Handwritten Signature Verification: New Advancements and Open Issues

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***Abstract*—Recently, research in handwritten signature verification has been considered with renewed interest. In fact, in the age of e-society, handwritten signature still represents an extraordinary means for personal verification and the possibility of using automatic signature verification in a range of applications is becoming a reality. This paper focuses on some of the most remarkable aspects the field and highlights some recent research directions. A list of selected publications is also provided for interested researchers.**

Keywords- Biometry, Handwritten Signature Verification, Security.

I. INTRODUCTION

The recent years have been characterized by the growing interest toward personal identity authentication, along with the spreading of the internet and the increased demand for security issues. Biometrics is an important field that allows personal identity authentication through the analysis of personal characteristics. Two types of biometrics means can be considered: Physiological biometrics, which involves data derived from the direct measurement of some part of the human body; Behavioural biometrics, which involves data derived from an action taken by a person. Examples of physiological biometrics include fingerprint-, face-, palmprint-, retina-based verification. Examples of behavioral biometrics are speech-, keystroke dynamics- and signature-based verification [1].

Among the others, handwritten signature is one of the most widespread means for personal authentication. In all developed countries, people learn to affix the signature in the early age and practiced over a period of years. So handwritten signature is a very personal pattern that originates from a complex generation process involving the instantiation of an action plan stored in the brain of the signer and its execution by his/her body (arm, hand) using suitable writing devices (pen, pencil, paper, etc.) [2, 3, 4].

Therefore, it is not surprising that signature analysis is an extremely complex problem that involves aspects of diverse disciplines. Four comprehensive surveys that report the progress in the field of automatic signature verification respectively up to 1989, 1993, 2000 and 2008, provide a comprehensive overview of the efforts done in this research area [5, 6, 7, 72].

The aim of this paper is to highlight some of the most relevant issues at the frontier of research in the field of automatic signature verification. Throughout the paper, some of the most promising directions of research will be pointed out and discussed.

The organization of the paper is the following. Section 2 presents some aspects related to signature acquisition and with the use of new acquisition devices. Some of the crucial questions about signature modelling and representation are discussed in Section 3. The verification strategies are illustrated in Section 4. Section 5 introduce the problem of the assessment of signature verification systems. Some cross-cultural and health issues are presented in Section 6. Section 7 briefly introduces some inquiries concerning security, privacy and regulatory matters. Section 8 reports the conclusion of the paper

II. SIGNATURE ACQUISITION AND NEW DEVICES

Along with the increasing interest in signature verification, there is the need to use a varigate set of devices for signature acquisition. In addition to standard electronic tablets and scanners for dynamic and static signature acquisition, new devices have been used. This is the case of D. Wang et al. [8], that recently proposed – for dynamic signature verification - a compact pen-type force sensor able to detect 3-D forces between the pen tip and the paper. Great interest is also devoted to camera-based signature acquisition. Following the work of Munich and Perona [9], more recently D. Maramatsu et al [10] and S. Shirato et al. [11] proposed a camera-based dynamic signature verification system and verified the effect of camera position on accuracy. The motivation of this approach originated from the consideration that today webcams are inexpensive and widespread. In addition, when webcams are used for online signature acquisition, the user can sign naturally since he/she can write using a normal pen instead of a special electronic pen. Furthermore, the need to use signature verification systems in daily activities has lead several researchers to investigate the use of signature verification for mobile devices, since PDAs and smartphones are increasingly pervasive in our daily lives [12, 13, 14]. Of course, signature verification on mobile devices raises specific issues that do not apply in other scenarios. In particular, mobile devices have a very small pen input area and generally provide poor sampling frequency. In addition, the input device captures only position information and the signer has to use a touch screen instead of paper and a stylus instead of an ordinary pen [15, 16]. In this context,, the effects of constraints on signature characteristics has been the object of specific research [17, 18]. This is also the case for various administrative forms that generally use a line or box for the signature space. In this case, some results show that as the available space increases, signature length augments as well as the length of ascenders and discenders. Conversely, as the available space for signature apposition decreases, “mixed” and “stylized” signatures become less complex whereas no significant complexity changes can be registered for “text-based” signatures. Concerning dynamic features, some evidences demonstrated that no significant difference exists between constrained and unconstrained signatures in terms of pressure. On the contrary, velocity decreases as the available space is reduced. Other typical anomalies in constrained signatures are hesitation marks and lack of fluency. Of course, it is worth noting that, as the number of input devices increases, signature capture will become feasible in many everyday environments, and automatic signature verification will be used in even more applications.

