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A Perspective Analysis of Handwritten Signature Technology

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Handwritten signatures are biometric traits at the centre of debate in the scientific community. Over the last forty years, the interest in signature studies has grown steadily, having as its main reference in the application of automatic signature verification, as previously published reviews in 1989, 2000 and 2008 bear witness. Ever since, and over the last ten years, the application of handwritten signature technology has strongly evolved and much research has focused on the possibility of applying systems based on handwritten signature analysis and processing to a multitude of new fields. After several years of haphazard growth of this research area, it is time to assess its current developments for their applicability in order to draw a structured way forward. This perspective reports a systematic review of the last ten years of the literature on handwritten signatures with respect to the new scenario, focusing on the most promising domains of research and trying to elicit possible future research directions in this subject.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Security and privacy** → **Biometrics**; Access control; • **Theory of computation** → *Pattern matching*; • **Applied computing** → **Document analysis**; System forensics;

Additional Key Words and Phrases: Off-line and On-line handwritten signature, automatic signature verification, biometrics, surveys

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1 INTRODUCTION

During the last 40 years, a number of comprehensive surveys and state-of-the-art reviews in automatic signature verification (ASV) [171] have been published. Among a large number of papers, a couple of relevant academic articles have had a strong impact. One of the first state-of-the-art papers in this field was published in 1989 by Plamondon and Lorette [215]. Approximately ten years later, Plamondon and Srihari published another survey [219]. In a similar span of time, Impedovo and Pirlo [124] published a comprehensive survey in 2008.

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From this perspective, it can be deduced that 10 years is an acceptable period of time to make a substantial upgrade to the automatic signature verification state-of-the-art. With this in mind, we review the technology in this article, taking into account the novel advances and emerging issues of ASV in the last ten years, from 2008 up to now.

Moreover, shorter state-of-the-art papers have been published, mostly in conference proceedings or book chapters (e.g. [57, 80, 112, 127, 197]), further explaining specific advances in signature verification and also pointing out several research directions and milestones. The scope of the present manuscript aims at a wider breadth of consideration as compared with the published reviews in conferences or book chapters.

In fact, the spreading of low-cost technologies for handwriting acquisition and processing (PDA, tablet, smartphones, etc.), the excellent results obtained in a multitude of research on handwritten signature analysis and processing and the high acceptability for daily use of the signature for authentication (many countries have articulated legal procedures for using them), allows us to look at the handwritten signature as a biometric trait supporting a multitude of applications in several domains. Starting from this consideration, the aim of this paper is, on the one hand, to introduce a systematic review of the advancement of research in the last decade in the field of handwritten signature analysis and processing, with respect to both traditional applications and new application domains.

On the other hand, the use of the handwritten signature, in many cases worldwide, is mandatory. It has a double legal importance: first it establishes the identity of a person; second it states the intention of that person. Sometimes more than a handwritten signature is required, such as a signature in the presence of a public notary or lawyer. So far its use is well recognized by administrative and financial institutions [259] and it is well accepted [124].

The General Data Protection Regulation (GDPR2018) establishes the new rules for Personal Data processing within the EU as well as for their use outside the EU borders. GDPR2018 is expected to impact on the biometric research field. In fact, in the GDPR context, biometric data are considered a special category of personal data (article 9): processing of biometric data is prohibited until the subject has given explicit consent or it is authorized by law (article 9, par. a & b). Moreover, since the processing of such personal data implies high risks, a data protection impact assessment is required (article 35). A deep insight regarding the implications of the GDPR in respect of research activities can be found in [36], and also with respect to novel applications of signatures [217]. It appears quite clear that the assessment of the consent form for the acquisition phase is a non-trivial problem as well as the one of acquiring a licence agreement for research data set release.

1.1 Classical Scheme of Automatic Signature Verification

A typical ASV scheme is illustrated in Figure 1. When an individual signs into an ASV system a particular tool (e.g. pen and paper) is used and a sensor S_i typically digitizes the sample. There are a large number of possible sensors for digitizing the signature, e.g. a scanner, a digital tablet, a PDA, a mobile phone and even a specialized pen. In addition to capturing the signature, some perturbations usually affect the acquired sample. The perturbations are external factors which refer to the tool used to sign, the posture of the individual, the jewellery worn or environmental changes, such as background noise, or sensor limitations, including resolution or sample rate.

Another factor which modifies the signature sample during the repetitions is intra-personal variability. Intra-personal variability means the dissimilarity between signatures executed by the same writer. It is an internal factor, which might refer to the emotions, stress, tiredness, alcohol or drug influences, neuromotor conditions, biological aging effects, cognitive-motor impairment and other factors as a consequence of the individual's mood, the time available to write the signature or the willingness to cooperate. Therefore, we can describe a measured signature as the sum of external and internal perturbations \hat{v}_i over the execution of the signature action plan learned over the years through practice.

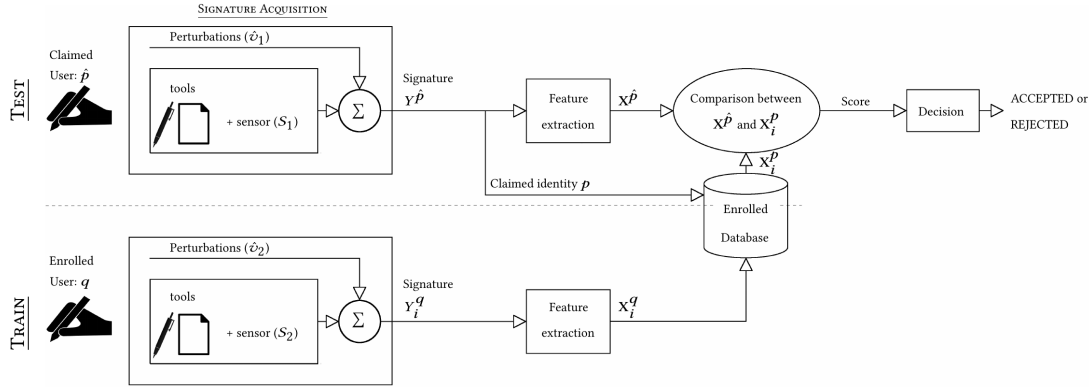


Fig. 1. Typical scheme of an Automatic Signature Verifier (ASV)

In an ASV, there are two operating modes: training and testing. In the training mode, a genuine user, let's say q , provides one or several repetitions of his signature, denoted as Y_i^q . These signatures are parameterized and their parameters, X_i^q , are stored in a database. In the testing mode, the ASV builds a feature matrix ($X^{\hat{p}}$) from questioned user \hat{p} 's signature $Y^{\hat{p}}$. Since this questioned user claims to be a previously enrolled subject p , a comparison of the signature's parameters $X^{\hat{p}}$ and the signatures' parameters X_i^p of enrolled user p is worked out. As a result, a score is obtained. Finally, the ASV makes a decision by accepting or rejecting the claimed hypothesis of $\hat{p} = p$, usually based on a decision threshold. Figure 1 shows these stages using this nomenclature.

Beyond the intra-personal variability, the greatest challenge faced by ASV systems is the unpredictable inter-personal variability. This means the similarity between signatures executed by different writers. Inter-personal variability can be reduced by faking the identity of signers through three main kinds of forgeries: (1) *Random Forgeries (RF)*: This is the situation in which an impostor, without previous knowledge of a specific signature, tries to verify the identity of a signer by using his own genuine signature. (2) *Simple Forgery (SF)*: This occurs when the forger knows the writer's name, but has no access to a sample of the signature. Its importance in signature verification depends on the country of origin of the signature style. In some countries, many people sign simply by writing their own name and surname, whereas in other countries signers design illegible signatures with complex flourishes or rubrics. (3) *Skilled Forgeries (SK)*: These are produced by an impostor who has learned the signature of his or her victim and tries to reproduce it with a similar intra-class variability. The test for this type of forgery is the most relevant in signature verification.

Additionally, it is worth mentioning that there are two modalities in signatures: (1) *Off-line (or static) signatures*: here the signature information is typically contained in a scanned image where the inked signature is deposited on a piece of paper through the use of a tool held in the hand like a pen or pencil, among others. (2) *On-line (or dynamic) signatures*: their main characteristic is that they contain the temporal and dynamic order in which the signer executed the signature. To register this kind of signature, a device such as a digitizing tablet is required.

Although all the ASV systems operate according to the general scheme illustrated in Figure 1, the strategy for extracting the features and producing the final classification is generally different between on-line and off-line systems. Nevertheless, to test an ASV, a meaningful statistical signature database is required in both cases.

The paper is organized as follows: Section 2 discusses aspects related to handwritten signature databases, which have become a crucial aspect of the research. Best practices in automatic signature verification are discussed in Section 3.

In Section 4, a summary of the main competition results is reported by highlighting the state-of-the-art in the field. The forensic aspects related to signature analysis are discussed in section 5. Some of the most promising new research directions are addressed in Section 6. Section 7 concludes on a positive and optimistic note regarding the future of this technology.

2 DATABASES

Handwritten signatures are the product of a complex human process. There are, therefore, innumerable variables and parameters which cannot be represented in a single signature database of a practical size. ASVs typically model the peculiarities in the signatures found in a particular signature database and this limits their applicability. This effect probably leads to biased results since not all human behaviour is taken into account in the data sets.

As such, the challenge is not only to improve the state-of-the-art results with current databases, but to develop incremental signature databases, which consider more and more examples of human behaviour: temporal evolution, aging, posture, emotions, multi-scripts, collection devices, user skills in using new devices, occlusions (e.g. lines, printed or handwritten text or stamps), and so on. As more aspects and conditions of human behaviour are considered, the ASV algorithm is tested more realistically. For a reliable test of current and forthcoming algorithms, large projects to collect huge handwritten signature databases or open government data initiatives are needed.

These real databases must be built according to ethical aspects such as the privacy of the donors. This issue hinders the acquisition of the signatures (the signers should be asked to sign an agreement) and database maintenance (the signers should have the right to remove their signature from the database at their convenience). To alleviate this problem, an alternative has been to develop databases with disguised genuine signatures, where the signers invent a pretended genuine signature (e.g. [141, 272]). The main consideration of these signatures is that the donors have not over-learned the trajectory of their own signatures. Such lack of learning leads to the generation of genuine signatures with unrealistic properties (e.g. poor kinematic properties).

Another interesting solution is the development of synthetic signature databases which allow the integration of a large number of users under a wide variety of situations. In this case, studies of the human neuromotor system are necessary to design a human-like synthesizer. Obviously, synthetic databases can be useful until an equivalent real database is developed.

We present below a list of publicly available databases, give a description of their common limitations and point out the best practices to use such signature databases in automatic signature verification.

2.1 Most Popular Publicly Available Handwritten Signature Databases

There is a long list of signature databases used in research. In this paper, we have included most publicly available corpuses since they are more accessible for creating common benchmarks and for comparing results. These signature databases are listed in Table 1. Beyond pointing out some characteristics of each database, we have also included a similar description of some databases often reported in some studies but which are not freely distributed at this time. A controversial aspect to take into account is the way to label the types of forged signatures in the databases. As previously mentioned, depending on the research project, the forgeries can be referred to as skilled forgeries [16] or deliberate forgeries [75] or disguise [151] or random or impostor signatures [101] or simulated or highly skilled forgeries [192]. This nomenclature suggests a categorization of the degree of closeness to genuine signatures. It is worth pointing out that the majority of databases have been collected in laboratories. This implies that the forgeries are typically produced by non-professional forgers but by volunteers like students or other staff.

