Assessment of Finger-based On-Line Signature Verification

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Abstract. The high acceptance of the society towards the use of smartphones and tablets on a daily basis has raised the interest of many sectors on the use of finger patterns as a way of authentication. In this paper we carry out an assessment on the use of the finger as the writing tool for handwritten signature verification. The new e-BioSign database is considered in the experimental work. This database is comprised of 5 devices in total, three Wacom devices and two Samsung general purpose tablets. For these two Samsung tablets data is collected using a pen stylus but also the finger to study the performance of signature verification in a mobile scenario. A signature baseline evaluation based on Dynamic Time Warping (DTW) is carried out for the case of using the finger as the writing tool. Good results are achieved for the case of random forgeries (less than 1.0% EER), but the performance is significantly degraded for skilled forgeries compared to the case of using the pen stylus as the writing tool.

1. Introduction

New methods of authentication are modifying the traditional way people access to their personal applications. The improvement of sensors quality and the great deployment of smartphones and tablets in the last years have boosted the application of biometric recognition schemes (Meng & al. (2015)). However, some biometric traits have shown some vulnerabilities against attacks (Liu & al. (2016)) and different variability conditions (Xie & al. (2011)) in real scenarios. On-line handwritten signature verification systems have become very important in the last years in the commercial sector to facilitate payments, also in banking to facilitate the digital storage of all the signed paperwork, and in many other sectors such as e-government, healthcare or education (Impedovo & al. (2012)). These systems based on the signature have recently shown to be very robust against attacks. In (Tolosana & al. (2015a)) an extreme approach for on-line signature verification systems was proposed as critical information (i.e. X and Y pen coordinates and its first- and second-order derivatives) was not stored anywhere. The proposed approach achieved results below 7.0% and 1.0% EER for skilled and random forgeries respectively.

Traditionally, the stylus has been considered as the writing tool in on-line handwritten signature verification systems as users have been asked to perform their signatures on devices specifically designed for capturing signatures and handwriting (i.e. Wacom devices) and under controlled scenarios (Plamondon & al. (2014); Malik & al. (2015)). However, the high acceptance of the society towards the use of their own devices for the access of personal applications has spread the interest on the use of the finger as the writing tool (Reillo & al. (2016)). We consider this last scenario as the universal case as everyone can have access to it. The use of the finger on devices for authentication purposes has been widen studied in the last years. In (Anthony & al. (2012)), interaction and recognition challenges based on touch and surface gesture interaction tasks were analysed for children and adults. Regarding the signature trait, some preliminary studies have been carried out for the on-line signature verification. In (Martinez & al. (2013)), both stylus and finger writing tools were considered in the experimental work. For the finger case, users had to perform a simplified version of their signature (a.k.a. pseudo-signatures). Results using both writing tools were analysed although different users and devices were considered for each writing tool. In (Robertson & al. (2015)), a statistical analysis was conducted to assess consistency between signatures acquired using the stylus and the finger. Results showed a set of static and dynamic features that keep stability in both scenarios. However, the effect of the system performance was not analysed in previous works and in addition, the devices considered were devices not commercially available nowadays.

The main goal of this work is to carry out an assessment on the use of the finger as the writing tool in handwritten signature verification systems considering the new Commercial Off-The-Shelf (COTS) devices of the e-BioSign database. Skilled and also random forgeries are included in the experimental work. A signature baseline evaluation based on DTW is carried out for each of the devices, achieving a benchmark performance.

The remainder of the paper is organized as follows. Sec. 2. describes the new e-BioSign database considered in the experimental work. Sec. 3. describes the experimental protocol and the results achieved. Finally, Sec. 4. draws the final conclusions and points out some lines for future work.

Fig. 1. Acquisition setup for e-BioSign database.