III. Signature Modelling and Representation

Signature modelling and representation is fundamental research area in the field of signature verification. In fact, a handwritten signature is the result of a complex process originating in the signer’s brain as a motor control “action plan”, executed through the neuromuscular system and left on the writing surface by a handwriting device. In general, several computational models can be considered to describe how the central nervous system generates and controls the kinematics of human movements. Among these, a very general model underlying the signature generation process is the Sigma-Lognormal model, that considers the velocity of the pen tip as the result of an action of the neuromuscular system, described by a vectorial summation of lognormal primitives [19, 20, 21].

Of course, the problem of signature modelling involves also aspects like signature stability and complexity. Signature stability can be estimated directly or indirectly.

Direct approaches estimate signature stability from the signature signal. On-line signature stability can be estimated directly using DTW that allows to derive a local stability function [22, 23]. When the analysis of local stability is used to measure short-term modifications—which depend on the psychological condition of the writer and on the writing conditions—it can be used to select among the best subset of reference signatures [24] and the most effective feature functions for verification purposes [25] while providing useful information to weight the verification decision obtained at the stroke level [26]. Indirect approaches estimate the stability of a set of common features used for signature representation and modelling. These approaches have shown that there is a set of features that remains stable over long periods, while there are other features that change significantly with time, as a function of signer age [27, 28, 29]. Of course, signature variability is affected more by fluctuations of the parameters associated with the central neural coding than the peripheral parameters reflecting the timing properties of the muscular system activated by the action plan [30]. In signature analysis, signature complexity is thought to be a predictor for the ease or difficulty with which a forger can simulate a signature. A first attempt to estimate signature complexity was performed by Brault and Plamondon [31], that developed an imitation difficulty coefficient, based on movement dynamics, to estimate the difficulty that a simulator would have in producing an acceptable forgery. More recently, Found and Rogers [32] proposed a complexity theory, which is based on the theoretical relationship between the complexity of features of the handwriting process and the number of concatenated strokes, the likelihood of two writers having identical handwriting characteristics, and the ease or difficulty with which an image is simulated. Vincent at al. [33] used the fractals dimension as an estimator of handwriting complexity. A client-entropy measure was also proposed, based on HMM local density estimation, to group signatures in categories depending on signature complexity and variability [34, 35].

In addition, it is worth mentionning that, depending on the signature model, features can be derived at the global or the local level. The global features reflect the holistic characteristics of the signature action plan, and the local ones highlight some very specific and personal patterns in the instantiation of this plan. Guru and Prakash [36] represented online signatures by interval-valued symbolic features. They used parameter-based features derived by a global analysis of signatures and achieved the best verification results when a writer-dependent threshold was adopted for distance-based classification. Of course, the use of a universally applied feature set is not effective for signature verification, since signatures from different writers generally contain very few common characteristics. The knowledge that an individual’s signature is unique has led many researchers to devote special attention to the selection of the personal features more effective for signature verification [37]. Genetic algorithms have been used for parameter selection [38], and in some cases the feature set was personalised by assigning a different weight to each feature [39], as well as selecting the optimal prototype function [40]. Sometimes, the most valuable function feature for verification is selected for each signature segment based on the specific characteristics of that segment. For instance, information on the local stability of a signature can be derived from different representation domains, and can be used for selecting the best function feature [41].

In the field of signature modelling, Hidden Markov Models (HMM) based on Left-to-Right topologies were found to be very effective, since they are adaptable to personal variability [42]. Moreover, many researchers have been recently attracted by new signature representation approaches based on graphical models. Wang et al. [43]

used a graph representation for on-line signature verification in which nodes and edges describe respectively certain properties at sample points and relationship between points. Piekarczyk [44] used a hierarchical random graph model for off-line signature recognition. Information about the shapes of specimen signature is presented in the form of a language based on random graphs and stochastic grammars, which makes it possible to take into consideration signature variability. Lv et al. [45] used a probabilistic graphical model able to capture the variations and dependence of signature landmark points for off-line signature verification. Also the use of pseudo-dynamic features for signature verification is a field of growing attention. Pseudo-dynamic features can be derived from microscopic inspections of the writing trace, as in the case forensic document examiners. Conversely, in the field of the image processing, pseudo-dynamic features mainly concerns with grey-level analysis to infer pressure information of the underlying writing process. High pressure points/low pressure points can be selected as those signature pixels which have grey level upper/lower suitable thresholds [46].