Table 1. Description of the most common handwritten signature databases

Corpus	Modality	Script	Characteristics	Distinction
Common publicly available off-line signature databases				
MCYT-75 [81, 192]	Off-line	Western	G:1125, F:1125, W:75	Taken in two sessions
CEDAR [135]	Off-line	Western	G:1320, F:1320, W:55	
4NSigComp2010 [153] (Scenario 1)	Off-line	Western	G:113, F:194, D:27 W:2	300dpi, BMP
4NSigComp2012 [151]	Off-line	Western	G:113, F:273, D:64, W:3	300dpi, BMP
SigWlcomp2015 [161]	Off-line	Western (Italian)	G:479, F:249, W:50	Taken in several sessions
Tunisian SID-Signature [2]	Off-line	Tunisian	G:6000, F:4000, W:100	300dpi. Collected in different sessions
SigWlcomp 2015 [161]	Off-line	Bengali	G:240, F:300, W:10	
Off QU-PRIP [6]	Off-line	Arabic	G:12000, W:1017	600dpp. JPEG. Several nationalities
UTSig [242]	Off-line	Persian	G:3105, F:4830, D:345, W:115	
PHBC [5]	Off-line	Persian	G:1000, F:200, W:100	300dpi, tiff
BHSig260 [193]	Off-line	Bengali	G:2400, F:3000, W:100	
BHSig260 [193]	Off-line	Devanagari	G:3800, F:4800, W:160	
Common publicly available on-line signature databases				
MCYT-100 sub-corpus [81, 192]	On-line	Western	G:2500, F:2500, W:100	This is a subset of on-line MCYT-330.
SUSIG-Visual sub-corpus [141]	On-line	Western	G:1880, F:940, W:94	
SUSIG-Blind sub-corpus [141]	On-line	Western	G:820, F:880, W:88	Volunteers did not see visual feedback while signing
SG-NOTE database [168]	On-line	Western	G:500, W:25	Taken in two-sessions
e-BioSign-DS1-Signature DB [247]	On-line	Western	G:520×5, F:390×5, W:65×5	5 different writing tools (stylus and finger). Taken in two-sessions
BSEC 2009 [120]	On-line	Western	G:6480, F:4320, W:432	Taken in two sessions. Digitizing tablet and a PDA.
SigWlcomp 2015 [161]	On-line	Western (German)	G:450, F:300, W:30	
MOBISIG database [14]	On-line	Western (Hungarian)	G:3735, F:1660, W:83	Finger-drawn signatures. Donors did not use their real signature
Signature Long-Term DB [95]	On-line	Western	G:1334, W:29	Acquisition in a 15 month time span
SVC-Task1 sub-corpus [272]	On-line	Chinese and English	G:800, F:800, W:40	Only dynamic trajectory. Donors did not use their real signature
SVC-Task2 sub-corpus [272]	On-line	Chinese and English	G:800, F:800, W:40	Pressure and pen inclination. Donors did not use their real signature
NDSD [268]	On-line	Persian	G:3575, F:2200, W:55	Taken in two sessions, professional forgers
Common publicly available dual on-line and off-line signature databases				
BiosecurID-SONOF [91]	On- and off-line	Western	G:2112×3, F:1584×3, W:132×3	Taken in four sessions. Real on/off and synthetic off data
NISDCC database [8, 28]	On- and off-line	Western	G:1200×2, F:600×2, W:100×2	Real on/off data
Synthetic MCYT-300 [75]	On- and off-line	Western	G:8250×2, F:8250×2, W:330×2	Imitation of the performance and appearance of [192]
Synthetic BiosecureID-UAM [75]	On- and off-line	Western	G:2112×2, F:1584×2, W:132×2	Imitation of the performance and appearance of [91]
Synthetic NISDCC [75]	On- and off-line	Western	G:1200×2, F:600×2, W:100×2	Imitation of the performance and appearance of [8, 28]
Synthetic SVC2004 [75]	On- and off-line	Western	G:1600×2, F:1600×2, W:80×2	Imitation of the performance and appearance of [272]
Synthetic SUSIG-Visual [75]	On- and off-line	Western	G:1880×2, F:940×2, W:94×2	Imitation of the performance and appearance of [141]
Synthetic SUSIG-Blind [75]	On- and off-line	Western	G:820×2, F:880×2, W:88×2	Imitation of the performance and appearance of [141]
SigComp2009 [28]	On- and off-line	Western	G:1260×2, F:2613×2, W:112×2	NISDCC and NFI datasets
SigComp2011 [152]	On- and off-line	Western (Dutch)	G:3162×2, F:1491×2, W:128×2	400 dpi, PNG
SigWiComp2013 [162]	On- and off-line	Western (Dutch)	G:270×2, F:972×2, W:27×2	
SigComp2011 [152]	On- and off-line	Chinese	G:946, F:1598, W:40	400 dpi, PNG
SigWiComp2013 [162]	On- and off-line	Japanese	G:2604×2, F:2232×2, W:62×2	
Off/On QU-PRIP [6]	On- and off-line	Arabic	G:1164×2, D:582×2, F:200×2, W:194×2	Mostly Arabic donors
SIGMA. Malaysian [3]	On- and off-line	Malaysian	G:6000×2, F:2000×2, W:265×2	Taken in three sessions
Synthetic OnOff SigBengali-75 [47, 74]	On- and off-line	Bengali	G:24×2, W:75×2	Imitation of the performance and appearance of [74]
Synthetic OnOff SigHindi-75 [74]	On- and off-line	Devanagari	G:24×2, W:75×2	Imitation of the performance and appearance of [74]
Common non publicly available databases				
4NSigComp2010 [29] (Subset of GPDS960 [257] - Scenario 2)	Off-line	Western	G:9600, F:1200, W:400	300dpi, BMP
GPDS-960 Signature DB [29, 78, 257]	Off-line	Western	G:21144, F:26430, W:881	Current database contains 881 users
GPDS-300 Signature DB [29, 78, 257]	Off-line	Western	G:7200, F:9000, W:300	This is a subset of GPDS960 database
Brazilian (PUC-PR) [89]	Off-line	Western	G:6720, F:2280, W: 168	
MCYT-330 [81, 192]	On-line	Western	G:8250, F:8250, W:330	Two-sections. Fingerprints and signatures from the same donors
BiosecurID [79]	On-line	Western	G:6400, F:4800, W:400	Taken in four sessions.

Number of G: genuine, F: forgery, D: disguised, W: writers

In Table 1 we can observe that the majority of corpuses belong to Western scripts. However, other scripts have been also considered in the literature. Although they are not as large as the Western corpuses, we can find databases in Malaysian [3], Arabic [6], Bengali [47, 74], Devanagari [74], Persian [98], Chinese [152] and Japanese [162]. It is worth pointing out that these databases are typically collected in the off-line mode. It is expected that the development of real dynamic signature databases in non-Western scripts will introduce stimulating and novel findings in automatic signature verification.

2.2 Considerations on Handwritten Signature Databases

Signature databases are supposed to gather realistic intra-class and inter-class variability with all their specimens. Although many designers have made great efforts in approaching such reality in their corpuses, signatures are generally executed according to the willingness of the donors. Parental authorization for underage, signing a large quantity of documents, signing an employment contract, signing in an awkward or uncomfortable way or the use of different stylus devices to sign, are a few situations where the context and the motivation to sign could dramatically affect the intra-class variability. In addition to failing to reproduce this intra-class realism in public signature databases, further considerations are highlighted in the following.

2.2.1 General Considerations in Database Development. Signature databases are not subject to Quality Assessment (QA) regarding the limitations in capturing intra-class and inter-class variability. Further factors such as the emotions of the signers, the temporal evolution of children or adults [95, 147], behavioural disorders, neurodegenerative diseases or other cognitive impairments in fine motor control [265] are not easily introduced in the current corpuses. Moreover, size limitation results in the difficulty of carrying out statistically meaningful validation and performance evaluation. Also, as in any biometric trait, data protection law is the main limiting factor to sharing the signatures freely among the research community, even though research is the only motivation. In addition, human mistakes, such as the mislabelling of specimens, could introduce a bias in the evaluation of algorithm performance.

2.2.2 General Considerations in Off-line Database Development. Off-line signatures are recorded from paper sheets. Often, static signatures can overlap the space available for another signature, e.g. signatures signed in a sheet, divided into several boxes [257]. In such a case, some signatures could cross the box borders or even overlap other signatures. Because of this effect, some signatures are manually discarded during the development of the database, although they should possibly be kept for the sake of realism. Low resolution scanning can lead to poor image quality. Obviously, the higher the resolution, the more information can be extracted for image processing. 600 dots per inch (dpi) is the average resolution found in off-line signature databases. There are further external factors that can limit the performance, such as noise in the imaging system, type of sensor used, blurring in the greyscale images, deficient ink deposition on the paper, etc.

2.2.3 General Considerations in On-line Database Development. Some inconsistencies can be observed in the sampling rate. Although the data from a digitizing tablet may indicate that the sampling rate is, for instance, 100 Hz, the time stamp, which is commonly used, may not reflect such a sampling rate during the whole signature acquisition. The velocity profile sometimes shows discontinuities during the transition from pen-down to pen-up. Such discontinuities could be attributed to inconsistencies in the device used, e.g. when the pen loses contact with the tablet.

2.2.4 General Considerations in On-line and Off-line Database Development, Simultaneously Acquired. To capture simultaneously on-line and off-line signatures, a piece of paper is usually placed over the digitizing tablet (e.g. [74, 75]).

Table 2. Most popular algorithms for ASV used during the last ten years.

Preprocessing	Techniques
- Enhancement	Background removal [48]**, filtering noise [52, 53, 83]*, printed text removal [78]**, Morphological operations [273]**, ...
- Size normalization	Cropping [48, 98, 273]**, fixed area [251]*, [50, 210]**, length equalization [207, 268]*, alignments [251, 268]* [273]**, ...
- Structural	Skeleton-based [279]**, ...
- No preprocessing	[82]*, ...
Features	Techniques
- Function-features	Position [102, 247]*, velocity [52, 53, 247]*, acceleration [83]*, pressure [56, 91]*, pen direction [228, 247]*, length [236]*, pen inclination [118, 150]*, ...
- Global parameters	Number of strokes/lognormals [83, 249]*, mathematical transformations (Wavelet [98, 201, 203, 204]*, Radon [269]*, fractal [84]**, or others like total number, mean and maximum of intra/inter-stroke intersections, the number of X-axis, zero-crossings and the signature length [81, 91, 93, 155, 203, 247, 251]**), symbolic representation [7]*, code-vectors [235]*, Sigma-Lognormal-based [83, 102]*, ...
- Component-oriented	Geometric [48, 230]**, energy [182]**, stroke thickness [130]**, directions [224]**, curvature [22]**, graphometric [22]**, ...
- Pixel-oriented	Keypoints (SIFT [45]**, SURF [164]**, BRISK [61]**, KAZE [185]**, FREAK [160]**), run-length [30]**, texture [256]**, quad-tree [233]**, grid-based [279]**, shadow-code [66, 224]**, ...
Verifiers	Techniques
- Template Matching	Dynamic Time Warping (DTW) [52, 82, 83, 102, 141, 177, 235–237]*, Manhattan [228]*, Direct Matching Points [207]*, Euclidean [98, 230]**, ...
- Statistical measures	Mahalanobis [247]*, [139]**, membership functions [42]**, [12]*, [7]**, cosine [209]**, ...
- Statistical models	Neural Networks (NN) [145] and Deep Learning (Recurrent Neural Networks (RNN) [4, 146, 248]*, Convolutional Neural Networks (CNN) [269]*, [11, 46, 110, 111, 140]**, Deep Neural Networks (DNN) [221]**, Deep Multitask Metric Learning (DMML) [241]**, DCGANs [276]**), Hidden Markov Models (HMM) [15, 72, 158, 252]*, [48, 74]**, Support Vector Machine (SVM) [103]*, [54, 56, 76, 104, 199, 275]**, Random Forest [204]*, ...
- Structural	Decision Tree [210, 224]**, graph models [206]**, [264]**, ...
- Fusions	Ensemble of classifiers [21, 22]**, [125]*, template level [91]**, score level [237, 251]*, [91]*/*, ...