2. On-Line Signature Database

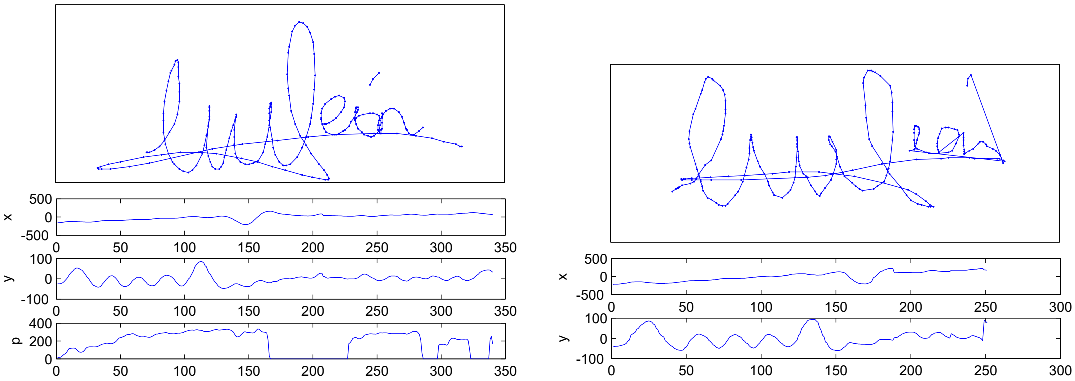
The complete e-BioSign database, which was preliminary presented in (Vera-Rodriguez & al. (2015)), is considered in this work. This database is comprised of 65 users and 5 capturing devices of dynamic signatures, three of them are specifically designed for capturing handwritten data (Wacom devices), while other two are general purpose tablets not designed for that specific task (Samsung tablets). Figure 1 shows an image of the setup used to acquire the database, with all five capturing devices.

It is worth noting that the five devices were used with their own pen stylus. For the two Samsung devices data was also collected using the finger. The same capturing protocol was used for all five devices, they were placed on a table and subjects were told to feel comfortable when writing on them, so small rotation of the devices were allowed.

The software for capturing the signatures and names was developed in the same way for all the devices in order to minimize the variability of the user during the capturing process. All devices had a rectangular area with an horizontal line in the bottom part, with two buttons "OK" and "Cancel" to press after writing if the sample was good or bad respectively. If the sample was not good, then it was repeated (See Figure 1). A brief description of the devices used in e-BioSign is given next:

(1) **W1: WACOM STU-500**. 5-inch TFT-LCD B/W display, with VGA resolution of 640×480 pixels. It has a sampling rate of 200 Hz, and 512 pressure levels. This device gives a very natural feel of writing.
(2) **W2: WACOM STU-530**. Newer version of the previous. 5-inch TFT-LCD color display, with VGA resolution of 640×480 pixels. It has a sampling rate of 200 Hz, and 1024 pressure levels. This device allows safe transactions as it has an AES 256 bit / RSA 2048 bit data encryption embedded in the signature pads.
(3) **W3: WACOM DTU-1031**. This device has a larger 10.1-inch color LCD display, with a resolution of 1280×800 pixels. It has a sampling rate of 200 Hz, and 512 pressure levels. It also provides the same data encryption as the STU-530. It allows to visualize documents on the display before signing them.
(4) **W4: SAMSUNG ATIV 7**. This is a device with Windows 8 operative system (OS). It has a 11.6-inch LED display with a resolution of 1920×1080 pixels. It has 1024 pressure levels and regarding the sampling rate is not uniform as in the Wacom devices as it depends on the system time in this case. This tablet allows to use its own stylus or also the finger, but no pressure information is recorded in this last case.
(5) **W5: SAMSUNG GALAXY NOTE 10.1**. This is a device with Android OS. It has a 10.1-inch LCD display with a resolution of 1280×800 pixels. It has 1024 pressure levels and not uniform sampling rate. This device also allows to use its own stylus or the finger.

