Online Signature Verification Method Based on the Acceleration Signals of Handwriting Samples

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Abstract. Here we present a method for online signature verification treated as a two-class pattern recognition problem. The method is based on the acceleration signals obtained from signing sessions using a special pen device. We applied a DTW (dynamic time warping) metric to measure any dissimilarity between the acceleration signals and represented our results in terms of a distance metric.

Keywords: online signature, biometrics, signature verification.

1 Introduction

Several types of biometric authentication exist. Some of them have appeared in the last few decades, such as DNA and iris recognition and they provide more accurate results than the earlier methods did (e.g. fingerprint, signature). Hence they are more difficult to forge. However, a signature is still the most widely accepted method for identification (in contracts, bank transfers, etc.). This is why studies tackle the problem of signature verification and examine the process in detail. Usually their aim is to study the mechanics of the process and learn what features are hard to counterfeit.

There are two basic approaches of recognising signatures; namely the offline and the online. Offline signature recognition is based on the image of the signature, while the online case uses data concerning the dynamics of the signing process (pressure, velocity, etc.). The main problem with the offline approach is that it gives higher false accept and false reject errors, but the dynamic approach requires much more sophisticated techniques.

The online signature recognition systems differ in their feature selection and decision methods. Some studies analyse the consistency of the features [1], while others concentrate on the template feature selection [2]; some combine local and global features [3].

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An important step in signature recognition was the First International Signature Verification Competition [4]. Reviews of automatic signature verification were written by Leclerc and Plamondon [5,6].

Many signals and therefore many different devices can be used in signature verification. Different types of pen tablets have been used in several studies, as in [7,8]; the F-Tablet was described in [9] and the Genius 4x3 PenWizard was used in [10]. In several studies (like ours), a special device (pen) was designed to measure the dynamic characteristics of the signing process.

In [11], the authors considered the problem of measuring the acceleration produced by signing with a device fitted with 4 small embedded accelerometers and a pressure transducer. It mainly focused on the technical background of signal recording. In [12], they described the mathematical background of motion recovery techniques for a special pen with an embedded accelerometer.

Bashir and Kempf in [13] used a Novel Pen Device and DTW for handwriting recognition and compared the acceleration, grip pressure, longitudinal and vertical axis of the pen. Their main purpose was to recognise characters and PIN words, not signatures. Rohlik et al. [14,15] employed a similar device to ours to measure acceleration. Theirs was able to measure 2-axis accelerations, in contrast to ours which can measure 3-axis accelerations. However, our pen cannot measure pressure like theirs. The other difference is the method of data processing. In [14] they had two aims, namely signature verification and author identification, while in [15] the aim was just signature verification. Both made use of neural networks.

Many studies have their own database [8,9], but generally they are unavailable for testing purposes. However some large databases are available, like the MCYT biometric database [16] and the database of the SVC2004 competition[1] [4].

In this paper we propose an online signature recognition method that is based on a comparison of the 3-axis acceleration of the handwriting process. We created our database with genuine signatures and unskilled forgeries, and used the dynamic time warping method to measure the dissimilarities between signatures. The novelty of our approach is a detailed investigation of the contribution of acceleration information in the signature verification process.

2 Proposed Method

2.1 Technical Background

We used a ballpoint pen fitted with a three-axis accelerometer to follow the movements of handwriting sessions. Accelerometers can be placed at multiple positions of the pen, such as close to the bottom and/or close to the top of the pen [11,13]. Sometimes grip pressure sensors are also included to get a comprehensive set of signals describing the movements of the pen, finger forces and gesture movements. In our study we focused on the signature-writing task, so we placed the accelerometer very close to the tip of the pen to track the movements as accurately as possible (see Figure 1).