**off-line signatures, *on-line signatures

Thus the same signature is collected for the two modalities without scale or rotation variation between them. However, small movements between the paper and the tablet could introduce small and non-linear distortions in some parts of the signatures. Because of such limitations in both off-line and on-line signature databases, the accuracy of a system could be correlated to the database used. One possibility for avoiding incorrect conclusions is to use as many signature databases as possible without adapting the ASV to each database. This should lead to evaluating the accuracy of a system for different cases of intra-class and inter-class variability, thus avoiding over-fitting between a system and a database.

3 AUTOMATIC SIGNATURE VERIFICATION: A SUMMARY OF BEST PRACTICES

Automatic Signature Verification can be considered a two-class problem where the target is to decide whether a signature belongs to an enrolled individual or not. Although this challenge has been taken up in the past [124, 215, 219], many new algorithms and verification techniques have been reported in the last ten years. ASV consists mainly of the pre-processing, feature extraction and verification stages. For examples of the latest developments, see Table 2 which shows a non-exhaustive list of some of the most relevant algorithms for each stage.

At the pre-processing stage, the aim is to enhance the signature through image and signal processing techniques for static and dynamic signatures. At the feature extraction stage, the techniques can be divided into function-based features, which use the timing information in the signature; global parameters which describe particular aspects of a signature (e.g. loops or baselines [143]); component-oriented features which focus on particular characteristics, such as a pen-ups or pen-downs; and pixel-based techniques. At the verification stage, various strategies, some quite classical, are described in the recent literature. For example, Dynamic Time Warping (DTW) [52, 82, 83, 102, 141, 177, 235–237] or Support Vector Machines (SVMs) [54, 56, 76, 104, 199, 275]. However, Deep Learning [4, 11, 46, 110, 111, 140, 146, 221, 241, 248, 276] seems to be one of the hot topics in ASV. It is worth pointing out that most biometric systems are nowadays based on deep learning approaches [23]. Furthermore, fusion approaches have also been popular in recent years, such as ensembles of classifiers [21, 22].

In the early research in signature verification, most of the systems reported in the literature were developed and evaluated for Western languages. Successively, Chinese and Japanese signatures were considered and in recent years,

along with the increasing size of the community working on this topic, a number of systems specialized in performing verification of signatures written in different scripts, such as Arabic, Persian, Hindi, and Bengali, have been described. Signature verification systems developed for different scripts can use similar approaches but, more frequently, they differ since they try to capture some specific characteristics of the particular script. In fact, although the general model underlying the signature generation process is invariant in terms of cultural habits and language differences between signers, the enormous diversity in the signatures of people from different countries has led to the development of script specific solutions. For instance, in some countries, the habit is to sign with a readable, written name, whereas in other countries signatures are not always legible. As the need for cross-cultural applications increases, it is more and more important to evaluate both the extent to which the personal background affects signature characteristics and the accuracy of the verification process. In order to emphasize the efforts of the scientific community in adapting systems to different scripts, this Section is organized on a script basis.

First of all, Table 3 gives an overview per script of the best system performance achieved with random (RF) and skilled forgeries (SK), taking into account the algorithm used, the number of genuine reference signatures (#T) per user and the databases most used in the previous decade.

3.1 Western Signature Verification Systems

For *off-line signatures*, we can find either writer-dependent proposals [166], which build a mathematical model per writer, or writer-independent proposals [113], which develop a unique model in the ASV. One was a set of global features based on the boundary of a signature, such as its total energy, the vertical and horizontal projections and the overall box size in which the signature is contained [182]. Also, in [230] a system based on simple geometric features is presented, with results similar to some others [124, 215, 219]. In this work a centroid feature vector was obtained, for each user, from a set of genuine samples. The centroid signature was then used as a template for verifying a claimed identity, through a Euclidean distance based approach and by using a localized threshold.

Other authors focused on the global image level and measured the grey level variations in the signature strokes by identifying statistical texture features [256]. In [224], a multi-feature extraction method was proposed which allows one to extract a range of global to very local features by varying the scale of a virtual grid used to partition each signature image. The signature can also be described by a quad-tree structure and an Artificial Immune Recognition (AIR) system for verification [233] or through interest points such as SIFT [45], SURF [164], BRISK [61], KAZE [185] or FREAK [160]. Additionally, fuzzy membership functions are still used in signature verification. For example, in [7] a fuzzy similarity measure is used to classify a symbolic representation of off-line signatures and this method also achieves a competitive performance.

In recent years, there has been a growing interest in feature representation learning: instead of relying on hand-crafted feature extractors, feature representations are learned directly from the signature images by applying deep learning techniques, as seen in Table 2, such as Convolutional Neural Networks (CNNs), Deep Multitask Metric Learning (DMML) [241] or Deep Convolutional Generative Adversarial Networks (DCGANs) [276]. For example, a Siamese network based on twin CNNs is developed in [46]. CNN [11] is applied to the learning of features in a writer independent format in [110]. Here the model is used to obtain a feature representation for another set of users, which feeds into writer dependent classifiers. Such work was extended in [111] by a novel formulation of the problem that includes applying a knowledge of skilled forgeries during the feature learning process. A similar approach based on deep metric learning [241] can be found in [221]. Comparing triplets extracted from two genuine and one forged signature, the proposed system learns to embed signatures into a high-dimensional space, in which the Euclidean distance is used as a

Table 3. Performances (%) for some published ASV systems in different scripts

WESTERN									
Database	Method	#T	RF	SK	Database	Method	#T	RF	SK
GPDS-300 <i>Off-line</i>	Curvelet+OC-SVM [104]	4	-	AER:8.70	MCYT-100 <i>On-line</i>	VQ+DTW [235]	5	-	EER:1.55
	Learning Feat.+CNN [111]	5	-	EER:2.42		WP+BL DTW fusion [237]	5	-	EER:2.76
	HOG,DRT+DMML[241]	5	EER:2.15	EER:20.94		Histogram+Manhattan [228]	5	EER:1.15	EER:4.02
	LBP, LDP+SVM[48]	2	EER:1.43	EER:21.63		Sigma-Lognormal+DTW [83]	5	EER:1.01	EER:3.56
	Quad-tree+(AIR) [233]	10	-	EER:9.30		Symbolic representation [109]	5	EER:1.85	EER:5.84
	Grid Feat.+SVM[279]	12	-	EER:3.24		GMM Feat.+DTW [236]	5	-	EER:3.05
CEDAR <i>Off-line</i>	Learning Feat.+CNN [111]	4	-	EER:5.87	SVC2004 <i>On-line</i>	Function-based+RNN [146]	10	-	EER:2.37
	Surroundedness+NN [145]	1	-	AER:8.33		VQ+DTW [235]	5	-	EER:2.73
	Quad-tree+(AIR) [233]	10	-	EER:18.15		DCT+Sparse Rep. [150]	10	EER:0.45	EER:5.61
	Grid Feat.+SVM[279]	10	-	EER:3.02		Fuzzy modeling [12]	5	EER:5.49	EER:7.57
MCYT-75 <i>Off-line</i>	Learning feat.+CNN [111]	5	-	EER:3.58	SUSIG-Visual <i>On-line</i>	DTW+Lineal Classifier [141]	5	EER:4.08	EER:2.10
	HOG,DRT+DMML[241]	5	EER:1.73	EER:13.44		Sigma-Lognormal+DTW [83]	5	EER:1.48	EER:2.23
	LBP, LDP+SVM[48]	2	EER:0.69	EER:16.03		Target-wise+DTW [52]	1	EER:1.55	EER:6.67
	Grid Feat.+SVM[279]	10	-	EER:4.01		Histogram+Manhattan [228]	5	EER:2.91	EER:4.37
CHINESE									
Database	Method	#T	RF	SK	Database	Method	#T	RF	SK
Own Database <i>Off-line</i>	Segm.+Similarities [132] [†]	3	FRR:13.23 FAR:0.03	FRR:13.23 FAR:29.75	Sigcomp2011 <i>On-line</i>	FHE-based Feat.+RF [204]	80%*	-	EER:7.45
						FHE-based Feat.+RF [203]	80%*	-	EER:5.98
Own Database <i>Off-line</i>	Segm.+Weig. Sim. [130] [‡]	5	FRR:3.32 FAR:0.09	FRR:3.32 FAR:21.20		Legendre poly.+RF [202]	80%*	-	EER:8.93
JAPANESE									
Database	Method	#T	RF	SK	Database	Method	#T	RF	SK
Own Database <i>Off/on-line</i>	Off-/On-line ASV [129]	3	-	ACC:89.65	Own Database <i>Off-line</i>	Gradient+Mahalanobis [138]	3	-	ACC:92.25
Own Database <i>Off/On-line</i>	Off-/On-line ASV [137]	3	-	ACC:95.47	SigWiComp2013 <i>Off/On-line</i>	Off-/On-line ASV [170]	11	-	EER:5.51
ARABIC									
Database	Method	#T	RF	SK	Database	Method	#T	RF	SK
Own database <i>Off-line</i>	Geometrical+DTW [70]	N/A	FRR:8.00 FAR:13.00	-	QU-PRIP <i>On-line</i>	Function-based+DTW [63]	4	EER:0.3	-
Own database <i>Off-line</i>	Mult. feat.+fuzzy [42]	N/A	ACC:98%	-					
PERSIAN									
Database	Method	#T	RF	SK	Database	Method	#T	RF	SK
UTSig <i>Off-line</i>	Geom. Features+SVM [242]	12	-	EER:29.71	NDSD <i>On-line</i>	Function-based+SVM [268]	3	-	EER:5.15
	HOG,DRT+DMML[241]	12	-	EER:17.45		RT+CNN [269]	5	-	EER:2.07
INDIC									
Database	Method	#T	RF	SK	Database	Method	#T	RF	SK
BHSig260 (Bengali) <i>Off-line</i>	Contour Feat.+SVM [194]	12	-	AER:12.33	OnOffSigBen- gali75 <i>On-line</i>	Function-based+DTW [74]	2	EER:0.27	-
	Texture Feat+SVM [51]	2	EER:1.78	EER:10.67		Histogram+Man [74]	2	EER:8.19	-
	Texture Feat+NN [193]	8	-	EER:33.82					
BHSig260 (Hindi) <i>Off-line</i>	Texture Feat+NN [193]	8	-	EER:24.47	OnOffSigHin- di75 <i>On-line</i>	Function-based+DTW [74]	2	EER:0.41	-
	Texture Feat+SVM [51]	2	EER:1.34	EER:11.88		Histogram+Man [74]	2	EER:9.77	-

EER: Equal Error Rate, AER: Average Error Rate, ACC: Verification accuracy. *Percentage of available genuine signatures per user.

FAR was also reported for simple forgeries: [†]FAR:9.28, [‡]FAR:16.52.

similarity metric. In [241] a classification method based on DMML is studied. This approach makes use of knowledge from the similarities and dissimilarities between genuine and forged samples in order to learn a distance metric that is applied to measure the similarity between pairs of signatures.

