described in two comprehensive surveys that report the progress in automatic signature verification specifically: up to 1989 in one [78] and up to 1993 in the other [47]. In 1994, a special journal issue and a book summarizing the most relevant research activities were published [74]. The increasing number of research efforts in this field, up to 2008, has also been summarized in a recent survey [37].

Today, in the era of the networked society, the automatic confirmation of personal identity is a fundamental requirement, and the need to integrate signature verification technologies into other standard equipment for a wide range of applications is increasing rapidly. In fact, the verification of a person's identity by signature analysis does not involve an invasive measurement procedure, and people have long agreed to the use of signatures in their daily lives. Furthermore, handwritten signatures are a long been established means of personal identification, and their use is widespread and well recognized by administrative and financial institutions. Consequently, several national associations and international bodies have recently supported the standardization of signature data interchange formats, and specific rules and regulations on signature-based personal identity verification have been approved in many countries [2, 39].

This chapter, which provides an overview of the field of online signature verification, is organized as follows: section "Overview" presents an outline of the signing process, along with the main aspects of signature verification. Section "Modeling and Description" deals with the modeling and description of signatures. A model of the neuromuscular system that underlies the generation of signatures is introduced, and then the problems related to signature description for verification purposes are addressed, focusing on both the signature acquisition and feature extraction steps. Section "Verification" describes the main verification techniques. Certain aspects of verification system evaluation are discussed in section "Evaluation," and a comparative analysis of the state-of-the-art systems for online signature verification is presented in section "Online Signature Verification: A Comparative Analysis." A brief summary of the key issues raised in the chapter is provided in the conclusion, as well as an indication of the most valuable research directions for the field in the future.

Overview

The signature is quite different from the other identification modalities that can be used as potential candidates for biometric applications because it is a behavior-based identifier. A signature is a rapid movement that has been defined, learned, and practiced over a period of years, in literate populations, to become a person's characteristic identifying pattern. The distinct imprint that is left on a surface is the outcome of a complex generation process that occurred while that person was engaged in the signing process. To design an efficient online verification system, several aspects have to be taken into account. Figure 27.1 schematizes the entire verification process.

The first aspect to take into account is the context: What is the intention of the subject producing a signature? The usual context is an approval procedure, but this might not always be the case. Depending on the signer's intentions, a signature instance will be either a genuine gesture or a forgery. In the first case, it can be the result of an honest action in response to an identity challenge to gain access or get an authorization, a compelled response to a threat or a gesture that the author is planning to deny later on. In the second, the false specimen can indicate an attempt to deceive or a random error. The initial challenge is to design a system capable of operating under these various conditions and ideally of recognizing them.

Whatever the motivation for the signature, the signer has to access an action plan, which is a spatiotemporal map that has been memorized and stored in the motor cortex of the brain. This plan is an activation sequence that represents a signature model. It is instantiated by signature "components," which represent portions of a trajectory between pen-up and pendown movements. Each component is itself made up of a sequence of strokes that are considered as the basic units of human handwriting movements.

In other words, every time a person writes his signature, whatever the context of his action, he has to recall a map of the overall gesture from his motor memory,

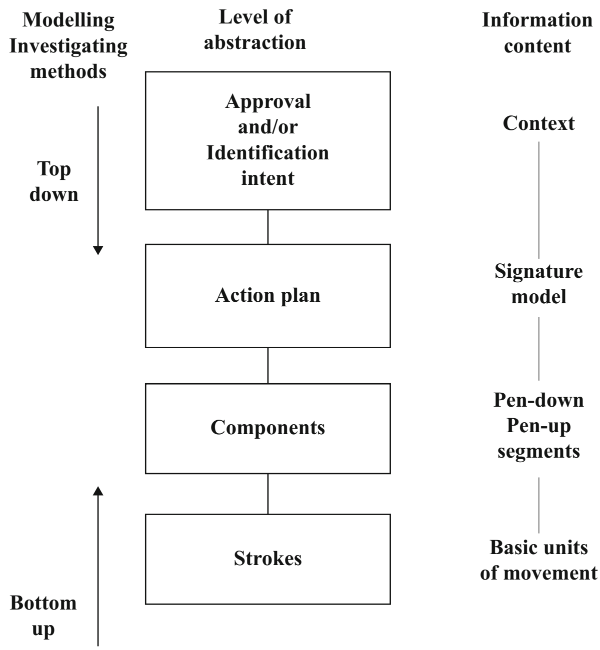

Fig. 27.1 A model of the signature generation process in terms of the information content and the level of abstraction that have to be taken into account in the design of a verification system

which is a premeditated image. Depending on the complexity of this map, which can be considered as a "motor program," this image will be instantiated in a fairly large number of pieces, separated by pen-up and pen-down links. Each of these pieces, or "chunks," is itself the outcome of activating a sequence of strokes.

The overall process can be modeled and studied using a top-down or a bottom-up approach. In the former case, the gesture is first analyzed as a whole to extract global features and then on smaller portions of the movement to extract local features, at various levels of representation. In the latter case, the analysis starts with local features and a more global representation is built up by combining the initial representations. These two methodologies lead to various algorithms and techniques aimed at designing a successful verification system, as shown below.

Modeling and Description

As explained above, a handwritten signature is the result of a complex generation process, and suitable schemes and strategies must be defined to model and describe signatures for the design of an online signature verification system. This section describes the Sigma-Lognormal model, which is the general model underlying the signature generation process The problem of signature acquisition is addressed step by step. Finally, some important strategies related to signature description are presented.

Neuromuscular Representation

To better illustrate the signature generation process, Fig. 27.2 schematically shows the production of a typical specimen, according to the Sigma-Lognormal model [64]. This model is invariant with respect to cultural or language differences and can be applied to any type of signature: Asian, Arabic, European, or American. This illustration shows that the action plan is made up of virtual targets, each pair of them linked to an arc of a circle. This map represents a sequence of discontinuous strokes. The plan involves activating a motor command generator which produces a series of impulses that activates a neuromuscular system which is itself characterized by its lognormal impulse response [76]. For each impulse, a lognormal velocity profile is generated at the pen tip, and the temporal superimposition of these strokes results in a smooth well-controlled signature. According to this model, strokes are hidden in the signal, which makes segmentation a very difficult and often unreliable process.