[1] Available at `http://www.cse.ust.hk/svc2004/download.html`

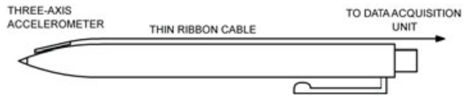


Fig. 1. The three-axis accelerometer is mounted close to the tip of the pen

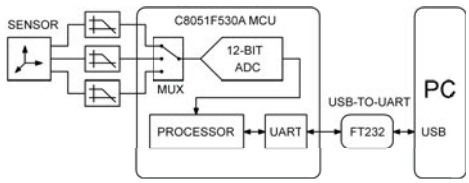


Fig. 2. Block diagram of the data acquisition system

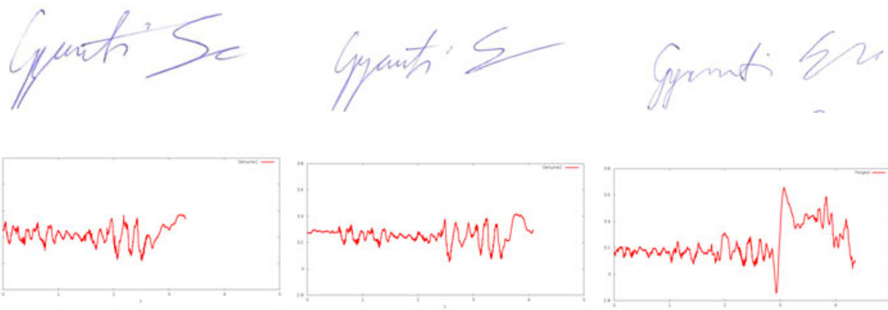
In our design we chose the LIS352AX accelerometer chip because of its signal range, high accuracy, impressively low noise and ease-of-use. The accelerometer was soldered onto a very small printed circuit board (PCB) and this board was glued about 10mm from the writing tip of the pen. Only the accelerometer, the decoupling and filtering chip capacitors were placed on the assembled PCB. A thin five-wire thin ribbon cable was used to power the circuit and carry the three acceleration signals from the accelerometer to the data acquisition unit. The cable was thin and long enough so as not to disturb the subject when s/he provided a handwriting sample. Our tiny general purpose three-channel data acquisition unit served as a sensor-to-USB interface [17].

The unit has three unipolar inputs with signal range of 0 to 3.3V, and it also supplied the necessary 3.3V to power it. The heart of the unit is a mixed-signal microcontroller called C8051F530A that incorporates a precision multichannel 12-bit analogue-to-digital converter. The microcontroller runs a data logging program that allows easy communication with the host computer via an FT232RL-based USB-to-UART interface. The general purpose data acquisition program running on the PC was written in C#, and it allowed the real-time monitoring of signals. Both the hardware and software developments are fully open-source [18]. The block diagram of the measurement setup is shown in Figure 2.

The bandwidth of the signals was set to 10Hz in order to remove unwanted high frequency components and prevent aliasing. Moreover, the sample rate was set to 1000Hz. The signal range was closely matched to the input range of the data acquisition unit, hence a clean, low noise output was obtained. The acquired signals were then saved to a file for offline processing and analysis.

2.2 Database

The signature samples were collected from 40 subjects. Each subject supplied 10 genuine signatures and 5 unskilled forgeries, so we had a total $40 \cdot 15 = 600$



(a) Genuine1 (b) Genuine2 (c) Forgery

Fig. 3. The images and acceleration signals of two genuine signatures and one forged signature

signatures in total. The signature forgers were asked to produce 5 signatures of another person participating in the study. Each participant supplied forged samples and genuine samples.

In order to make the signing process as natural as possible, there were no constraints on how the person should sign. This led to some problems in the analysis because it was hard to compare the 3 pairs of curves (two signatures). During a signing session, the orientation of the pen can vary somewhat (e.g. a rotation with a small angle causes big differences for each axis). That was why we chose to reduce the 3 dimensional signals to 1 dimensional signals and we only compared the magnitudes of the acceleration vector data.

Figure 3 shows the acceleration signals of 2 genuine signatures and 1 forged signature. Figures 3a and 3b belong to the same author, and they appear quite similar. Figure 3c is a corresponding forged signature, which differs significantly from the first two.

2.3 Distance between Time Series

An elastic distance measure was applied to determine dissimilarities between the data. The dynamic time warping (DTW) approach is a commonly used method to compare time series. The DTW algorithm finds the best non-linear alignment of two vectors such that the overall distance between them is minimised. The DTW distance between the $u = (u_1, \ldots, u_n)$ and $v = (v_1, \ldots, v_m)$ vectors (in our case, the acceleration vector data of the signatures) can be calculated in $\mathcal{O}(n \cdot m)$ time.

We can construct, iteratively, a $C \in \mathbb{R}^{(n+1)\times(m+1)}$ matrix in the following way:

$$
\begin{aligned}
C_{0,0} &= 0, C_{i,0} = +\infty, C_{0,j} = +\infty, \qquad i = 1, \ldots, n, j = 1, \ldots, m \\
C_{i,j} &= |u_i - v_j| + \min\left(C_{i-1,j}, C_{i,j-1}, C_{i-1,j-1}\right), \\
&\qquad\qquad i = 1, \ldots, n, j = 1, \ldots, m.
\end{aligned}
$$

After we get the $C_{n,m}$ which tells us the DTW distance between the vectors u and v. Thus

$$d_{\mathrm{DTW}}(u, v) = C_{n,m}.$$

The DTW algorithm has several versions (e.g. weighted DTW and bounded DTW), but we decided to use the simple version above, where $|u_i - v_j|$ denotes the absolute difference between the coordinate i of vector u and coordinate j of vector v.