Ensemble strategies to classify signatures have also been investigated where multiple classifiers are trained on the same data set. For instance, an ensemble of classifiers is proposed in [22]. These are based on graphometric features to improve classification performance in the off-line case. The ensemble was built using a standard genetic algorithm which selects a subset of models based on different fitness functions. An analogous approach in [21] used multiple Hidden Markov Models for learning signatures at different levels of perception.

One of the main constraints for commercializing an ASV is the required number of genuine signatures to be taken per user. This leads to the necessity to adapt and evolve these systems [124]. To address this problem, the use of One-Class SVM (OC-SVM) is proposed in [104, 105, 113]. OC classification attempts to classify just OC of objects (only the genuine signature, in this particular case), thus distinguishing them from all other possible objects. In [66] a hybrid

writer independent/writer dependent system is proposed: when a user is enrolled in the system, i.e. when only few signatures are available, a writer independent classifier is used to verify the signature. However, once the number of collected genuine samples passes a threshold, a writer dependent classifier replaces the previous one for the specific user. Unfortunately, the low number of genuine samples taken represents a critical drawback of this strategy. Instead, in [48, 51, 73] augmenting the training signatures by generating synthetic off-line handwritten signatures is suggested for neuromotor inspired models.

For *on-line signatures*, in recent years, an increasing effort has been devoted to applying function features based on pressure and force. In [262], for example, specific devices were developed to capture these functions directly during the signing process. The directions of the pen movements and the pen inclinations have created a growing interest [118, 201] as well as the turning angle representations [19]. In [123], the authors proposed a novel approach for on-line signature verification based on the directional analysis of velocity based partitions of the signature. In [150], the ASV was based on the discrete cosine transformation (DCT) and a sparse representation by fixing a certain number of coefficients. A similar approach was studied in [201] on the basis of a discrete 1-D wavelet transform.

Concerning the verification phase, whatever the technique adopted, the need to improve verification performance has led researchers to investigate multi-expert approaches [125] for combining sets of verifiers based, for example, on global [81, 168] and local strategies [179]. Up to now, 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. Moreover, fusion schemes at score level or feature level are also popular nowadays [91, 237, 251].

Proposals for on-line ASVs, designed on the basis of a DTW [52, 82, 83, 102, 141, 177, 235–237], have often been used over the years [124, 215, 219]. It seems that such elastic matching copes adequately with the problem of specimens with different lengths and internal variations. Some recent approaches focus on the normalization of the DTW (e.g. [52, 82, 141, 177]) while others focus on fusing stable local multi-domains in a signature [207] or by the exploitation of the optimization matrix [237], which can be calculated by using Euclidean or Cityblock distances, among others. Moreover, DTW is commonly used in combination with Vector Quantization [235], GMM features [236], Sigma-Lognormal based features [83, 102] or with a kernel function such as SVM [103] or OC-SVM [174].

A scheme based on fuzzy measures of signatures segments was designed in [12]. Also in [39, 40], a neuro-fuzzy classification stage of partitioning features (vertical [39] and horizontal [40]) was studied. A representation of on-line signatures by interval valued, symbolic parameter based features is studied in [109]. These authors achieved the best verification results when a writer dependent threshold was adopted for distance based classification. A similar scheme based on interval valued symbolic features can be found in [108], which was based on both a symbolic and conventional representation of on-line signatures.

The measure, based on local density estimation by an HMM, can be used to ascertain whether a signature contains sufficient information to be successfully processed by a signature verification system. Statistical models like HMM [158] or histogram features [228] are nowadays also used in signature verification. However, the popularity of schemes based on RNN is emerging [4, 146, 248].

Finally, notwithstanding the numerous measures that have been proposed so far, performance evaluation still remains a critical and complex task. For example, as shown in [10], a significant degradation in the verification of on-line signatures can be observed as the quality of the forgeries used increases.

3.2 Chinese Signature Verification

Much work has been carried out in the field of Chinese signature verification, both for off-line and on-line systems.

For *off-line signatures*, a proprietary data set was collected in [130–132]. In [131], it is proposed that, after pre-processing, the signatures are divided into chained segments, represented by seven geometric features. A similarity measure is then used for computing the FAR and FRR for genuine, random and simple forgeries. Signature segmentation in different regions of the script was carried out in [130, 132]. Then seven features, grouped into three types (geometric centres, segment tracks, and stroke thickness in each segment), were extracted. The experiments were performed with and without applying different thresholds and weighting factors. The system generally had problems with skilled forgeries as compared to simple and random forgeries and genuine signatures. A system for identifying off-line Chinese signatures was presented in [198]. It was based on foreground and background features. The authors used a database of 1120 (640 English and 480 Chinese) signatures and report an identification rate of about 97%. In [148] the authors summarize the major issues, challenges, and future directions regarding forensic document and handwriting examination in China.

For *on-line signatures*, orthogonal series expansions of Legendre polynomials and wavelet decomposition was used as features in [204], followed by a random forest (RF) classification. Improvements were found in [203] through a RF classifier and global features (e.g. total time, pen up/down duration, maximum pressure time, etc.), and wavelet representation of the time functions. Experiments in both of these studies were conducted with the Sigcomp2011, Chinese data set. An interesting aspect of each study, i.e. [203, 204], was the use of relevant features as identified by Forensic Handwriting Examiners (FHEs). A different proposal applied to the same data set is found in [202]. In this case, the authors used Legendre polynomials from function based features and a RF classifier. A methodology in [149] was focused on verifying on-line signatures collected on mobile devices. The features used included xy-coordinates, pressure, and contact area. User-dependent classification was performed using four classifiers, i.e., SVM [275], Logistic Regression, AdaBoost, and RF. Adaboost performed the best on a small data set of 42 persons collected for this study. In [37], function-based features and template matching was applied to a proprietary Chinese signature data set of 90 subjects.

In [184], on-line Chinese signatures from Sigcomp2011 were converted to off-line [56]. The authors then carried out a combined signature verification using greyscale gradient features and Mahalanobis distances for off-line signatures and dynamic programming matching with function-based features for on-line signatures.

3.3 Japanese Signature Verification

It is common practice in Japan that people who possess their name seals/stamps prefer using them for the purpose of authenticating documents instead of using handwritten signatures¹. Because of such a tradition, handwritten signatures are less practised there. This leads to lack of stability and individuality in handwritten Japanese signatures. For this reason, only a limited number of approaches have been recently reported for Japanese signature verification.

Apart from specific benchmarks [162], we found in the literature combined approaches for *off-line* and *on-line* Japanese signature verification. An in-house, on-line data set of 45 individuals was collected for the work presented in [139]. The on-line data were converted to off-line by using the velocity profile. The verification system consisted of Gradient features and a Mahalanobis distance. The authors obtained a FAR and FRR of 91.87% and could improve the accuracy of the system by 4.9% when signatures from other individuals were used. In [129] the authors used two ASVs for on-line and off-line data, which were generated in a way similar to [139]. The static ASV was based on Gradient features and a Mahalanobis distance, whereas the dynamic ASV, was function based and used dynamic programme

¹sljfaq.org/afaq/seals.html

matching. Finally, both techniques were combined with a SVM, thus obtaining promising results on a data set of 44 individuals. A similar strategy was presented in [137] with a data set of 19 writers. The experiments included cases where the signatures were first segmented and cases where the complete signatures were used during verification. Also, in [138] a static ASV [139] is presented by using a non-public data set of 19 individuals. Again, data were collected on-line and converted into off-line [139]. Finally, in [170] an off- and on-line combined system is presented by using as input the on-line Japanese signatures from SigWiComp2013 [162].

3.4 Arabic Signature Verification

Arabic communication is full of gesture. This is also seen in handwriting, especially in signatures. Consequently, an ASV has to pay attention to this peculiarity.

For *off-line signatures*, in [128], the authors present a two-stage system for off-line Arabic signature identification and verification. The first stage applies image morphology and focuses on the extraction of various global and local geometric features. Verification is performed at the second stage. Evaluation is conducted on a data set of 330 handwritten Arabic signatures (220 genuine and 110 forged). The system achieved an identification rate of 95 % and a verification rate of 98 % when trained on genuine signatures (132 samples) only and was tested on both genuine and forged signatures (198 samples). In [6], two data sets were introduced for off-line and on-line, Arabic signature verification. The off-line data contain 12,000 signatures from about 1,000 writers and the on-line/off-line data set contains 1,750 signatures from 190 writers. The data were collected from individuals belonging to different age groups, nationalities, genders, and academic qualifications. Geometrical features, such as diagonal and polar measures, were extracted from image based signatures and a DTW was the ASV used in [70]. Authors built their own database with genuine signatures from 10 volunteers. Additionally, a proposal based on multiple feature fusion with fuzzy modelling can be found in [42]. Similarly, in [165] a system was proposed based on various geometrical and grid features. This has been evaluated on a small data set of 360 signatures (60 writers with 6 signatures each) and gave a false rejection of less than 1 %.

For *on-line signatures*, function-based features and a DTW was the strategy used in [63]. Authors used 43 signatures from the Arabic Off/On QU-PRIP data set [6].

3.5 Persian Signature Verification

Persian and Arab scripts are very similar though, in Persian, people generally draw shapes and this brings new challenges to signature verification [98]. Recent approaches to Persian signature verification are reviewed below.

For *off-line signatures*, several approaches have been published utilizing private databases. For example, [98] presented a system based on a Discrete Wavelet Transform (DWT) and the Euclidean distance for matching. A similar approach was published in [99], where the authors created a reference pattern of users by fusing registered signatures. In [140] the authors used deep learning, i.e. CNN, to conduct the random forgery experiment. Additionally, a method based on estimating fractal dimensions of Persian off-line signatures can be seen in [84]. More recently, authors propose to use geometrical features based on fixed point arithmetic followed by a SVM as a classifier in [242]. Experiments were conducted with the UTSig database in terms of EER using, as non-target classes, random and skilled forgeries. The same authors obtained better results in [241] with the same data set by using a DMML method.

For *on-line signatures*, several techniques based on DTW with Multivariate Autoregressive (MVAR) modelling and a multilayer neural network were presented in [278]. The authors validated their system with their own data set, which was later known as the Zoghi data set. A system based on global information from on-line signatures, adjusted with an adaptive network based, fuzzy inferencing algorithm, was introduced in [44]. This work introduced another data set,

named the Dehghani data set, and considered both random and skilled forgeries. In [268] a system based on robust features and a SVM was developed and evaluated on three data sets of Persian signatures [44, 278] and on the NDSD. Most recently, a Radon transform (RT) and a CNN was used in [269]. The authors evaluated the system on three data sets (Dehghani [44], Zoghi [278], and NDSD [268]) of Persian signatures.

3.6 Signature Verification in Indic Languages

India is a country rich in languages. In spite of the fact that there are 122 main languages in India and 1,599 secondary [260], Hindi and Bengali are the official languages. Hindi is expressed in Devanagari script. This explains why the majority of papers in this area consider only Hindi and Bengali scripts. In this sub-section, we summarize the contributions reported in the last few years.