Specifically, the Sigma-Lognormal model technically considers the velocity of the pen tip as the result of an action of the neuromuscular system, as described by a vectorial summation of lognormal primitives:

$$\vec{v}(t) = \sum_{i=1}^{N} \vec{v}_i(t; t_{0i}, \mu_i, \sigma_i^2) = \sum_{i=1}^{N} D_i \begin{bmatrix} \cos(\theta_i(t)) \\ \sin(\theta_i(t)) \end{bmatrix} \Lambda_i((t; t_{0i}, \mu_i, \sigma_i^2); N \geq 2 \tag{27.1}$$

As expressed in this equation, each lognormal defines a stroke which is scaled by a command parameter (D) and time shifted by the time occurrence of this command (t_0), the overall stroke pattern being described by a lognormal time function:

$$\Lambda(t\,;\,t_0\,,\,\mu_i\,,\,\sigma_i^2) \;=\; \frac{1}{\sigma_i\sqrt{2\pi}(t-t_0)}\,\exp\left(\frac{-\,[\ln(t-t_0)\,-\,\mu_i]^2}{2\sigma_i^2}\right) \tag{27.2}$$

Each of these strokes also occurs along a pivot, and the angular position of the pen tip can be calculated using an error function (erf) (27.3):

$$\theta_i(t) = \theta_{bi} + \frac{(\theta_{ei} - \theta_{bi})}{2}\left[1 + \operatorname{erf}\left(\frac{\ln(t - t_{0i}) - \mu_i}{\sigma_i\sqrt{2}}\right)\right] \tag{27.3}$$

where θ_{bi} and θ_{ei} refer to the beginning and ending angular direction of each stroke, respectively. In these equations, μ_i and σ_i represent the log time delay and the log response time of the neuromuscular system, respectively, as it reacts to the ith command [77]. Finally, the synergy emerging from the interaction and coupling of many of these neuromuscular systems results in the sequential generation of a complex signature pattern as depicted in Fig. 27.2.

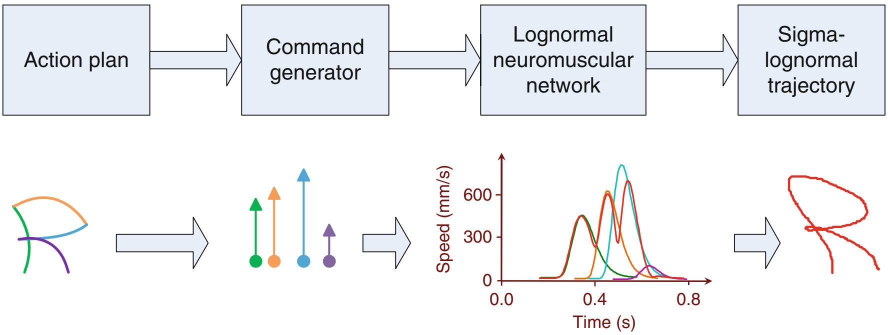

Fig. 27.2 The production of a signature according to the Sigma-Lognormal model: illustrative sketches

Below, the main features of this model are used as a framework to present the various sections of our survey and to point out the major difficulties that have to be overcome by researchers in designing a reliable online signature verification system.

Data Acquisition and Preprocessing

Data acquisition devices for online signatures generate a spatiotemporal representation of the signature. A wide variety of data acquisition devices is available, such as electronic pens capable of detecting position, velocity, acceleration, pressure, pen inclination, and writing forces and digitizing tablets with digital ink technologies providing immediate feedback to the writer [90]. Other approaches do not require the use of a special stylus, using instead a video camera focused on a user writing on a piece of paper with an ordinary pen [57].

Other methods use computer vision techniques to capture handwriting. For instance, a special stylus containing a small CCD camera that captures a series of snapshots of the writing process has recently been proposed. This system recovers the whole handwritten trace by analyzing the sequence of successive snapshots. The stylus is also equipped with a stress sensor for detecting the pressure applied on the ballpoint and determining the pen-up/pen-down information [59].

In addition, a wired-glove device for virtual reality applications has been used for online signature verification. This device can provide data on both the dynamics of the pen motion during signing and the individual's hand shape [41].

Of course, interoperability problems arise when signature verifiers are required to work with specimens acquired from a multitude of diverse input devices, ranging from a mouse to input devices for mobile computing [36]. In particular, signature verification on handheld devices is assuming ever-greater practical relevance, since PDAs and smartphones are increasingly pervasive in our daily lives, as they allow access to a multitude of new applications and services. Of course, it is worth noting that signature verification on handheld devices raises specific issues that do not apply in other scenarios. In particular, handheld devices have a very small pen input area and generally provide poor sampling quality. In addition, the input device captures only position information, and the signer has to use a touch screen instead of paper and a stylus instead of an ordinary pen [56]. Finally, the basic underlying hypothesis of considering a signature as a well-learned movement might not be fully appreciated from the start with these new devices. Degradation in the verification performance in the first tests could then be expected, as well as the need to update more frequently the reference signatures, as a user learning curve evolves.

After data acquisition, the input signals can be enhanced using standard filtering and noise reduction algorithms, based on the Fourier transform, as well as normalization techniques to standardize signatures in terms of position, size, orientation, and duration. This is followed by signature segmentation, which is a critical task, since it strongly determines the elements of the signature model and influences all the successive phases of signature verification [37, 43, 102, 104].

Some segmentation techniques derive from specific characteristics of handwritten signatures and reflect specific handwriting models. For instance, a signature can be considered as a sequence of writing units, delimited by abrupt interruptions. Writing units are the "regular" parts of the signature, while interruptions are the "singularities" of the signature. Thus, as explained in section "Overview," pen-up/pen-down signals can be used to segment a signature into components, as can the analysis of curvilinear and angular velocity signals [37, 76, 78]. Another way to segment a signature is to use its perceptually important points. The importance of a point depends on the extent of change in the writing angle between the selected point and its neighbors [6]. A modified version of this technique considers the end points of pen-down strokes as significant splitting points. Other approaches use perceptually important points for segmenting signatures while considering the evolutionary distance measure, based on arc-length distance, for segment association [37, 84].

In some cases, segmentation techniques are based on splitting strategies supporting specific signature verification approaches. For example, with Dynamic Time Warping (DTW), two or more signatures can be segmented into the same number of segments that correspond more or less perfectly. After the first signature has been split, based on uniform spatial criteria or on the position of geometric extremes, DTW is applied to determine the corresponding set of points on other specimens [12, 49]. A model-guided segmentation technique has also been proposed, which uses DTW to segment an input signature based on its correspondence to the reference model [37]. Again, all these techniques provide "operational strokes" that constitute a fairly reliable estimation of the real strokes that are hidden in the signal (see Fig. 27.2).

Table 27.1 Function features

Functions	References
Position	Y. Hongo et al. [29], Y. Komiya et al. [46], J. Ortega-Garcia et al. [68], R. Plamondon [75], and Q.-Z. Wu et al. [96]
Velocity	V. Di Lecce et al. [10, 11], M. Fuentes et al. [18], K. Huang and H. Yan [32], A. K. Jain et al. [40], J. Ortega-Garcia et al. [68], R. Plamondon [75], T. Qu et al. [81], C. Schmidt and K.-F. Kraiss [83], and Q.-Z. Wu et al. [95]
Acceleration	C. Schmidt and K.-F. Kraiss [83]
Pressure	Y. Hongo et al. [29], K. Huang and H. Yan [32], Y. Komiya et al. [46], J. Ortega-Garcia et al. [68], T. Qu et al. [81], and C. Schmidt and K.-F. Kraiss [83]
Force	R. Martens and L. Claesen [55] and D. Wang et al. [90]
Direction of pen movement	M. Fuentes et al. [18] and J. J. Igarza et al. [34]
Pen inclination	J. J. Igarza et al. [34], Y. Komiya et al. [46], R. Martens and L. Claesen [55], and J. Ortega-Garcia et al. [68]

Feature Extraction

Function and parameter features can be used for online signature verification. When function features are used, the signature is characterized by a time function, the values of which constitute the feature set. When parameter features are used, the signature is characterized as a vector of parameters, each of which represents the value of one feature [78].