This database was collected in two sessions with a time gap of at least three weeks between them. In each session there were three capturing blocks namely *Genuine 1*, *Genuine 2* and *Forgeries*. In *Genuine 1* block, two signatures plus the full name are performed for each device using their own pen stylus, and then two signatures and a number sequence comprised of numbers from 0 to 9 plus a random letter for



(a) Pen Stylus (b) Finger

Fig. 2. Examples of genuine signatures acquired using the Samsung Galaxy Note 10.1 device.

the two Samsung devices with the finger. Next, *Genuine 2* block is recorded, which is comprised of the same information as *Genuine 1* block, but in this case the full name is written in capital letters. Finally, the last block *Forgeries* is performed, where each user carries out a forgery of the signatures of the three previous users in the database for each of the 5 devices using the stylus, and also with the finger for the two Samsung devices. Regarding forgeries of the full name, this is only performed for the Wacom STU-530 both for lower and upper case writing. In order to perform good forgeries, users are allowed to visualize a recording of the dynamic realization of the signature to forge for a few times.

In the second session, the procedure is identical, but the only difference is in the *Forgeries* block. In this case, users forge the same users as in session one, but this time a paper with the image of the signatures and names to forge is placed over the devices and they can trace the lines to perform the forgery. They are not allowed to see the recording of the signatures in this case. This will allow to study which of the two types of forgeries is more accurate.

It is worth noting that data collected using the finger for the Samsung ATIV 7 and Galaxy Note 10.1 do not contain pressure information as this was not provided by these devices, and also there is no information of the trajectory (X and Y pen coordinates) when having a pen-up. This information is only available when the stylus is considered as the writing tool and has been used in the evaluation reported in this paper.

In this work the two Samsung general purpose devices (i.e. W4 and W5) are considered in the experimental work as signatures were acquired using the stylus and also the finger as writing tools. Figure 2 shows examples of two genuine signatures acquired using the stylus (left) and the finger (right) as writing tools for the Samsung Galaxy Note 10.1 device.

3. Experimental Work

This section reports the benchmark evaluation carried out for on-line signature verification on the e-BioSign database using the finger as the writing tool. Sec. 3.1 describes the features of the signature verification system considered in the experimental work. Then, Sec. 3.2, gives the experimental details considered for the benchmark evaluation. Finally in Sec. 3.3 the results obtained for both stylus and finger writing tools are analysed.

3.1 On-Line Signature Verification System

An on-line signature verification system based on time functions (a.k.a. local systems) is considered in the experimental work. For each signature acquired using the stylus, signals related to X and Y pen coordinates and pressure are used to extract a set of 23 time functions whereas for those signatures acquired using the finger, only time functions related to X and Y coordinates are considered as pressure information is not available. Information related to pen angular orientation (azimuth and altitude angles) has been always discarded in order to consider the same set of time functions that we would be able to use in general purpose devices such as tablets and smartphones. The Sequential Forward Feature Selection (SFFS) algorithm (Tolosana & al. (2015b)) has been performed over a development dataset to obtain optimal subsets of the time-functions, improving the performance of the system in terms of EER (%).

The considered local system is based on previous works (Tolosana & al. (2015b)). The DTW algorithm is used to compute the similarity between the time functions from the input and training signatures. The configuration of the DTW algorithm considered in this work is the same as it was recently proposed in (Martinez & al. (2015)).

Table 1
System performance results (EER in %). B = Baseline and P = Proposed.

	STYLUS				FINGER			
	W4		W5		W4		W5	
	B	P	B	P	B	P	B	P
Skilled	10.0	7.9	12.9	10.7	24.0	22.1	27.0	26.4
Random	0.8	0.7	2.1	1.0	1.4	0.3	2.3	1.0

3.2 Experimental Protocol

The experimental protocol has been designed to analyse the feasibility of finger-based on-line signature verification systems in practical applications. The e-BioSign database is divided into two different datasets, one for development the systems and the other one for evaluation. The first 30 users of the e-BioSign database are used in the development phase while the remaining 35 users are considered in the evaluation phase.

Regarding the development phase, two different approaches are considered in this work. First, Baseline systems whose time functions are fixed from previous works (Tolosana & al. (2015c))). Second, the local system is adjusted in order to improve the system performance for each device by using the set of time functions selected by the SFFS algorithm on the 30 users of the development dataset. In order to do that, the 4 genuine signatures of the first session are used as training signatures, whereas the 4 genuine signatures of the second session are left for testing in order to consider inter-session variability. The time-function selection SFFS algorithm has been individually applied to each device and writing tool. This second approach will be considered as Proposed.