For *off-line signatures*, an ASV which uses Zernike moments and gradient features and SVM for classification for Hindi signatures was introduced in [201]. Competitive error rates in terms of FAR and FRR were obtained with a subset of the BHSig260 [193] corpus. Similarly, [194] presented a system utilizing contour features, such as the intersection and end-point chain code methods, along with a SVM classification for Bengali signature verification. The system was evaluated on a Bengali data set [193]. Another ASV based on texture features and SVM was applied to both Hindi and Bengali signatures in [51, 74]. Thus, Local Binary Patterns (LBP) and Uniform LPB strategies were used for parameterized Bengali and Hindi signatures in [193]. The classification was carried out through a NN technique for Hindi and Bengali signatures separately. By using the same data set, promising results were found in [7] using a symbolic interval representation of signatures and fuzzy similarities. In this case, the authors performed experiments without separating Bengali and Hindi signatures. In [46] deep learning was considered for both languages and obtained competitive performance for Bengali signatures.

For *on-line signatures*, little work has been published. In [74] an ASV based on function features and DTW was used for OnOffSigBengali-75 and OnOffSigHindi-75 data sets. Only random forgery experiments were performed. Also, an in-house implementation of the algorithm proposed in [228] was tested on the same data sets as used in [74].

4 COMPETITIONS: THE STATE-OF-THE-ART

In Section 3, we presented the best results obtained when authors evaluated their own systems under particular experimental protocols. These results were not directly comparable. Indeed, it could be said that every contribution has a particular experimental protocol which makes them completely incomparable in terms of accuracy. Nevertheless, in the Pattern Recognition (PR) community, several competitions have been organized during the last ten years as part of the most relevant conferences in the field such as ICDAR and ICFHR. These competitions established common benchmarks and common challenges to test third party ASVs. These external comparisons give a more objective evaluation of the state-of-the-art in automatic signature verification and define the goal for publishing results on new systems. A comprehensive summary of the best ASV systems from these competitions is provided in Table 4.

At the ICDAR 2009 Signature Verification Competition (SigComp2009) [28], a new challenge attracted the participation of 24 systems. It consisted in designing one reference signature system for skilled forgery detection. The systems were tested to cope with off-line and on-line signatures. Additionally, only one system combined both on-line and off-line signatures in a single system. The evaluation was based on Equal Error Rates (EER).

The BioSecure Signature Evaluation Campaign (BSEC'2009) [120] was the next competition and was organized during the ICB 2009. The organizers developed an on-line signature database acquired from a Wacom digitizing tablet and another database acquired on a PDA HP [191]. Both included the same number of 382 signers. Twelve systems

Table 4. Summary of signature verification competitions organized in the last ten years.

Competition	Datasets	Verification Tasks	Metrics	Best Results
BSEC2009	DS2-382(digitizer tablet):382(A) DS3-382(PDA):382(A)	T1 (DS2-382): On-line T2 (DS3-382): On-line	(EER)	T1: 0.51(RF), 2.20(SF) T2: 0.55(RF), 4.97(SF)
SigComp2009	1920(S), 100(A), 12(G)/(A), 6(F)/(A)	T1: On-line T2: Off-line T3: Combined	(EER)	T1: 2.85(SK) T2: 9.15(SK) T3: 8.17(SK)
4NSigComp2010	Scenario 1: 2(A), 334(S), 113(G), 194(F), 27(D) Scenario 2: GPDS960 data (Author 301 to 960)	T1 (Scenario 1): Off-line T2 (Scenario 2): Off-line detection of (RF) and (SK)	(EER) (OE)	T1: 55.0 T2: 8.94
ESRA2011	DS2-382 (digitizer tablet): 382(A) DS3-382 (PDA): 382(A)	T1: Impact of forgery quality T2: SK categorization	(EER)	T1 (DS2): 2.73(BQ), 2.85(GQ) T1 (DS3): 6.05(BQ), 7.15(GQ) T2 (DS2): 3.32(BQ), 4.31(GQ) T2 (DS3): 1.67(BQ), 2.43(GQ)
SigComp2011	Dutch: 4653(S), 128(A), 3162(G), 1491(F) Chinese: 2544(S), 40(A), 946(G), 1598(F)	T1: Chinese off-line T2: Dutch off-line T3: Chinese on-line T4: Dutch on-line	(\hat{C}_{llr}^{min})	T1: 0.69 T2: 0.08 T3: 0.22 T4: 0.12
4NSigComp2012	450(S), 3(A), 113(G), 273(F), 64(D)	T1: Off-line verification	(\hat{C}_{llr}^{min})	T1: 0.43
SigWiComp2013	Dutch: 1242(S), 27(A), 270(G), 972(F) Japanese: 4836(S), 62(A), 2604(G), 2232(F)	T1: Dutch off-line T2: Japanese off-line T3: Japanese on-line	(\hat{C}_{llr}^{min})	T1: 0.64 T2: 0.33 T3: 0.74
SigWiComp2015	Bengali: 540(S), 10(A), 240(G), 300(F) Italian: 728(S), 50(A), 479(G), 249(F) German: 750(S), 30(A), 450(G), 300(F)	T1: Italian off-line T2: Bengali off-line T3: German on-line	(\hat{C}_{llr}^{min})	T1: 0.02 T2: 0.03 T3: 0.29

Signature (S), Genuine Signatures (G), Disguised Signatures (D), Forgeries (F), Random Forgeries (RF), Simple Forgeries (SF), Skilled Forgeries (SK), Number of Authors (A), Bad Quality Forgery (BQ), Good Quality Forgery (GQ), Overall Error (OE), Equal Error Rate (EER), Minimum Cost of Log Likelihood Ratios (\hat{C}_{llr}^{min})

participated in this competition, and were evaluated in two tasks on skilled and random forgeries on the two data sets. The BioSecure Evaluation of Signature Resistance to Attacks (ESRA2011) was organized in 2011 using data from BSEC'2009 with 13 participating systems. This competition focused on assessing on-line ASV systems in terms of the impact of forgery quality (good or bad) on the systems' performance (Task 1), and on testing the systems using various categories of skilled forgeries (Task 2) [116]. The results for the winning systems are presented in Table 4.

Note that Forensic Handwriting Experts (FHEs) point out various issues related to these signature verification competitions. For example, verifying one questioned signature against one reference signature (such as in SigComp2009) as well as focusing exclusively on on-line data. This makes sense in terms of developing future on-line commercial applications of ASV, but the duty of the FHE [153] is the verification of only off-line signatures. Furthermore, these competitions did not look into different genres/categories of signatures as encountered by forensic examiners, and the results were not reported in a way required in forensic casework [62]. In summary, the underlying motivation of organizing these competitions differed from the FHEs' requirements. For this purpose, FHEs joined with the Pattern Recognition community to collectively organize a series of signature verification competitions targeting the basic signature verification requirements of FHEs.

Two Signature Verification Competitions (4NSigComp2010) were proposed during the ICFHR 2010: Scenario 1 [153] and Scenario 2 [29]. Scenario 1 [153] was proposed to detect genuine signatures, skilled forgeries, and also disguised signatures, which are personal signatures falsely executed by the original writers. Seven verification systems participated and their results were compared with FHE evaluations using the same set of signatures. It was observed that the systems were not able to satisfactorily detect disguised and skilled forgeries at the same time. In fact, when disguised signatures were included in the evaluation set, the performance worsened significantly [153]. An interesting fact, however, was that the performance of the competing ASVs was really close to the performance obtained by the FHEs [163]. In Scenario 2 [29], ten off-line ASVs were evaluated for detecting random and skilled forgeries at the same time. The results were given in terms of Overall Error (OE). The best performing system achieved an OE of 8.94 %.

In the Signature Verification Competition (SigComp2011) [152] held in the ICDAR 2011, a close approximation to the methods of the forensic community was attempted through the performance evaluation by EER and the use of the minimum cost of the log-likelihood ratios (LRs), C_{llr}^{min} . A unique feature of SigComp2011 was that the thirteen participating systems were required to report continuous scores which could be converted into LR or Log LR (LLRs) by various calibration procedures. The cost of log-likelihood ratios C_{llr} and the minimum possible value of C_{llr} , i.e., C_{llr}^{min} , were then computed. The smaller the value of C_{llr}^{min} , the better the system. In addition to these measures, forensic-like databases were used: on-line and off-line Western and Chinese corpuses. A single system able to deal with all cases was not found. Best results for different tasks are reported in Table 4. One interesting finding was that the best minimal cost of log-likelihood ratio did not imply the best EER. This is attributed to the sensitivity of C_{llr}^{min} to a few important errors during the verification process.

In ICFHR 2012, C_{llr}^{min} was used to rank the systems in the competition (4NsigComp2012) [151]. In this competition, genuine, disguised, and forged signature detections were evaluated. Five systems participated and the winning system reached C_{llr}^{min} of 0.43. When disguised signatures were removed from the test set, once again the same system succeeded with a C_{llr} of 0.36.

At ICDAR 2013, the competition (SigWiComp2013) [162] focused on on-line and off-line signature verification against skilled forgery detection. Three sub-corpuses designed by forensic experts were used: a Western off-line (Dutch signatures) and an on-line and off-line Japanese data set, the latter being the off-line Japanese counterpart generated directly from the on-line data. Thirteen systems participated, some with optimized versions for different tasks. One interesting finding in this competition was that the C_{llr}^{min} results tended to be more sensitive to a few large errors than the EER. It must be remembered that this is the clue to using such a metric in forensic casework, where omitting large errors would necessarily result in making a dramatically wrong decision in a court of law.

The SigWiComp2015 [161] signature verification competition was held during ICDAR 2015. The tasks dealt with off-line signature verification using Western (Italian) and Indian (Bengali) signatures as well as Western on-line specimens (German). Only the C_{llr}^{min} results were presented. Thirty systems participated for different verification tasks. One of the main outcomes from this competition was the evaluation of useful ASVs for forensic daily practice and this was suggested as the future direction to follow. This is a questionable move, considering the widespread availability of hand-held devices with their new handwriting digitizing ability and their increased computing power which allows an easy implementation of a built-in ASV. We briefly come back to this point in the conclusions.

Many of these competitions were organized by the Netherlands Forensic Institute in conjunction with Pattern Recognition researchers. This has led to the use of signatures found in typical forensic casework and the development of systems useful for both communities. Furthermore, multi-script tasks have also gained attention in recent competitions. In fact, it can be seen that participants optimized their systems for each task in SigWiComp2015 [161]. A more practical and challenging scenario could consider different intra-writer scripts for the training and evaluation set in order to prove fairly the performance of the state-of-the-art technology for several scripts at the same time. Also, despite its necessity in commercial transactions and applications, the random forgery scenario has become of low interest in many of the latest competitions, which focus mainly on skilled forgeries. However, recent papers still show results for the random forgery scenario [43, 279].

5 FORENSIC ASPECTS

Forensic Handwriting Examiners (FHEs) perform signature comparison along with conducting signature verification as they address the identity of a signer [153]. During the examination, a FHE compares a questioned signature against

various known specimens. A FHE assumes that different writers do not write the same way and every piece of handwritten signature they write is essentially influenced by the so-called intra-writer and inter-writer variations. In order to show that the questioned and specimen signatures were written by the same writer, a FHE must establish that the degree of variation is more consistent with the intra-writer variations than with the inter-writer variations. However, in some cases, e.g., tracing, the intra-writer variations are so negligible that a FHE can consider it with high likelihood [183] as a simulation. After an examination, a FHE tends to express an opinion about the observations supported by one of the following hypotheses [17, 85, 86, 176]: (1) The questioned signature is genuine, i.e., naturally written by the original writer in her/his own style. (2) The questioned signature is not genuine (is a simulation), i.e., unnaturally written by some writer, other than the specimen writer. The writer tried to make a false copy of the specimen signature. (3) The questioned signature is naturally written by a person in his/her own style but falsely claiming to be some other person. (4) The questioned signature is not genuine, i.e., unnaturally written by the writer of the questioned specimen, i.e., the writer tries to make his/her signatures look like a forgery attempt (referred to as “disguise” behaviour). The purpose could be for the later denial of writing the signature in which case it is also termed as “auto-simulation”. Note that both genuine and disguised signatures are written by the author of the specimen but with different intentions. A signer produces a genuine signature to be identified when needed. Whereas, a disguised signature is written with the purpose of making it look like a forgery for a possible later denial [153, 176]. (5) The questioned signature is unnaturally written by the specimen writer under the influence of internal or external factors, e.g., illness, alcohol.