As Table 27.1 shows, position, velocity, and acceleration functions are widely used for online signature verification. The position function is conveyed directly by the acquisition device, whereas the velocity and acceleration functions can be provided by the acquisition device and numerically derived from position [10, 96]. In recent years, pressure and force functions have frequently been used, and specific devices have been developed to capture these functions directly during the signing process [90]. The directions of the pen movements and the pen inclinations have been also considered [34, 68]. In fact, a comparative study of the consistency of features for online signature verification has demonstrated that the position, velocity, and pen inclination functions can be considered to be among the most consistent, when a distance-based consistency model is applied. This model starts by considering that the characteristics of a feature must be estimated by using the distance measure associated with the feature itself [50]. More recently, personal entropy has been used to assess the robustness to short-term and long-term variability of the position, pressure, and pen inclination functions. The results show that position is the most robust to time variability. Pressure is not recommended in the long-term context, although it may give better performance results in the short-term context. This latter result is consistent with those of a study dealing with pressure control in handwriting [84] where it is shown that subjects can be classified into three groups with regard to the control of pressure: those who are consistent controllers throughout the script, those who are consistent during some specific time windows,

Table 27.2 Parameter features

Parameters	References
Total signature duration	R. S. Kashi et al. [43], J. Lee et al. [49], L. L. Lee et al. [48], W. Nelson et al. [63], R. Plamondon [75], and T. Qu et al. [81],
Pen-down time ratio	R. S. Kashi et al. [43] and W. Nelson et al. [63].
Number of pen-ups/pen-downs	J. Lee et al. [49], L. L. Lee et al. [48], and T. Qu et al. [81]
Direction-based	R. S. Kashi et al. [43], J. Lee et al. [49], W. Nelson et al. [63], T. Qu et al. [86], and M. Zou et al. [104]
Curvature-based	A. K. Jain et al. [40]
Moment-based	R. S. Kashi et al. [43]
AVE/RMS/MAX/MIN of posit., displ., speed, accel.	M. Fuentes et al. [18], R. S. Kashi et al. [43], M. A. Khan et al. [44], J. Lee et al. [49], L. L. Lee et al. [48], W. Nelson et al. [63], and T. Qu et al. [81].
Duration of positive/negative posit., displ., speed, accel.	R.S. Kashi et al. [43], J. Lee et al. [49], L.L. Lee et al. [48], and W. Nelson et al. [63].
X-Y correlation of posit., displ., speed, accel.	M. Fuentes et al. [18], R. S. Kashi et al. [43], W. Nelson et al. [63], and R. Plamondon [75]
Fourier transform	G. Dimauro et al. [13] and Q. Z. Wu et al. [95, 97].
Wavelet transform	D. Letjman and S. George [51], R. Martens and L. Claesen [55] and I. Nakanishi et al. [60].

and those who apparently have no reliable control. This kind of investigation has found that pen inclination is a very unstable feature [30], contrary to the results reported in [50]. In fact, some of these results are consistent with the bottom-line conclusion in Fig. 27.2 to the effect that the pen tip velocity is the basic control variable exploited by the central nervous system for the generation of a signature.

Table 27.2 lists some major parameter features for online signature verification. Total signature duration [43, 48, 81], the pen-down/pen-down time ratio [43, 63], and the number of pen lifts (pen-down, pen-up) [48, 49, 81] are some of the parameters most often used for signature verification. Other parameters are derived from the analysis of direction, curvature, and moments of the signature trace. Parameters can also be numerically derived from the representative time functions of a signature, like the average (AVE), root mean square (RMS), maximum (MAX), and minimum (MIN) values of position, displacement, speed, and acceleration [48, 63, 81]. Parameters derived from correlations and time-dependent relations between function features can also be considered [43, 48, 49, 63], as can coefficients derived from Fourier [13, 95, 97] and Wavelet [51, 55, 60] transforms. Concerning the variability of parameter features, a recent study shows that the long-term temporal variability of online signatures is very high although no typical evolution occurs over time. Furthermore, since inter-session variability is very high, systems can give less accurate results in real-time applications if they are trained using data from only one acquisition session [36, 78].

It is worth noting that depending on the signature model, features can be derived at the global or the local level. The global features reflect the holistic characteristics of the signature action plan, and the local ones highlight some very specific and personal patterns in the instantiation of this plan. When function features are considered, they can be defined for the whole signature or for individual signature segments. Similarly, two kinds of parameter features are considered in the literature: global and local. Typical global parameters are the total duration, number of pen lifts, number of components, and global orientation of the signature. Local parameters are related to features derived from specific parts of the signature, so that direction-based, curvature-based, and moment-based parameters are generally considered at the local level. Even when coefficients obtained by mathematical transforms are considered as parameter features, they can be extracted at the global or local level, depending on the signature model that has been adopted [24, 80].

Of course, the use of a universally applied feature set is not effective for signature verification, since signatures from different writers generally contain very few common characteristics. The knowledge that an individual's signature is unique has led many researchers to devote special attention to the selection of the most suitable features to use in signature validation, for genuine signatures as well as for random and skilled forgeries. The basis for this approach is the evidence that some features are well suited to distinguishing skilled forgeries from genuine signatures, while others are better at distinguishing random forgeries. Genetic Algorithms have also been used for parameter selection, and in some cases the feature set is personalized by assigning a different weight to each feature, as well as selecting the optimal prototype function. Sometimes, the most valuable function feature for verification is selected for each signature segment based on the specific characteristics of that segment. For instance, information on the local stability of a signature can be derived from different representation domains and can be used for selecting the best function feature [38].

Verification

In the verification process, the authenticity of the test signature is evaluated by matching its features against those stored in the knowledge base developed during the enrolment stage. The result for the authenticity of a signature is provided as a Boolean value. In some systems, uncertainty is incorporated into the decision process. When this occurs, the signer is required to sign again, and the system generally increases its acceptance thresholds, to make the success of this second attempt more difficult to achieve.