IV. Verification Strategies

In the recent literature, signature verification approaches can be classified in two categories: writer-dependent and writer-independent [47]. When writer-dependent approaches are used, a specialized classifier is trained for each writer. The writer-independent approach uses a single classifier for all writers, which is trained using genuine and forged specimens of the entire population of individuals considered for training. The writer-independent approach is generally considered superior to the writer-dependent approach, since the writer-independent system can be trained from previously collected specimens of other individuals.

Concerning matching technique, both distance-based and model-based verification techniques have been considered. When function features are used, Dynamic Time Warping (DTW) has been used extensively used with function features and several data reduction techniques have been proposed to reduce the computational load [7]. Also edit-distances [43] have been recently considered for signature comparison. When parameter features are used, Support Vector Machines (SVM) are another effective approach for signature verification, since they can map input vectors to a higher dimensional space, in which clusters may be determined by a maximal separation hyper-plane. In particular Vargas et al. [46] use the pseudo-cepstral coefficients of grey-scale histogram along with a Least Squares Support Vector Machines for signature classification. Gruber et al. [48] use SVM for online signature verification and demonstrates their effectiveness depending on the kernel function considered. In particular they showed that SVM based on longest common subsequences (SVM- LCSS) are superior with respect to SVM based on other kernel functions.

So far the cognitive and connexionist approaches relying on neural networks have not been extensively explored, as well as the use of swarm intelligent and biomimetic inspired methodologies.

Whatever technique is adopted, the need to improve verification performance has led researchers to investigate multi-expert strategies for combining sets of verifiers based on global and local verification approaches [49, 50]. The use of handwritten signatures within multi-modal biometric systems is also a promising field of research. In fact, multi-modal biometrics addresses the problem of non-universality, and is expected to achieve better performance than the uni-modal approaches, that are generally not considered adequate for large-scale security applications, no matter which biometric trait is used. In this direction of research new operative scenarios using so-called spoken signatures are evaluated, in which user authentication is based on a combined acquisition of on-line pen and speech signals, that are recorded simultaneously simply asking the user to utter what she/he is writing. User authentication by spoken signatures improves the results in comparison of either modalities (handwritten signature and speech) used alone. In addition, it presents no extra costs in terms of acquisition time, as both modalities are recorded simultaneously [51]. Li [52] combine signatures and utterance of pronounced names to authenticate a person. Unlike typical signature verification methods, the dynamic feature of signatures are captured as sounds in his work