The results of signature comparisons, carried out by FHEs, are subjective. They usually construct weighted hypotheses. FHEs often express their opinion on a five or nine-point scale ranging from “identification” of a definite match between the questioned and specimen signatures to “elimination”. The latter represents the full confidence of the FHE that the questioned and specimen signatures are not written by the same writer.

However, some automatic tools have recently been developed specifically to support FHEs in their daily casework, e.g., FLASH ID [261] in 2013, iFOX [244] in 2013, and D-Scribe [231] in 2013. It is, however, interesting that with respect to signature authentication, FHEs have traditionally made very limited use of such automated tools. One reason for this is that many of these tools have been designed to perform comparison tasks and present results in a form that FHEs are not comfortable with. Furthermore, some tools have certain drawbacks which affect the possibility of their usage in the real world of forensic casework. For example, CEDAR-FOX, introduced by the Center of Excellence for Document Analysis and Recognition for supporting a semi-automated analysis for handwritten input, has an output based on the assumption that the appearance of each occurrence of a character is independent of the next. If this assumption were true, there would be no point in comparing handwriting with the purpose of source attribution. The behaviour of the system differs from that which would be expected in many forensically relevant scenarios [258].

The Forensic Language-Independent Analysis System for Handwriting Identification (FLASH ID) [261] identifies writers by analysing grapheme topology and geometric features. The system iFOX [244] (interactive FOrensic eXamination) and D-Scribe [231] have been introduced more recently to assist in handwriting interpretation through automation. Unfortunately, none of these systems is in such widespread use such that its utility can be fully established.

6 RECENT PROGRESS IN AUTOMATIC SIGNATURE VERIFICATION

While Section 3 gave an overview of novel ways to solve a well-known challenge, i.e. automatic signature verification, various hot topics are discussed in this section. These bring new challenges to the research community as well as providing a source of opportunities and accomplishments. As such, we focus this section on ASV systems that

process signatures in more than one script (Section 6.1), on the developed stability and complexity measurements on signatures (Section 6.2), on international standards and systems which operate independently of the data acquiring device (Section 6.3), on the algorithms proposed to encrypt a person's signature (Section 6.4), on signature-based e-health applications to aid objective medical decision-making (Section 6.5), on generative models to reproduce synthetically handwritten signatures (Section 6.6) and on touch-screen devices (Section 6.7).

6.1 Multi-script Signature Verification Systems

Multi-script refers to a scenario where signatures in several different scripts (i.e. using letters or characters in different languages) can be verified by using the same ASV. Despite not being extensively studied [197], multi-script is a common scenario for international commercial transactions, international companies or international security for forensic paradigms. In all these cases, signatures are typically executed in the original script and can be aggregated to a common database. To evaluate an ASV under multi-script conditions, proposals in the literature usually combine several single-script databases. As an example, in [200] the authors evaluated an ASV after merging databases in several scripts. These authors presented two off-line signature verification experiments: first without initial script identification and second with initial script identification for English, Hindi, and Bengali. The system developed for this study utilized chain code features and signature gradients along with support vector-based classification. Results indicated that initial script identification improves the final verification results by almost 4%.

Most recently, [43] presented a study on the evaluation of multi-script vs single script signature verification scenarios and a technique for generating a multi-script off-line signature database from several single script databases. The study considers eight off-line public signature data sets, available in five different scripts (Western, Bengali, Devanagari, Chinese, and Arabic). The authors showed that similar results are obtained when merging the data sets or keeping them singular thereby implying multi-script verification as a generalized problem.

In [195] gradient features and chain code features were fused at the template level for verification of Bengali and English signatures. High accuracies of 99.41 %, 98.45 % and 97.75 % were obtained by studying different techniques. In [198] English and Chinese signatures were combined. In this multi-script scenario, the authors applied a foreground and background technique for the identification stage. They achieved an accuracy of 97.70 % in identification.

Only Bengali, Devanagari and Western scripts were evaluated in [196]. From their analysis these authors observed large errors in the classification of Bengali and Devanagari signatures. Their follow-up work in [199] consisted in using a modified gradient feature and a SVM for identification and verification. Some 66 % of the signatures from each script were used for training and 33 % for testing. The system achieved a script identification accuracy of 98 % and the false acceptance and false rejection rates for Hindi signature verification was 8 % and 4 % respectively; and, for English signatures, it was 12 % and 10 %, respectively. LBP and Uniform LBP features were studied in [193] for off-line verification of signatures written in two Indic scripts which were Bengali and Hindi. The presented system was evaluated on BHSig260 as well as on the publicly available GPDS-100 signature data set. The system achieved an EER of approximately 34 % on Bengali, 24 % on Hindi, and 33 % on GPDS-100 data.

Furthermore, three data sets from three languages (Dutch, Chinese and Japanese) were combined to create a training data set in [170]. The authors found competitive results when an ordered sampling method based on OC-SVM was used for genuine samples of other scripts in the forgery class. Also, geometrical features and a DTW-based system seem to be competitive in static signatures from Persian (Farsi) and Arabic scripts [70]. Finally, a strategy to enlarge the training set by using static synthetic signatures is tested in Indic and Western scripts in [51]. In this report on multi-script ASV, the authors used static signatures as a proof of concept.

Here again, further advances are required in on-line multi-script signatures, which remains an open issue.

6.2 Stability and Complexity

In recent years, the analysis of signature stability has been one of the key research topics in the field of signature analysis and verification. It could be said that two types of signature variability can be generally considered: while *short-term* variability is evident on a day-to-day basis and depends on the psychological condition of the writer and on the writing conditions, *long-term* variability is apparent over longer periods of time, years or even decades, and depends on the modification of the motor programme in the signature writer's brain [59, 214]. According to [218], the stability can be estimated by three approaches: (1) Data-based approaches use raw data to estimate signature stability. (2) Feature-based approaches consider specific function features or parameters extracted from the signature to derive stability information. (3) Model-feature approaches, where the signatures of an individual are first described according to a well-defined model. Signature stability is then estimated by considering the range of variability of model parameters.

The *stability* information can be obtained by the identification of Direct Matching Points from DTW elastic matching [207]. In this work, moreover, a multi-domain signature verification is performed by using only the most stable domain of representation for each region in the signature. In other approaches, stability regions of signatures are defined as the longest similar sequences of strokes between a pair of genuine signatures [205]. This definition is based on the assumption that signing is the automated execution of a well-learned motor task and, therefore, repeated executions should ideally produce similar specimens. More recently, the analysis of stability has been applied directly to the processes underlying handwriting production [58]. For this purpose, the Sigma-Lognormal model [187] is used. The estimation of local stability is applied, starting from the extreme points of the velocity profile [211, 213].

Hidden Markov Models (HMM) have been considered for model-based stability analysis [97]. Stability measures have also been used to determine whether a feature contains enough information to be successfully processed by a verification system [118, 269]. When static signatures are considered, the stability of each region of a signature can be estimated by a multiple pattern matching strategy [127]. A preliminary step can be used to determine the best alignment of the corresponding regions of the signatures in order to diminish any differences between them [205]. The analysis of the optical flow is also an option for providing information about local stability [50, 210]. This technique assumes that there is a certain deformation between two genuine signatures, which is estimated on the basis of the Horn and Shunk approach. Additionally, strategies based on cosine similarity [209] or based on Speeded Up Local Features (SURF) [164] have been recently evaluated for estimating the stable regions in static signatures.

Signature *complexity* [121, 134] is another aspect that is considered with interest in the research community. In fact, for many years, the effect of signature complexity on signature verification performance has been specifically investigated [31, 69]. Notwithstanding that no common meaning of handwriting complexity has yet been defined, a signature's complexity can be thought to be an estimator of the difficulty for its imitation and therefore related to its legibility [9]. A new approach for complexity estimation is based on DMPs derived when a genuine signature is matched against a set of forgeries by DTW [212]. More recently, a statistical complexity measure, based on the concept of differential entropy in information theory has been proposed [117]. This approach measures the complexity and stability of genuine signatures through the personal and relative entropy. A complete framework for statistical assessment of signature complexity has been also defined. This is based on static and dynamic features, for example, the number of strokes (defined in terms of lognormals in [249]), the total number of intra/inter-stroke intersections, the means of intra/inter-stroke intersections, the maximum of intra/inter-stroke intersections, the number of X-axis

intersections, the sums of the horizontal and vertical components of the velocity and acceleration at zero-crossings and the signature length [155].

6.3 Acquisition Devices and Standards

Manual signature verification performed by experts has a long history [124, 215, 219]. Automatic off-line and on-line signature verification have evolved with advancements in technology [13, 178]. For automatic off-line verification, signature acquisition today is mainly performed through scanning or by photographing the signatures using digital cameras. In both cases, scanned and photographed, though the pre-processing (to deal with different distortions) differs, the underlying verification techniques are similar [161]. For on-line verification, signatures are usually acquired through digitized/graphic tablets, digitizing pens [159] or even gloves [136]. A graphic tablet enables a user to write her/his signatures (along with performing various other actions like drawing, writing, etc.) with the help of a pen like device such as a stylus. These digitized signatures are then transferred to a verification engine for testing. The most common categories of graphic tablets are: (1) Passive Tablets: these tablets use electromagnetic induction². They have specialized wires spread horizontally and vertically within the tablet. These wires send and receive signals as a stylus moves in the field created by these wires (without needing the stylus to touch the tablet). The stylus draws power from the tablet beneath and does not need a battery of its own. (2) Active Tablets: in such tablets, the styluses have their own batteries giving them a heavy feel, but with less jitter as compared to passive tablets since the tablet can constantly read signals from the stylus. (3) Optical Tablets: such tablets have a special stylus with an integrated camera. The tablet underneath has an image of the dot patterns which correspond to the signature. (4) Acoustic Tablets: these tablets make use of sound waves by estimating the position of a sound emitting stylus on the drawing region during the writing process. (5) Capacitive Tablets: these tablets use electrostatic signals to detect the location of the stylus on the tablet, whether the stylus is touching or hovering above it.

For the above mentioned categories of tablets, the position of the stylus, its angle of inclination on the tablet, its pressure, proximity etc., are usually computed by the tablet. Apart from tablets, digital pens are also used for acquiring on-line signatures. A digital pen digitally captures the handwriting strokes made on paper. Digital pens differ from styluses both in terms of internal electronics as well as in their dimensions, thickness, weight, etc. These pens usually have an internal memory to store information captured during the handwriting process. Most of them also possess communication channels, e.g., Bluetooth, to directly connect to computer systems. Such pens are usually shipped with software that is installed on the data receiving computers. Once data is acquired by the pen and sent to the computer, it can be used for performing on-line identification or verification tasks [159]. Some important categories of digital pens are: (1) Inertial pens which reconstruct trajectories, e.g. IMUPEN [263]. (2) Active pens which identify the pen location, point pressure, etc., with the capacity to write directly onto LCDs. (3) Trackball pens which directly detect handwriting strokes written by the pen. (4) Camera based pens which digitize handwritten strokes, e.g., the Anoto dot pattern. (5) Those that measure finger pressure during handwriting acquisition (e.g. the BiSP-M device [20]).