As Table 27.3 shows, different techniques can be considered for signature comparison. In terms of distance-based verification techniques, Dynamic Time Warping (DTW) has been used extensively with function features, since this allows the time axis of two time sequences that represent a signature to be compressed or expanded locally, in order to obtain the minimum of a given distance value [37, 72]. The fact that a comparison between the complete time sequences results in higher

Table 27.3 Comparison techniques

Technique		References
Dynamic Programming		J. Lee et al. [49] and I. Nakanishi et al. [60]
Dynamic Time Warping (DTW)	Continuous	L. Bovino et al. [4], V. Di Lecce et al. [10, 11], G. Dimauro et al. [12, 14], K. Huang and H. Yan [32], M. E. Munich and P. Perona [57], and R. Plamondon [75]
	GA-based	M. Wirotius et al. [92]
	PCA-based	A. Kholmatov and B. Yanikoglu [45] and B. Li et al. [52]
	MCA-based	B. Li et al. [52]
	PA-based	M. Wirotius et al. [92]
	EP-based	H. Feng and C.C. Wah [17]
	Random-based	M. Wirotius et al. [92]
	Asymmetric	R. Martens and L. Claesen [55]
Correlation		M. Parizeau and R. Plamondon [72] and R. Plamondon [75]
Split and merge		Q. Z. Wu et al. [96]
String/graph/tree matching		Y. Chen and X. Ding [7], A. K. Jain et al. [40], and M. Parizeau and R. Plamondon [72]
Structural description graph		G. Dimauro et al. [13] and K. Huang and H. Yan [32]
Euclidean distance		M. A. Khan et al. [44].
Mahalanobis distance		R. Martens and L. Claesen [55] and K. Zhang et al. [103]
Membership functions		T. Qu et al. [81]
Dynamic similarity measure		Q. Z. Wu et al. [97]
Support vector machine (SVM)		M. Fuentes et al. [18], M. T. Ibrahim et al. [33], and A. Kholmatov and B. Yanikoglu [45]
Hidden Markov Models (HMM)	Left-to-Right topology	J. G. A. Dolfing et al. [16], M. Fuentes et al. [18], J. Galbally et al. [19, 20], J. J. Igarza et al. [34, 35], R. S. Kashi et al. [43], M. Martinez-Diaz et al. [56], J. Ortega-Garcia et al. [68], M. M. Shafiei and H. R. Rabiee [85], B. Van et al. [87], T. Wessels and C. W. Omlin [91], H. S. Yoon et al. [101], and M. Zou et al. [104]
	Ergodic topology	T. Wessels and C. W. Omlin [91]
Neural network (NN)	Multilayer perceptrons (MLP)	M. Fuentes et al. [18] and K. Huang et al. [31]
	Backpropagation network (BPN)	D. Z. Letjman and S. E. George [51]
	Self-organizing map	T. Wessels and C. W. Omlin [91]

computational load has led to the development of data reduction techniques based on Genetic Algorithms (GA) Principal Component Analysis (PCA), Minor Component Analysis (MCA), and Linear Regression (LR), among others [37]. Asymmetric DTW has also been defined to avoid deformation of the reference signatures when they are matched against test specimens [55]. Similarity measures [97], split-and-merge strategies [96], and string matching [7] have also been considered for signature comparison. Other techniques use the Mahalanobis distance [55, 103], the Euclidean distance [44], or membership functions [81] for matching the target specimen to the parameter-based model of the declared signer's signatures. Support vector machines (SVMs) are another effective approach for online signature verification, since they can map input vectors to a higher dimensional space, in which clusters may be determined by a maximal separation hyperplane [18, 45].

Of the model-based techniques, Hidden Markov Models (HMM) have been found to be well suited to signature modeling. They are highly adaptable to personal variability [18, 56, 87] and yield superior results to other signature modeling techniques [32]. Although both Left-to-Right (LR) and Ergodic (E) topologies have been used for online signature verification, the former is considered best suited to signature modeling [34, 91, 104]. Neural networks have also been considered for signature verification, since they have demonstrated good generalization capabilities. In this group, multilayer perceptrons (MLP), time-delay neural networks, backpropagation networks, self-organizing map, and radial basis functions (RBF) have been used [18, 31, 51, 91]. Of course, the use of neural networks for online signature verification is strongly limited by the fact that they generally require large amounts of learning data, which are not available in many current applications [37, 47].

Whatever technique is adopted, the need to improve verification performance has led researchers to investigate multi-expert approaches for combining sets of verifiers based on global and local strategies [61, 62] and through boosting methods [29]. So far, several multi-expert systems have been proposed in the literature, based on abstract-level, ranked-level, and measurement-level combination methods as well as on serial, parallel, and hybrid topologies. In particular, multi-expert approaches have been found be to be well suited for implementing top-down and bottom-up signature verification strategies [80]. Concerning bottom-up strategies, it is worth noting that multi-expert approaches allow effective implementation of a stroke-based signature verification approach, in which a signature is verified starting with an analysis of its basic elements. Furthermore, this approach can lead to lower error rates, compared to global approaches, since a large amount of personal information is conveyed in specific parts of the signature and cannot be detected when the signature is viewed as a whole [6, 12, 13, 83]. Furthermore, verification at stroke level can be performed by DTW, also considering multiple function features for stroke representation (like position, velocity, and acceleration), in order to verify both the shape and dynamics of each part of the signature [4, 11].

Concerning the use of the multi-expert approach in top-down verification strategies, the hybrid topologies are capable of achieving the performance advantages of serial approaches in quickly rejecting very poor forgeries while retaining the reliability of parallel combination schemes. This is the case for multilevel verification systems: for example, those first verify the structural organization of a target signature and then analyze in detail the authenticity of its individual elements [13, 32].

Along with the matching techniques, attention has been paid to knowledge-based structures in relation to signature modeling techniques. Two approaches can be considered for signature verification: writer dependent and writer independent. When writer-dependent approaches are used, a specialized classifier is trained for each writer, using only genuine specimens. In this case, one approach uses a single prototype of a genuine signature for each writer. Several techniques have been proposed for the development of the optimal average prototype for a signer, including shape and dynamic feature combination, time- and position-based averaging, and selecting the genuine specimen with the smallest average difference when compared to the other true signatures available. Once the prototype has been determined, the decision threshold is generally defined on the basis of the distances between genuine signatures [37]. In another approach, a set of genuine signatures is used for reference. In this case, the selection of the optimal subset of reference signatures from among the specimens available is performed either on the basis of an analysis of variance within samples [26, 27] or by considering the high-stability regions in the signatures [9, 10]. The selection of the best subset of reference signatures can be avoided but at the expense of using multiple models for signature verification. The writer-independent approach uses a single classifier for all writers, which is trained using genuine and forged specimens of the entire population of individuals considered for training. The writer-independent approach is generally considered superior to the writer-dependent approach, when a limited number of reference signatures is available for each author. This is because the writer-independent classifier can be trained from previously collected specimens of other individuals [37].