Regarding the evaluation phase, the 4 genuine signatures of the first session are used as reference signatures, whereas the remaining 4 genuine signatures of the second session are left for testing. Skilled forgery scores are obtained by comparing the reference signatures against the 6 available skilled forgeries per user whereas random (zero-effort) forgery scores are obtained by comparing the reference signatures with one genuine signature of each one the remaining users. The average score of the four one-to-one comparisons is performed to get the final score.

3.3 Experimental Results

In this experiment an evaluation of the e-BioSign database is carried out for both stylus and finger writing tools in order to analyse the system performance and feasibility of this new scenario in real applications. Table 1 shows results for both Baseline and Proposed approaches considering the 35 users of the evaluation dataset.

Analysing Table 1 for the case of using the stylus as the writing tool, the baseline systems achieve an average EER of 11.5% and 1.5% for skilled and random forgeries respectively whereas for the proposed systems the average EER improves to 9.3% and 0.9% for skilled and random forgeries respectively. These results show the benefits of using the time-function selection SFFS algorithm over a development dataset. In addition, it is important to highlight the good results obtained for both devices, showing the possibility of considering general purpose devices in real banking and commercial applications.

Analysing Table 1 for the case of using the finger as the writing tool, the baseline systems achieve an average EER of 25.5% and 1.9% for skilled and random forgeries respectively whereas for the proposed systems the average EER improves to 24.3% and 0.7% for skilled and random forgeries respectively, showing again the benefits of using the time-function selection SFFS algorithm. An important effect that can be observed from Table 1 is how the system performance changes regarding the writing tool (i.e. stylus and finger) considered during the acquisition process. Additionally, it is important to note the high EER obtained for skilled forgeries when the finger is considered as the writing tool (almost three times worse than the stylus case). The reason for this effect can be due to the very challenging scenario considered for the finger case as forgers had access to the dynamic realization of the signatures to forge. A recommendation for the usage of signature recognition on mobile devices would be for the users to protect themselves from other people that could be watching while signing as this is more feasible to do in a mobile scenario compared to an office scenario. This way skilled forgers might have access to the global shape of a signature but not to the dynamic information. Therefore, signatures acquired using the finger seem to be a real possibility for many practical applications specially for the random forgeries case where similar or even better results are achieved compared to the stylus case.

4. Conclusions

This paper has carried out an assessment on the use of the finger as the writing tool for handwritten signature verification. The new e-BioSign database has been considered in the experimental work. This database is comprised of 65 users and data is collected in two sessions. The database was designed to collect data from five devices, three of them specifically developed for signature and handwriting applications and two general purpose tablets that can collect data using a pen stylus and also the finger. These are some of the most common used devices in commercial, banking, and e-health applications nowadays, so research in the areas of inter-device and mixed writing-tool (pen stylus and finger) recognition can be carried out. This database will be made publicly available for the research community.

A signature baseline evaluation based on DTW is carried out for the case of using the finger as the writing tool. Results obtained in the experimental work show the feasibility of considering general purpose devices in practical applications. Regarding the case of using the finger as the writing tool, good results are achieved for the case of random forgeries (less than 1.0% EER), but the performance is significantly degraded for skilled forgeries compared to the case of using the pen stylus as the writing tool. For future work, an exhaustive analysis will be carried for signatures acquired using the finger as the writing tool. In addition, novel successful configurations of the DTW algorithm (Fischer & al. (2015)) will be considered in order to improve the performance of skilled forgeries cases. Finally, the number of users and sessions of the e-BioSign database will be extended in order to make it feasible to conduct research on template aging for signature and handwriting biometrics.

Acknowledgment

This work has been supported by project TEC2015-70627-R MINECO/FEDER and by UAM-CecaBank Project. Ruben Tolosana is supported by a FPU Fellowship from Spanish MECD.

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