Since these devices are used for signatures and handwriting, there are certain standards that need to be maintained so that the accuracy and the legitimacy of the handwritten input can be assured. These standards specify the exact requirements for the entire process that need to be fulfilled in order for the system to be considered authentic and trustworthy in the sense of being equivalent to creating an actual signature.

²thoughtco.com/before-you-buy-a-graphics-tablet-1701241

In the European Union, the electronic IDentification, Authentication and trust Services (eIDAS) standard is deployed. The eIDAS focuses on the European Single Market and was formulated in 2014. The standard deals with electronic transactions and their corresponding electronic signatures. The standard, which is widely recognized, focuses on interoperability and transparency and operates across a number of platforms. Similarly, Switzerland uses the ZertES standard for electronic signature verification.

6.4 Signatures and security

A well-known problem with biometrics and signatures is feature template security. In fact, solutions typically adopted with standard authentication technologies, e.g. changing the password, cannot be carried out: it is almost impossible to modify the biometric (human characteristic) trait.

Biometric feature template security relies on the use of a non-invertible feature set: the computation of the original raw data acquired by the device should be computationally difficult. In case of feature disclosure, a new set of cancellable features must be assessed. Examples of non-invertible features are total duration, number of pen ups, sign changes in velocity and acceleration, average jerk, number of local minima, etc. In general, non-invertible features are parameter based. Any non-invertible transformation can be considered to be made up of several steps [158, 253]. One technique for achieving this is based on the symbolic representation of the signature’s global features [108, 109]; another on histograms which represent raw feature statistics [228].

In general, cryptography can also be considered. Cryptography refers to the study of mathematical techniques aimed at satisfying objectives related to information security. These objectives mainly concern confidentiality, integrity, authentication and non-repudiation. Most cryptographic techniques rely on the adoption of keys in order to encrypt and subsequently decrypt messages to be exchanged. Biometric-based authentication provides a means to not having to remember or store these keys. This is inherently a more reliable solution as biometric traits cannot be stolen or forgotten and they are extremely difficult to copy or share. One of the pioneering encrypted transaction systems was presented in [255], where authentication was complemented by additional biometric protection, based on handwritten signatures, to ensure non-repudiation.

A major problem here is how to unite biometrics and encryption under the requirements of confidentiality, integrity, authentication and non-repudiation. In fact, symmetric encryption algorithms (e.g. 3DES,) fail to be compliant with the confidentiality requirement since the verification phase is not allowed in the encrypted domain. This is because the template is exposed during every verification attempt [222]. A practical solution which allows template protection is the use of asymmetric (e.g. RSA) or homomorphic encryption [100] since the verification is conducted in the encrypted domain. However, template protection has also been addressed by the “bio-cryptosystem”, that is, the use of the biometric trait to manage cryptographic keys. In other words, the key is generated directly from the signature so that it is not explicitly stored [254]. The problem is that the key has to be evaluated at each verification given the signature received as input and, due to intra-class variation, it is impossible to obtain exactly the same key at each submission. In order to solve this problem, which is common to other biometrics, a Fuzzy Vault (FV) schema is suggested because of its ability to (fuzzily) deal with intra-class variations [133].

The FV schema has been applied to off-line signature verification in [88]. The authors considered minima and maxima of the upper and lower contour of the signature as template. They observed that the variability among users made it impossible to settle on a unique operating point of the fuzzy vault. Authors of [65], employed the concept of dissimilarity representation between the locking and the unlocking FV points. If the dissimilarity was less than a specific threshold, then the decoder succeeds in unlocking the bio-cryptographic key. Therefore, these decoders can be

viewed as simple two-class thresholding classifiers which operate in a dissimilarity space. Several features aimed at enhancing accuracy and security were discussed in [67], which mainly concern: adaptive matching of FV points; an ensemble of multiple FV schemes, where the key is released on the basis of a majority vote rule; a cascading approach, which adopts a traditional signature verification classifier before triggering the FV decoder and an adaptive key length, depending on each specific user [64]. FV has also been applied, to some extent, to on-line signatures [157]. The approach is based on a set of non-invertible transformations. Unfortunately, these approaches result in performance degradation along with reliability problems (i.e. the possibility of revoking a compromised template and defining a new one). Similar results have been observed when simple, non-invertible features have been used [250].

Finally, according to [94], skilled forgeries can be considered as a case of presentation attack [1]. To achieve unified criteria in biometrics and signature verification, some authors recommend introducing presentation attack detection in ASV [94].

6.5 Signatures for Medical Applications

For many years, the effects of health conditions on handwriting have been a field of study by graphologists and forensic experts [122, 126, 245], as well as psychologists and neuro-scientists [154]. Handwriting is a complex activity resulting from cognitive, kinesthetic and perceptual-motor abilities [186, 232]. Furthermore, visual and kinesthetic perception, motor planning, eye-hand coordination, visual-motor integration and manual skills are involved in this sensory-motor task. For this reason, psychiatric, neurological or peripheral illnesses can generally have strong effects on handwriting, so changes in handwriting are good candidates as biomarkers for the assessment of several diseases. As the number of devices for data capturing and processing is increasing, the use of handwriting to detect and monitor health conditions is becoming more and more attractive. Handwriting analysis will not, of course, compete with traditional medical strategies. It can provide a different and complementary approach to analysing health problems in a non-invasive way and at low cost.

Recent research has focused on relations between handwriting and Parkinson's disease [226], Alzheimer's disease [35], agraphia [238], dysgraphia [41], psychosis [34] and other pathologies [33, 60, 169]. For instance, the handwriting of individuals affected by Parkinson's disease [38, 232] is smaller than normal; moreover, it is produced more slowly and with lower pressure on the writing tablet [225, 240]. Conversely, although it has been observed that handwriting impairment is heterogeneous within the population affected by Alzheimer's disease, there are certain aspects of the writing process that are more vulnerable than others and may present diagnostic signs. In particular, handwriting of individuals affected by Alzheimer's disease is less consistent in length and duration [270]. In general, it has been found that during the clinical course, dysgraphia occurs during both the early as well as the later stages of the disorder progression [239, 271].

In the light of the observations above, handwriting could be considered as a valuable tool for characterizing aging [266, 267] and for detecting early signs of disease [114, 188–190, 216, 267], as well as for monitoring the evolution of illnesses [32] and the effect of therapies [24], and it can be used as a tool for the analysis of the emotional state [68]. Despite the large number of works focusing their attention on handwriting tasks in general, few studies have focused specifically on handwritten signatures. In the following, some of the most recent work is taken into account. In [156] the relation between handwritten signature and personality traits was studied by considering both the static and dynamic features of signatures. The results reveal significant correlations between personality traits and these features. In addition, it was found that gender and weight could be predicted effectively, especially using signature velocity characteristics. Conversely, the relation between the handwritten signature, and more precisely the signature position

on or below a dotted line, and other cognitive functions were further investigated in [262]. The findings of the study suggest that signature positioning may be a marker of vulnerability for the mechanisms involved in visuospatial abilities.

A machine learning algorithm to automatically discriminate between Alzheimer’s disease patients and healthy control subjects was employed in [208]. The work was based on a previously annotated data set of handwritten signatures. For this purpose, the Sigma-Lognormal model [187] was used to extract dynamic features of the signatures and to obtain sets of attributes for building classification models. Experimental results show that the proposed approach is inexpensive and effective. Therefore, it can be considered as a promising direction for future research, for example for implementing a screening standard routine for the early diagnosis of Alzheimer’s disease. The work published in [223] was specifically focused on initial cognitive impairment, and investigated whether it is possible to make inferences on decision-making capacity through the analysis of signatures and spontaneous writing. Unfortunately, while significant correlations were found between spontaneous writing indices and neuropsychological test results, no correlation was found between signature deterioration and cognitive decline. Therefore, the authors concluded that the integrity of the graphic pattern of a signature is not indicative of the cognitive capacity of individuals with cognitive impairment, so they recommend using great caution in attributing validity to the signature of such individuals for this purpose.

The objective in [225] was aimed at finding simple characteristics of handwriting capable of accurately differentiating between Parkinson’s disease patients and healthy control subjects. Participants in this study were requested to write their name and to copy an address. Statistical analysis, used to test group differences in spatial, temporal and pressure measures for each of the writing tasks, showed significant group effects: compared to the control, patients wrote smaller letters, applying less pressure and required more performance time. In conclusion, the authors highlighted the importance of analysing handwriting not only “on paper” but also “in air”, i.e. when the pen has not yet touched the paper, since significant differences were observed between these two writing conditions. In fact, “in air” time is a manifestation of the “planning of the next movement”, which reflects the cognitive ability and supplies information about the writer [234]. A similar study was conducted in [225], in which the analysis of name writing, together with the analysis of two other tasks, i.e. paragraph copying and free-style writing, was applied to the study of the characteristics of children affected by high-functioning autism spectrum disorder. The handwriting process analysis across the three tasks indicates that the pen tilt of the children affected by the disorder was significantly lower than control subjects. Their pen stroke duration “on paper” was significantly higher as well as their letter sizes. Furthermore, their stroke duration “in air” was significantly higher in the name and free-style writing tasks. It is worth noting the works in [225, 227] which focus on the analysis of name writing, which is a slightly different task from signing.

6.6 Synthetic Signature Generation Models

Models and methods for generating synthetic handwritten signatures provide an opportunity to clarify and learn the biological processes that characterize such specimens. Among the number of advantages of synthesized signatures, some of the most relevant can be summarized as: (1) It is relatively effortless to produce a large amount of data (once the generation algorithm has been developed). (2) There is no size restriction (in terms of subjects and samples per subject) since the signatures are automatically produced by a computer programme. (3) Such signatures are not subject to legal constraints because they do not relate to a real user. (4) They eliminate human mistakes such as labelling the data which biases the performance evaluation of the algorithms. (5) They permit statistically meaningful evaluations of performance. (6) They can simulate aging or maturity level models. (7) They can simulate signatures affected by some behavioural disorders, neurodegenerative diseases or other cognitive impairments. (8) They can provide an opportunity to analyse the deterioration and loss of function in the organs involved in handwriting production.

The literature contains a number of novel proposals for the generation of synthetic identities. In some the algorithms define a new identity at the beginning without any real signature as a reference. Such models are then able to generate realistic intra-personal variability of a virtual writer. In this context, the statistical normality of signatures' lexical morphology [55] is useful for such purposes. One of the uses of these synthetic signatures is to test the systems in order to create common benchmarks with meaningful statistical results. Additionally, signature generation is dependent on the script that has to be reproduced. Thus special attention to the peculiarities in a given script needs to be taken into account. For instance, Western signatures are typically composed of text and flourishes; Chinese or Japanese signatures are designed with symbols, and so on. The full generation of on-line, flourish-based signatures using two algorithms was carried out in a linked pair of papers [93, 96]. One of the strategies was based on spectral analysis and the other on the Kinematic Theory of rapid human movement. Apart from a visual validation, quantitative evaluations were carried out, mainly in terms of comparative performance with real databases. On the generation of off-line signatures, a method based on the statistical distribution of global signature properties to generate flourish-based Western specimens can be found in [76]. In their proposal, the authors generated both genuine signatures and forgeries. A more elaborate procedure to generate signatures based on equivalence theory was proposed for Western off-line signatures [73] and for Western on-line signatures [75]. These authors defined a user grid based on the cognitive map in order to represent the name and the flourish engrams. The dynamics of the signature trajectory are calculated by lognormal sampling of the signature trajectory. The static version is eventually generated by applying an ink deposition model. A similar proposal for generating off-line Bengali and Devanagari signatures is reported in [47, 74].