It is important to note that knowledge base development and management requires handling multifaceted aspects related to signature type, complexity, and stability. For instance, short signatures could convey less information than long signatures, resulting in less accurate verification results [5]. Similarly, people with common names could be more likely to share similar signatures with other individuals – at least in terms of shape characteristics. In both cases, the system should be capable of adapting to the characteristics of the individuals enrolled. Furthermore, the complexity of a signature has been quantified by estimating the difficulty of imitating it, which corresponds to the estimated difficulty of perceiving, preparing, and executing each stroke of the signature itself [5]. Concerning signature stability, a local stability function can be obtained using DTW to match a genuine signature against other authentic specimens [8, 14, 32]. In this case, every match attempt is used to identify the *direct matching points* (DMPs), which are the unambiguously matched points of the genuine signature that indicate the presence of a small, stable region of the signature, in other words chunks of the action plan that are the best learned. The local stability function of a point of a genuine signature is then computed as the average number of times the point is a DMP, when an attempt is made to match the signature against other genuine specimens. Furthermore, the use of an analysis of local stability to measure short-term modifications – which depend on the psychological condition of the writer and on the writing conditions allows selection of the best subset of reference signatures and the most effective feature functions for verification objectives while providing useful information to weight the verification decision obtained at the stroke level [10, 32]. Long-term modifications depend on the alteration of the physical writing system of the signer at the effector level, finger, hand and arm as globally reflected by the logtime delays and logresponse times, as well as on the modification of the motor program in his or her brain (as expressed in terms of the five Sigma-lognormal command parameters). Overall, signature variability is affected more by fluctuations of the parameters associated with the central neural coding than the peripheral parameters reflecting the timing properties of the muscular system activated by the action plan [15].

When these modifications are evaluated, useful information can be gathered for updating the reference signature model by including additional information from new signatures as it becomes available. Other types of approaches estimate the stability of a set of common features and the physical characteristics of signatures to which they are most closely related, in order to obtain global information on signature repeatability, which can be used to improve a verification system [25, 26]. In general, these approaches have shown that there is a set of features that remains stable over long periods, while there are other features that change significantly with time, as a function of signer age. This is the case with features related to total execution time, velocity, and acceleration [25]. Since intersession variability is one of the most significant causes of verification performance deterioration, specific parameter-updating approaches have been considered [37]. A client-entropy measure has also been proposed to group signatures in categories depending on signature complexity and variability. Also, the measure based on local density estimation by an HMM can be used to ascertain whether or not a signature contains enough information to be successfully processed by a verification system [30].

Of course, although the general model underlying the signature generation process is invariant in terms of cultural habits and language differences among signers, the enormous diversity in the signatures of people from different countries has suggested the development of specifically designed solutions. For instance, Western-style signatures generally consist of signs that could form concatenated text combined with pictorial strokes. In some countries, the habit is to sign with a readable written name, whereas in other countries signatures are not always legible. Many more differences can be expected when considering signatures written by people from non-Western countries. To address these differences, specific approaches have been proposed in the literature for Chinese and Japanese signatures, which can consist of independent symbols, and for Arabic and Persian signatures, which are cursive sketches that are usually independent of the person's name. In general, as the need for cross-cultural applications increases, it is becoming more and more important to evaluate both the extent to which personal background affects signature characteristics and the accuracy of the verification process. For this reason, a set of metadata, sometimes called "soft biometrics," has been also considered.

Metadata are related to various aspects of a writer's background, such as nationality, script language, age, gender, and handedness. Some metadata can be estimated by statistically analyzing human handwriting, which means that it is possible to adapt signature verification algorithms to a particular metadata context in order to improve verification performance [94].

Security and privacy issues play a fundamental role in knowledge base development and management, as in all phases of the online signature verification process. In fact, identity theft can occur if biometric traits are stolen by a cyber-attacker, and sensitive information about a person's personality and health can be revealed. One advantage of the signature in this dramatic context is that it can be changed by an individual by simply changing the pattern of his or her signature – and changed altogether by that individual in the case of identity theft. It must be remembered however that more practiced movements lead to better performances. Also full-length signatures generally outperform shorter versions, like initials or handwritten passwords, although a password can be kept secret and changed regularly [71].

To summarize, the security and privacy of biometric data is a multifaceted field of growing interest. Valuable results have already been achieved in the field of cryptography in cryptographic key generation, for example [86], and in cancellable biometrics, where template protection has been accomplished by applying an intentional and repeatable modification to the original signature data, which should make it impossible, or computationally unfeasible, to obtain the original raw biometric data from the stored secure template [54].

Evaluation

Online signature verification systems are usually evaluated by analyzing their ability to accept genuine signatures and to reject forgeries. For this purpose, two types of error rates are considered: the type I error rate, which concerns the false rejection of genuine signatures (FRR – false rejection rate), and the type II error rate, which concerns the false acceptance of forged signatures (FAR – false acceptance rate). The equal error Rate (EER) has been widely considered as a measure of the overall error of a system. It is defined as the system error rate when FRR = FAR. More recently, the receiver operating characteristic (ROC) curve has also been considered for evaluating signature verification systems. Indeed, the ROC curve, which plots the FRR vs. the FAR, has several useful properties. The most important is the area under the curve (AUC) of the ROC, which can be used to estimate system performance by using a single value, since the AUC provides the probability that the classifier will rank a randomly chosen positive sample higher than a randomly chosen negative sample [47, 78].

However, it is worth noting that notwithstanding the numerous measures that have been proposed so far, performance evaluation still remains a very critical and complex task [78, 79]. In particular, FAR evaluation is difficult and generally imprecise, since the existence of skilled forgeries for a given signature is not certain, nor is the possibility of collecting good-quality forgery samples for the test. In fact, forgery quality strongly depends on the type and amount of information provided to the forger, as well as his or her training, effort, and ability [3]. In order to address this problem, different classes of forgeries have been considered [78]: *random* forgeries, in which the forger uses his/her own signature instead of the signature to be tested; *simple* forgeries, in which the forger makes no attempt to simulate or trace a genuine signature; and *freehand* or *skilled* forgeries, in which the forger tries and practices imitating as closely as possible the static and dynamic information of a genuine signature. Another attempt to grade forgery quality considers the following four categories [37]: an *accidental* forgery, which involves the use of arbitrary, non-authentic writing samples against some other reference; a *blind* attacker, who is a forger who only has a textual knowledge about the writing content; a *low-force* forgery, which occurs when the forger is in possession of an off-line representation of the signature image; and a *brute-force* attacker, who is a forger who has had the opportunity to observe the dynamics of the writing process of the victim. Of course, as demonstrated in a recent experiment, a significant degradation in the verification of online signatures can be observed as the quality of the forgeries that are used for the test increases [1].