V. Assessment of Signature Verification Systems

In the recent years the use of the Receiver Operating Characteristic (ROC) curve, that plots the FRR vs. FAR, has been extensively adopted for the assessment of signature verification performance. The Area Under the Curve (AUC) of the ROC estimates system performance by using a single value, since the AUC provides the probability that the classifier will rank a randomly chosen positive sample higher than a randomly chosen negative sample [53]. However, it is worth noting that performance evaluation still remains a very critical task. In particular, FAR evaluation is difficult and generally imprecise, since the existence of skilled forgeries for a given signature is not certain, nor is the possibility of collecting good quality forgery samples for the test. In addition, Liwiki et al. [54] observed that it is necessary to define a common terminology for signature forgeries since researchers from the pattern recognition community use different names for the same forgery type and sometimes the same name for different types of forgeries. Most important discrepances can also be registered with respect to the terminology used by forensic handwriting experts. Up to now, specific efforts have been made to develop both benchmark databases for the comparative assessment of the approaches proposed in the literature, as those reported in refs. [7, 55]. Synthetic signature generation was also considered for both evaluating system performance and improving the enrolment procedure [56, 57]. The synthetic sample generation approach uses well-defined transformations to generate synthetic samples from the real ones of a given individual – distortion-based techniques using elastic matching procedures [58] and variability estimation [56] have been considered for this purpose. The synthetic individual generation approach creates a model of the signature produced by a population of individuals and generate a new synthetic individuals by sampling the model. In this field, models based on spectral analysis [56] and delta-lognormal parameters [57] have been considered. Moreover, significant advancements in system benckmarking and performance evaluation has been achieved through international competitions for on-line and off-line signature verification systems, such as: SVC 2004 [59], BioSecure Signature Evaluation Campaign 2009 [60], SigComp 2009 [61], 4NSigComp2010 [62], SigComp2011 [63]. It is worth noting that competitions allow researchers and practitioners to systematically evaluate the performance of signature verification systems also with respect to different operating environment. For instance, in the Signature Evaluation Campaign of 2009 (BSEC'2009) [60], two different databases were considered, each containing data from the same individuals that were acquired by a digitizing tablet and a PDA, in order to measure the impact of a mobile device on the performance of signature verification systems. Finally, Liwiki et al. [54] observed the current systems provide the verification result as a Boolean value, that is a kind of classification that is not useful for forensic application. Forensic handwriting examiners need a value can be attached to the comparison results of the handwriting, for the competing propositions of the handwriting coming from either the same or different writers.

VI. Cross-Cultural and Health Issues

Of course, although the general model underlying the signature generation process is invariant in terms of cultural habits and language differences among signers, the enormous diversity in the signatures of people from different countries has suggested the development of specifically designed solutions.

For instance, Western-style signatures generally consist of signs that could form concatenated text combined with pictorial strokes. In some countries, the habit is to sign with a readable written name whereas in other countries signatures are not always legible. Many more differences can be expected when considering signatures written by people from non-Western countries. To address these differences, specific approaches have been proposed in the literature for Chinese and Japanese signatures, which can consist of independent symbols, and for Arabic and Persian signatures, which are cursive sketches that are usually independent of the person's name. In general, as the need for cross-cultural applications increases, it is becoming more and more important to evaluate both the extent to which personal background affects signature characteristics and the accuracy of the verification process. For this reason, a set of metadata, sometimes called "soft biometrics", has been also considered. Metadata are related to various aspects of a writer's background, such as nationality, script language, age, gender, handedness, etc. Some metadata can be estimated by statistically analyzing human handwriting, which means that it is possible to adapt signature verification algorithms to a particular metadata context in order to improve verification performance [64, 65].

Analysis of the individual characteristics of handwriting remains an interesting research area, and should encompass not only the features produced by people with normal abilities, but also those generated by people with disabilities and illnesses that constrain their handwriting abilities. Investigation of the human mechanisms involved in handwriting production is therefore deserving of greater attention, as well as studies on the feature selection techniques and signature modelling methods that produce the best possible description of the personal characteristics involved in signing. Techniques for analysing signature complexity and stability can offer new insights into the selection of the most useful signature fragments and features for various kinds of applications, and also to better understand time-based variations in signing [66, 67].

VII. Security, Privacy and Regulatory Issues

Data security and privacy are crucial issues to be addressed for assuring a successful deployment of signature verification systems in real life applications. As matter of the fact, feature transformation approaches and biometric cryptosystems have been considered. More recently, a general hybrid approach is proposed for ensuring the protection to biometric templates, that has been applied to on-line signatures. The feature transformation part of the protection scheme relies on the use of Universal Background Models (UBMs), whereas the cryptosystem part is given by a user-adaptive version of the fuzzy commitment cryptographic protocol [68]. Eskander et al. presented a bio-cryptography system that constructs Fuzzy Vaults based on Extended Shadow Codes features extracted from off-line signature images [69].

Legal and regulatory aspects of personal verification by handwritten signature are also very important. Significant results have been achieved recently, since governments and institutions have demonstrated a growing awareness and attention to this important field. As matter of fact, some regulatory aspects have been defined and introduced [70, 71].

VIII. Conclusions

Handwritten signature is an extraordinary product of human beings and, in the era of the internet, several questions on signature treatment for verification aims still remain open [72]. This paper has tried to point out some of the most remarkable issues of recent research in the field of automatic signature verification and suggested new directions of investigation.

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