Many proposals focus on modelling intra-personal variability for duplicating static or dynamic signatures (e.g. [70, 77, 90, 92, 107]). In this context, duplicating a signature means generating a new specimen artificially from one - or more than one - real signatures. Among its advantages, signature duplication can improve the training of ASV systems and allows the carrying out of statistically meaningful evaluations as well as enlarging the number of signatures in databases. It also helps match the baseline performances for real signatures, which are often difficult to obtain and it can improve the performance of existing automatic signature verifiers. The dynamic duplicated signature performance can be comparable to that for real signatures. By applying a random and new deformation, it is possible to improve the performance of an HMM-based classifier [92]. To increase the training set, a method based on a clonal selection of the enrolled signatures is studied in [243]. The properties of the Kinematic Theory of rapid movement have been used for these purposes [52, 53]. Additionally, other authors have worked on the replication of multiple off-line specimens from real on-line signatures applying geometrical [220] or cognitive-based [54] strategies. Other proposals have focused on duplicating off-line signatures from off-line specimens. In [90] an off-line signature data set is enlarged by applying some geometrical transformations. Another proposal applies neuroscience perspectives in a duplication method [48].

This work on synthetic signatures opens the opportunity to explore more intelligent systems as well as to understand better interrelated information which depends on the nature of the signatures. Indeed, the potential relationship between on-line and off-line signatures is still a matter of research. An ink deposition model is elaborated in [77] to generate static signatures from on-line ones. Some strategies based on the modification of on-line sampling rates and image resolution were proposed in [107]. The dynamic information (i.e. velocity, pressure) was used in [56, 91] to create images based on overlapping 2D Gaussian spots. To recover the dynamic information from a static signature, to the best of our knowledge, is a topic that has not yet been examined in any depth [49, 181] although many attempts have been made to address it for handwriting, for example, in [246]. The most critical stages relate to thinning and writing order recovery [181].

6.7 Signing on Touch Screens

The recent integration of low-cost data acquisition devices in a multitude of personal systems, i.e. smartphones, PDAs, etc., has stimulated several researchers into investigating dynamic signature verification on mobile devices [228]. Clearly, signature verification on such devices is affected by several factors not present in traditional devices specifically conceived for handwriting recognition. Mobile devices, in fact, are characterized by a small input area and poor ergonomics, which affect user interaction and leads to large intra-class variability [13]. The quality of signature acquisitions can show high disparity because of the quality of the touch screens and because the amount of information that can be captured is limited as pressure, pen-azimuth and other attributes, which could lead to improved performance, cannot typically be recorded. Furthermore, users are asked to sign on an unstable surface, often using a single finger [14, 178].

Migrating to mobile devices from traditional pen tablets has therefore raised several new issues: fine-tuning the verification algorithm for improving the performance, considering the execution platform and the acquisition properties, e.g. [25, 26, 119, 120, 144, 167–169, 173, 252, 274]; evaluating the impact on the performance of the implementation of the algorithm in a variety of platforms [250]; evaluating the usability of the new applications and redesigning them in accordance with the results obtained [27]; guaranteeing the security of the biometric data in the new mobile context [250].

Concerning performance, the article published in [167] was among the first to recognize the importance of adapting the traditional tablet-based signature verification systems in the context of handheld devices. This work presented a systematic comparison between the system proposed and a traditional pen tablet-based system by employing a subset of 120 users from BioSecure DS2 and DS3. BioSecure DS2 contains data captured under a control scenario where users had to sign while sitting; BioSecure DS3 considers a mobile scenario where users had to sign while standing and holding a PDA in one hand. The low discrimination power of dynamic features (time, speed and acceleration) observed in these PDA scenarios suggested that ergonomics, an unfamiliar surface and the signing device (touch screen and PDA stylus vs. traditional pen and paper) affect the dynamics of the signature acquisition process. In [172] the possibility of applying a pre-existing on-line signature verification algorithms to portable devices was studied. To gain an insight into the performance of the algorithm prior to its real implementation, the authors modified the MCYT signature database to simulate signatures taken from a mobile device. In particular, two main screen technologies were simulated: capacitive and resistive screens [142]. As expected by the authors, simulations of the resistive screens yielded better results than those obtained by simulating capacitive screens, as the former provide pressure information. In [168] the discriminative power of global and local features between mobile devices and pen tablets was compared. Results showed a decrease in the feature discriminative power and a higher verification error rate on handheld devices. It was found that one of the main causes of performance degradation on handheld devices was the absence of pen-up trajectory information. A mobile-biometric signature verification system was proposed in [274], which was based on ANNs and a comparative analysis of the performance of the proposed system for two data sets: one obtained using a standard device for biometric signatures, while the other was a mobile database obtained using a smartphone. The experimental results showed that the performance of mobile devices was low when compared to traditional biometric signature capturing devices. The main reason the authors found for this was the absence of pen-tilt angle information in the mobile device data set. Nevertheless, the variability in these databases is also significantly greater as the users are accustomed to sign on traditional tablets.

Due to the large variety of electronic devices employed today for signature acquisition, another relevant direction of research concerns the problem of interoperability. To investigate this problem, a two-stage approach was used in [251].

The former is a pre-processing stage where data acquired from different devices are pre-processed to normalize the signals in similar ranges. The latter consists in selecting the features that are most robust for further reducing the effect of device interoperability.

Usability is also a field of active research. The end user who interacts with the product can be dissatisfied with it. This can involve misuse because of poor results or even complete rejection of the technology. In the light of these observations, three experiments aimed at obtaining usability conclusions for improving future biometric implementations were carried out in [27]. The experiments considered different devices, platforms and technologies. Various scenarios, in which users had to sign in different postures, were analysed. The authors observed that the stylus-based devices obtained better results in performance when the user was sitting on a chair and the device was resting on a table (the most common situation for signing). On the other hand, the finger-based devices returned the best results in performance within the scenarios where the user had to handle the device without support. The better the visual feedback, the better are the performance and the usability: in fact, it was observed that users did not feel comfortable when no visual feedback was provided. Stress influenced negatively both performance and usability. Nevertheless, probably due to the increasing stress at the moment of signing, participants became used to sign quickly and carelessly, so that the performance results were close to the ones obtained without stress.

Another important direction of research concerns the security of our sensitive data in the context of mobile devices. Due to the high deployment of mobile devices and their increasing popularity in our society, the use of biometric traits, for example in commercial and banking applications, provides an easy, quick and reliable way to perform payments through these devices. As was remarked in [250], most state-of-the-art systems are based on extracting information contained in the trajectory coordinates of the signing process, which is stored in a biometric template. Protecting this sensitive information against possible external attack is critical: such attacks, in fact, would allow criminals to perform direct attacks on a biometric system or carry out high quality forgeries of the users' signatures. To this end, in [250] the extreme case of not considering the information related to trajectory and their derivatives in a biometric system was also studied. Such a system would be robust against attacks, as the critical biometric information would not be stored anywhere.

At present, the more common dynamic signature verification systems adopt the contact mode of signing on the mobile device. Therefore, these systems have a great dependence on the device technology. Considering that the development of biometrics seems to tend towards the long distance and non-contact modalities, in-air signature verification systems [18, 71, 106] open novel perspectives which demand further investigation.

It is important to note that a large database tailored to study signature verification in mobile scenarios, namely e-BioSign, has recently been made available to the research community [247]. This database was designed to collect data from five devices: three of them were Wacom devices specifically developed for signature and handwriting applications; the other two were general purpose Samsung tablets that could collect data not only by using a pen stylus but also by the use of a finger. The e-BioSign database may well enable future research towards a better understanding of human handwriting when captured in mobile scenarios.

It must be stated that, up to now, the same feature set has been considered whenever the signature has been written by using a finger or a stylus. Occasionally, some features have been removed in order to allow comparison or for security purposes. However, in general, the features which are considered are those related to the stylus domain. The finger signing scenario allows the consideration of features from the keystroke and touch dynamic domain [175, 229]. The touch size and the shape of the contact area have apparently never been considered within the task of signature verification. These features could be coupled with standard features, and could have an interesting impact since those

features can be considered, to some extent, to belong to the set of physiological biometrics (e.g. hand geometry, finger size, etc.). Moreover, the future availability of under-display fingerprint scanners will allow the synchronous combination of fingerprint and signature data [115]. Signing with a finger over a display also allows the taking into account of tapping behaviour [277]. In fact, it has been shown that touch analysis can be used to recognize users [87, 180].

7 CONCLUSION

We have presented in this paper an update on automatic signature verification and a prospective analysis of an active and dynamic field of research that challenges the image and signal processing research communities.

An analysis has been carried out of the weaknesses and strengths of the most common, publicly available off-line and on-line signature databases. ASV systems have traditionally been developed to cope with Western-based signatures. However, this paper also pays attention to the growing use of other scripts, e.g. Arab and Persian, among others. Beyond being a sign of maturity, such technological growth can be attributed to the high acceptability, in many cultures and countries, of the handwritten signature for use in authentication. Nevertheless, a comparison among the proposed ASV systems is really difficult to carry out. One of the main constraints is the different evaluation protocols in the different proposals. However, different competitions in handwritten signatures have been organized in the last decade, where it is clearly possible to assess the progress of this technology. Thus results from the competitions can be seen as the current state-of-the-art in this field, since they can guarantee the same benchmark under the same conditions. One of the most important areas seen in the last 10 years is the tendency to design systems useful for Forensic Handwriting Experts. To this end, this paper also reviews new proposals in this field. Additionally, some novelties and progress can be detected in the perspective analysis carried out here. We also include a summary of the uses of handwritten signatures in other related fields, which are briefly listed as: developments on stability and complexity measurements on signatures, international standards, advances on cryptosystems, the use of signatures on e-health applications, and the generation of models to synthesize handwritten signatures.

On top of reporting the most recent results, we have pointed out the new trends that might constitute the driving force for the next breakthrough in this field. To conclude, we can look into our crystal ball and go even further in these directions. Among these tendencies, it becomes more and more clear that the off-line applications, on the one hand, will align more and more with forensic practice but, on the other hand, the main off-line deployments will have to come back to large public applications. Such key applications are far from being evident with the decrease of cheque payments and paper contract signing, so this will probably rely more on the need for multi-script personalized cryptography where the number of practical uses is booming. In this context, Sigma-Cryptography is expected to become a key player, combining the naturalness of identifying ourselves by actual signatures with the robustness of digital signatures. From the on-line domain, the widespread availability of hand-held devices will become the driving force. Among other things, these mobile units will allow in the near future the merging of the handwriting and signing interactions into what has been recently labelled as Personal Digital Bodyguards [217]. PDBs will be able to supplement people's sensitive data protection with signature verification. Such equipment will use writer authentication and personalized handwritten CAPTCHAs processing, and enhance human-machine interaction performance through word spotting and handwriting recognition. For young children, these tools will turn into interactive tools helping them to learn and master their fine motor control and become better at handwriting. PDBs will also be able to provide the user with fine motor control monitoring, which can detect stress, aging and health problems, thus bringing medical applications to the forefront.

Finally, as for many fields where successful commercial applications have been developed, these breakthroughs come from the development of robust algorithms tested and validated on huge representative databases, from which

benchmarks can be designed and comparative analysis can be conducted. There is a move in this direction as we have seen using both real and synthesized signatures. This will become a must in the next decade, if we expect to design robust signature verification systems based on a small number of references at registration. These systems need to evolve with time and reach and maintain high accuracy.

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