In addition, the comparative assessment of the approaches proposed in the literature needs large, public signature databases and widely accepted protocols for experimental tests [70, 73]. Concerning public databases, it is worth noting that the development of a benchmark signature database is a time-consuming and expensive process. It involves not only scientific and technical issues, like those related to the statistical relevance of the population of individuals involved, as well as acquisition devices and protocols but also legal aspects related to data privacy and intellectual property rights. In contrast, since the development of benchmark databases is rightly recognized as a key aspect of the success and expanded usage of signature-based verification systems, specific efforts have recently been made to develop both unimodal benchmark databases (i.e., that contain only a single biometric trait of an individual) and multimodal ones (i.e., that contain two or more biometric traits of an individual). The Philips database [16, 73] contains 1,530 genuine signatures from 51 individuals and 3,200 forgeries. In this case, the acquisition process was carried out at a sampling rate of up to 200 Hz, and information on position, pressure, and "pen tilt" in the x and y directions were captured. This database divides forgeries into the following three categories: "over the shoulder," i.e., forgeries captured by the forger after seeing the genuine signature being written; "home improved," i.e., forgeries captured by the forger after having the opportunity of practicing the signature in private; and "professional," i.e., high-quality forgeries produced by experts. The BIOMET multimodal database [24] contains 2,201 signatures from 84 individuals: 1,252 genuine specimens and 949 forgeries. These signatures were acquired using an ink pen on a digitizing tablet at a sampling rate of 100 Hz. Information on position, pressure, and pen orientation (azimuth and altitude) are provided. Data acquisition occurred in two separate sessions. The MCYT database [69] is a bimodal database containing 16,500 online signatures, 8,250 of them genuine (produced by 330 individuals) and 8,250 skilled forgeries. Data acquisition was performed by a digitizing tablet at 100 Hz. The tablet captured the following information on the acquired signatures: position, pressure, and pen orientation (azimuth and altitude). The SVC2004 database [100] contains data from 1,600 signatures, 800 of them genuine specimens (produced by 40 individuals) and 800 forgeries. A 100 Hz sampling rate tablet was used for data acquisition. In order to help the forgers practice the signatures before producing the forgeries, a computer program was provided to them to enable them to visualize the writing sequence of the signature to be forged on a monitor. Information on position, pressure, pen orientation (azimuth and altitude), and pen-up/pen-down signals were recorded for each specimen. The BioSecure multimodal database [70] has two relevant datasets of online signatures: sub-corpus 2 (DS2) and sub-corpus 3 (DS3). DS2 contains data from 667 individuals acquired in two separate sessions using an ink pen on a digitizing tablet at a sampling rate of 100 Hz. The information obtained from the tablet included position, pressure, and pen orientation (azimuth and altitude). For each individual, 25 signatures (15 of them genuine and 10 forgeries) were collected in each session. DS3 contains the signatures of about 713 individuals. Signatures were acquired using a PDA at a frequency of 100 Hz. Each individual signs his/her name or another name using a touch pen while standing and keeping the PDA in his hand. For each signature, the acquisition device provides the position function and the elapsed time between the acquisitions of two successive points. For each individual and each session, 25 signatures (15 of them genuine and 10 forgeries) were collected. The Caltech database contains signatures acquired by a camera. About 25–30 genuine signatures and 10 forgeries from 105 individuals were collected [57].

Recently, in order to overcome the lack of online signatures, well-defined strategies for the generation of synthetic signatures have been considered. Two in particular have been proposed so far [22, 23]: (1) *synthetic sample generation*, in which well-defined transformations are used to generate synthetic samples from the real ones of a given individual – distortion-based techniques using elastic matching procedures [82] and variability estimation [18] have been proposed in the literature for this purpose – and (2) *synthetic individual generation*, in which a model of the signature produced by a population of individuals is created and new synthetic individuals can be generated by sampling the model – models based on spectral analysis [18] and Sigma-Lognormal parameters [21] have been considered for this purpose. Synthetic signatures have also been used for improving the enrolment procedure for a signature verification system [18] and for evaluating system resistance to brute-force attacks [21].

Finally, it is worth emphasizing that, to date, the characteristics of unimodal biometrics are not always considered adequate for large-scale deployment or for security critical applications, no matter which biometric trait is used. As a result, specific efforts are being made to incorporate multimodal biometrics into these applications. This addresses the problem of non-universality and is expected to achieve better performance than the unimodal approaches [22].

Concerning the definition of standards for experimental tests, international competitions are very important references for advancements in the field, since they provide common benchmark databases and testing protocols [100]. For instance, the Signature Verification Competition of 2004 (SVC2004), which considered signatures acquired by a digitizing tablet, demonstrated that signature verification systems are no less accurate than other biometric systems, like those based on facial features or fingerprints [89]. In addition, the competitions are designed to allow researchers and practitioners to systematically evaluate the performance of online signature verification systems not only for error rates but also for other parameters, like interoperability, processing speed, and security of data. In fact, the feasibility of a particular system in a specific operating environment should be determined by analyzing all these parameters. For instance, concerning system interoperability, in the Signature Evaluation Campaign of 2009 (BSEC'2009), two different databases were considered, each containing data from the same individuals that were acquired by a digitizing tablet and a PDA, in order to measure the impact of a mobile device on the performance of signature verification systems [70].

Online Signature Verification: A Comparative Analysis

Table 27.4 lists some online signature verification systems using distance-based classification techniques. In the approach proposed by Nakanishi et al. [60], the position signals of an online signature are decomposed into sub-band signals using the discrete wavelet transform (DWT), and Dynamic Programming was used for signature matching. Yeung et al. [100] reported the results of the First International Signature Verification Competition (SVC2004), in which teams from all over the world participated. SVC2004 considered two separate signature verification tasks using two different signature databases. The signature data for the first task contained position information only. The signature data for the second task contained position, pen inclination, and pressure information. In both cases, DTW-based approaches provided the best results. DTW was also used by Bovino et al. [4], who presented a multi-expert system based on a stroke-oriented description of signatures. Each stroke was analyzed in the position, velocity, and acceleration domain, and then a two-level scheme for decision combination was applied. For each stroke, soft- and hard-combination rules were used at the first level to combine decisions obtained by DTW from different representation domains. Simple and weighted averaging was used at the second level to combine decisions from different parts of the signature. Di Lecce et al. [11] performed signature verification by combining the efforts of three experts. The first expert used shape-based features and performed signature verification by means of global analysis. The second and third experts used speed-based features and a regional analysis. The expert decisions were combined by a majority voting strategy. Guru and Prakash [28] represented online signatures by interval-valued symbolic features. They used parameter-based features derived by a global analysis of signatures and achieved the best verification results when a writer-dependent threshold was adopted for distance-based classification. The system presented by Zhang et al. [103] used global, local, and function features. In the first verification stage, a parameter-based method was implemented, in which the Mahalanobis distance was used as a measure of dissimilarity between the signatures. The second verification stage

Table 27.4 System performances: distance-based techniques full database (*FD*), signature (*S*), genuine signatures (*G*), forgeries (*F*), random forgeries (*RF*), simple forgeries (*SF*), skilled forgeries (*SK*), and number of authors (*A*)

Matching technique	Main features	Database	Results	Reference
Dynamic Programming	Wavelet transform	**(Training)** 20(G) from(4(A)) **(Test)** 98 (G) (from 4(A)), 200(F) (from 5(A))	**EER**: 4 %	I. Nakanishi et al. [60]
DTW (best result)	**Task 1:** position **Task 2:** position, pen inclination (azimuth), pressure, etc.	**(Training)** 800(G)(20(G)x40(A)), 800(SK)(20(SK) x40(A)) **(Test 1)** 600(G)(10(G)x60(A)), 1200(SK)(20(SK) x60(A)) **(Test 2)** 600(G)(10(G)x60(A)), 1200(RF)(20(RF) x60(A))	**(Test 1) EER:** 2.84 % (Task 1) **EER:** 2.89 % (Task 2) **(Test 2) EER:** 2.79 % (Task 1) **EER:** 2.51 % (Task 2)	D.-Y. Yeung et al. [100] (1st Signature Verification Competition)
DTW (ME by simple averaging)	Position, velocity, acceleration	**(Training)** 45(G) (3(G) x 15(A)) **(Test)** 750(G) (50(G)x15(A)), 750 (F) (50(F)x15(A))	**EER**: 0.4 %	L. Bovino et al. [4]
DTW (ME by majority voting)	Shape-based features (segmentation dependent), velocity	**(Training)** 45(G) (3(G) x 15(A)) **(Test)** 750 (G) (50(G)x15(A)), 750 (F) (50(F)x15(A))	**FRR**: 3.2 % **FAR**: 0.55 %	V. Di Lecce et al. [11]
DTW	Velocity, pressure	**(FD)** 4600 (S)	**EER**: 4 %	K. Huang and H. Yan [32]
DTW (PCA, MCA)	Position, velocity	**(Training)** 405 (G) (5(G) x 81(A)) **(Test)** 405 (G) (5(G) x 81(A)), 405(F) (5(F) x 81(A))	**EER**: 5.00 %	B. Li et al. [52]
Distance-based	Total signature duration, number of pen-ups, STD velocity and acceleration in x and y direction, number of local maxima in x direction, etc.	**(FD1)** **(Training1)** 2000 (G) (20(G) x 100(A)) **(Test1)** 500 (G) (5(G) x 100 (A)), 9900 (RF) (99 (RF) x 100(A)), 500 (SK) (5(SK) x 100(A)) **(FD2) (Training2)** 6600(G) (20(G) x 330(A))	**(FD1)** **EER**: 3.80 % (Test 1 – SK) **EER**: 1.65 % (Test 1 – RF) **(FD2)** **EER**: 4.70 % (Test 2 – SK) **EER**: 1.67 % (Test 2 – RF)	D. S. Guru and H. N. Prakash [28]

(*continued*)

Table 27.4 (continued)

Matching technique	Main features	Database	Results	Reference
		(Test2) 1650 (G) (5(G) x 330(A)), 75570 (RF) (229(RF) x 330(A)), 8250(SK) (25(SK) x 330(A))		
Euclidean distance, Mahalanobis distance, DTW	Geometric-based, curvature-based	**(FD)** 306 (G), 302 (F)	**FRR**: 5.8 % **FAR**: 0 %	K. Zhang et al. [103]
Membership function	Total signature time, AVE/RMS speed, pressure, direction-based, number of pen-ups/pen-downs, etc.	**(Test)** 60 (G), 60 (F)	**FRR**: 6.67 % **FAR**: 1.67 %	T. Qu et al. [81]
Membership function	Speed, pressure, direction-based, Fourier transform	**(FD)** 1000 (G), 10000 (F)	**FRR**: 11.30 % **FAR**: 2.00 %	M. Zou et al. [104]
Dynamic similarity measure	Fourier transform (cepstrum coefficients)	**(Training)** 270(G) (from 27(A)) **(Test)** 560 (G) (from 27(A)), 650 (F)	**FRR**: 1.4 % **FAR**: 2.8 %	Q. Z. Wu et al. [97]
String matching	Velocity, curvature based	**(FD)** 1232 (S) (from 102 (A))	**FRR**: 3.3 % **FAR**: 2.7 % (common threshold) **FRR**: 2.8 % **FAR**: 1.6 % (writer-dependent threshold)	A. K. Jain et al. [40]

involved corner extraction and corner matching, as well as signature segmentation. In the third verification stage, an elastic matching algorithm was used, and a point-to-point correspondence was established between the compared signatures. By combining the three different types of verification, a high security level was reached. Zou et al. [104] used local shape analysis for online signature verification. Specifically, FTT was used to derive spectral and tremor features from well-defined segments of the signature. A weighted distance was finally considered, in order to combine the similarity values derived from the various feature sets. Fourier analysis was applied by Wu et al. [97] for online signature verification, as they extracted and used cepstrum coefficients for verification, according to a dynamic similarity measure. Jain et al. [40] used a set of local parameters which described both spatial and temporal information. In the verification process, string matching was used to compare the test signature to all the signatures in the reference set. Three methods were investigated to combine the individual dissimilarity values into one value: the minimum, average, and maximum of all the dissimilarity values. Common and personalized (signer-dependent) thresholds were also considered. The best results were achieved by considering the minimum of all the dissimilarity values combined with personalized threshold values.

Table 27.5 reports some online signature verification systems using model-based classification techniques. M. Martinez-Diaz et al. [56] presented a Left-to-Right HMM-based signature verification system for handheld devices. Signatures were captured by a PDA and described by the position function only. The best results were achieved by user-dependent HMM [56]. Igarza et al. [34] also used a Left-to-Right HMM for online signature verification and demonstrated its superiority over Ergodic HMMs. The superiority of Principal Component Analysis and Minor Component Analysis for online signature verification over DTW and Euclidean-based verification was also investigated and demonstrated by Igarza et al. [35]. The online signature verification system proposed by Kashi et al. [42] used a Fourier transform-based normalization technique and both global and local features for signature modeling. The global features captured the spatial and temporal information of the signature, and the local features, extracted by a Left-to-Right HMM, captured the dynamics of the signature production process. The verification result was achieved by combining the information derived by both global and local features. Muramatsu and Matsumoto [58] used HMM-LR to incorporate signature trajectories for online signature verification. Individual features were extracted as high frequency signals in sub-bands. The total decision for verification was carried out by averaging the verification results achieved at each sub-band. Ortega-Garcia et al. [68] presented an investigation of the ability of HMM-LR to model the signing process, based on a set of 24 function features (8 basic function features and their first and second derivatives). In Shafiei and Rabiee's system [85], each signature was segmented using its perceptually important points. For every segment, four dynamic and three static parameters were extracted, which are scale and displacement invariant. HMM was used for signature verification. Wessels and Omlin [91] combined a Kohonen self-organizing feature map and HMM. Both Left-to-Right and Ergodic models were considered. Yang et al. [99] used directional features along with several HMM topologies for signature modeling. The results demonstrated that HMM-LR is superior to other topologies in capturing the individual features of the signatures while at the same time accepting variability in signing. A polar coordinate system was considered for signature representation by Yoon et al. [101], whose aim was to reduce normalization error and computing time. Signature modeling and verification were performed by HMMs, which demonstrated their ability to capture the local characteristics in the time sequence data, as well as their flexibility in terms of modeling signature variability. Lee et al. [49] performed signature verification by

Table 27.5 System performances: model-based techniques full database (*FD*), signature (*S*), genuine signatures (*G*), forgeries (*F*), random forgeries (*RF*), simple forgeries (*SF*), skilled forgeries (*SK*), and number of authors (*A*)

Matching technique	Main features	Database	Results	Reference
HMM	Position	**(FD)**1000(G) (20(G) x 50(A)), 1000(SK) (20(SK) x 50(A)), **(Training)** 250(G) (5(G) x 50(A)) **(Test)** 750(G) (15(G)x50(A)), 2450 (RF) (49(RF) x 50(A)), 1000 (SK) (20(SK) x 50(A))	**EER**: 5.2 % (with **RF**) **EER**: 15.8 % (with **SF**)	M. Martinez-Diaz et al. [56]
HMM	Direction of pen movement, etc.	**(FD)** 3750 (G) (25(G)x150(A)), 3750 (F)	**EER**: 9.253 %	J. J. Igarza et al. [34]
HMM	Total signature time duration, X-Y (speed) correlation, RMS speed, moment-based, direction-based, etc.	**(Test)** 542 (G), 325 (F)	**EER**: 2.5 %	R. S. Kashi et al. [42]
HMM	Direction of pen movements	**(Training)** 165 (G) **(Test)** 1683 (G), 3170 (SK)	**EER**: 2.78 %	D. Muramatsu and T. Matsumoto [58]

HMM	Position, velocity, pressure, pen inclination (azimuth), direction of pen movement, etc.	**(Training)** 300(G) (from 50(A)) **(Test)** (450 (G) (from 50(A)), 750 (SK) (from 50(A))	**EER**: 1.21 % (global threshold) **EER**: 0.35 % (user-specific threshold)	J. Ortega-Garcia et al. [68]
HMM	AVE speed, acceleration, pressure, direction of pen movement, etc.	**(FD)** 622 (G) (from 69(A)), 1010 (SK)	**FRR**: 12 % **FAR**: 4 %	M. M. Shafiei and H. R. Rabiee [85]
HMM	Position, pressure, direction of pen movements, pen inclination	**(Training)** 750 (G) (15(G) x 50(A)) **(Test)** 750 (G) (15(G) x 50(A))	**FAR**: 13 %	T. Wessels and C. W. Omlin [91]
HMM	Direction of pen movements	**(FD)** 496 (S) (from 31 (A))	**FRR**: 1.75 % **FAR**: 4.44 %	L. Yang et al. [99]
HMM	Position	**(Training)** 1500 (S) ((15 (S) x 100 (A)) **(Test)** 500(S) (5 (S) x 100 (A))	**EER**: 2.2 %	H. S. Yoon et al. [101]
NN (with DP)	Position (geometric extrema), AVE velocity, number of pen-ups, time duration of neg/pos. velocity, total signing time, direction-based, etc.	**(FD)** 6790 (S) (from 271(A))	**EER**: 0.98 %	J. Lee et al. [49]

means of a backpropagation neural network, which integrated verification results at segment level, using a bottom-up strategy. They performed signature segmentation by means of a DP technique based on geometric extrema. Segment matching was performed by global features and a DP approach.

As Tables 27.4 and 27.5 show, experimental results achieved with small-to medium-sized [42] and large [68] datasets demonstrate the superiority of model-based approaches over distance-based approaches. HMMs in particular are highly adaptable to personal variability and are very effective compared to other techniques for online signature verification [87]. It is worth noting that system performances are generally overestimated in the literature, since they were obtained from laboratory tests, which usually involve very controlled writing conditions and poor forgeries produced by researchers [72]. In addition, laboratory tests do not generally consider long-term variability, which can significantly reduce the estimated performance of online signature verification systems [50].

Conclusion

Today, interest in online signature verification continues to grow, along with the increasingly stringent security requirements of a networked society. In fact, the handwritten signature is still one of the most widely accepted of the biometric traits, and automatic signature verification is generally welcomed as a noninvasive and nonthreatening process.

This chapter has presented an overview of online signature verification. In it, the fundamental aspects of the neuromuscular model underlying the signing process were addressed, as well as the main issues related to the design of an automatic signature verification system. Some of the most relevant state-of-the-art research was discussed and the most valuable results were summarized. In addition, a few of the most promising directions for research in this field were highlighted. In the near future, signature verification systems will be expected to operate in new working scenarios with specific constraints and challenging objectives. The net result will be that new research problems and challenges will emerge, and traditional and fundamental points of view will take on new meanings.

For instance, as the number of input devices and techniques for handwriting acquisition increases, device interoperability will become a more relevant issue and require investigation. Signature capture by both fixed and mobile devices will become feasible in many everyday environments, and automatic signature verification will be used in even more applications.

Analysis of the individual characteristics of handwriting remains an interesting research area and should encompass not only the features produced by people with normal abilities but also those generated by people with disabilities and illnesses that constrain their handwriting abilities. Investigation of the human mechanisms involved in handwriting production is therefore deserving of greater attention, as well as studies on the feature selection techniques and signature modeling methods that produce the best possible description of the personal characteristics involved in signing. Techniques for analyzing signature complexity and stability can offer new insights into the selection of the most useful signature fragments and features for various kinds of applications and also to better understand time-based variations in signing.

Even though very effective model-based and distance-based matching techniques have been proposed, signature verification accuracy still needs to be improved significantly. This will require further effort in terms of the adaptability and personalization of verification processes. Multi-expert systems can also play an important role, since they can combine decisions obtained through top-down and bottom-up strategies, using matching algorithms at both the global and the local levels. The multi-expert approach also represents an important area for further research, with a view to using multimodal biometrics in signature verification, as their performances are expected to be superior to those of the unimodal approaches.

In addition, it will be important to develop this field of research in the direction of real applications, strictly in terms of the need to have benchmark databases available to a wide research community, in order to enable comparative evaluation of signature verification systems under different application scenarios. Such efforts are also necessary to support the development of fully interoperable systems, which take into consideration signature variability over time, as well as to build large databases for multicultural and multi-language signature verification systems which consider metadata information.

Finally, in order to advance the integration of automatic signature verification into a wide range of applications as soon as possible, specific attention should be paid to the issues of personal privacy and the protection of personal signature data, along with a clear definition of legal and regulatory norms for the identification of individuals by means of their handwritten signature.

Many of these new challenges will require to go out of the beaten tracks. On the one hand, it is expected that new investigations will be based on various pattern recognition paradigms that have not been fully exploited yet: fuzzy logics, evolutionary algorithms, particle swarm systems, and immune systems, to name a few, as well as their hybrid combinations, for example, fuzzy particle swarm optimization, and neuro-swarm systems. It is far from being clear for the moment how these techniques could be adapted to the various problems and challenges described in the present chapter, neither which of these will be practically efficient in designing new systems. On the other hand, it is also expected that as biometric security systems using the handwritten signatures will become ubiquitous, the biometric analysis of signatures for developing identification systems that can discriminate the health conditions rather than the identity of a subject might become a brand new research field. So far such studies have been focused on the analysis of handwriting [53,65,66,88,93,98], but a preliminary study [67] dealing with the use of signatures to detect brain stroke risk factors is under way and looks very promising. As for many other challenges addressed in this handbook, the best has yet to come.

Description of Consolidated Software and/or Reference Datasets

The following is a brief list of reference databases containing online signatures:

- BIOMET [24]
- BioSecure [70]
- Caltech [57]
- MCYT [69]
- Philips [73]
- SVC2004 [100]

Cross-References

►Datasets and Annotations for Document Analysis and Recognition
►Online Handwriting Recognition
►Sketching Interfaces

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