Since the order of the sizes of n and m are around $10^3 - 10^4$, our implementation does not store the whole C matrix, whose size is about $n \times m \approx 10^6 - 10^8$. Instead, for each iteration, just the last two rows of the matrix were stored.

Table 1. Sample distance matrix

DTW	AE00	AE01	AE02	AE03	AE04	AE05	AE06	AE07	AE08	AE09	ME10	ME11	ME12	ME13	ME14
AE00	0	62	97	122	115	63	114	103	75	223	342	277	236	316	709
AE01		0	63	70	65	113	81	67	65	160	238	232	176	258	676
AE02			0	103	66	134	75	76	63	82	252	251	175	258	695
AE03				0	99	163	127	111	108	165	278	283	228	301	712
AE04					0	156	70	70	58	78	385	445	254	409	874
AE05						0	155	146	104	308	527	450	347	490	851
AE06							0	60	36	155	331	401	221	332	793
AE07								0	49	138	199	239	178	220	669
AE08									0	116	233	247	157	225	683
AE09										0	362	484	303	365	950
ME10											0	133	70	49	258
ME11												0	107	83	197
ME12													0	67	394
ME13														0	267
ME14															0

A distance matrix is shown in Table 1. The intersection of the first 10 columns and 10 rows shows the distance values between the genuine signatures (got from the same person). The intersection of the first 10 rows and the last 5 columns tells us the distances between genuine and the corresponding forged signatures. The rest (the intersection of the last 5 rows and last 5 columns) shows the distances between the forged signatures.

The distance between the genuine signatures varies from 60 to 308 (with average distance of 95), but between a genuine and a forged signature it varies from 157 to 950 (with average distance of 390).

The distance matrices are similar to that given above. In some cases the distance between genuine and forged signatures can be easily delimited, but in other cases we cannot define a strict line.

3 Results

The performance of a signature verification algorithm can be measured by the rate of Type I error (false reject), when a genuine signature is marked as forged and Type II error (false accept), when a forged signature is marked as genuine.

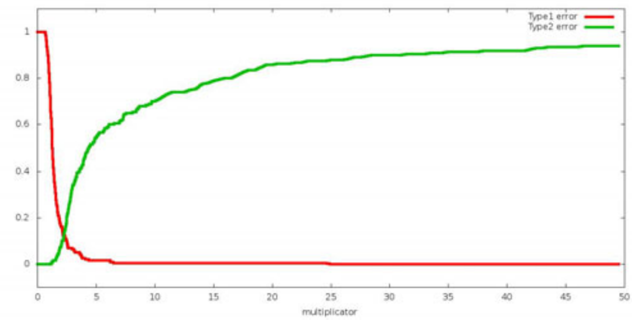


Fig. 4. False reject and false accept rates depending on the constant multiplier

For each person, 5 genuine signatures were chosen randomly as references, so they belonged to the training set. All the other signatures of this person and unskilled forgeries of their signature were used for testing. Thus the test set contained 5 genuine and 5 unskilled forged signatures for each person.

We first computed the average distance between the five elements of the training set ($D_{\mathbf{avg}}$). Then, for each signature in the test set, the average distance of the signature from the training set's five signatures was found ($D_{\mathbf{dis}}$). Now, if for some t in the set

$$D_{\text{dis}} < m \cdot D_{\text{avg}}$$

then t was accepted as a true signature, otherwise it was rejected.

Figures 4 shows the false reject and false accept rates depending on the constant multiplier m of the minimum distance got from the training dataset. We can see that we get a zero FA rate around $m = 7$. The curve decreases quite quickly while the increase of the FR is less marked.

Besides the average we also used two other metrics, namely the maximum and minimum distances. These were calculated from the training set via

$$\mathrm{D}_{max}(R) = \max_{i,j=1,\dots,|R|,i\neq j} \mathrm{d}_{\mathrm{DTW}}(r_i, r_j) \text{ and } \mathrm{D}_{min}(R) = \min_{i,j=1,\dots,|R|,i\neq j} \mathrm{d}_{\mathrm{DTW}}(r_i, r_j),$$

where the set R is the training data set, $|R|$ denotes the cardinality of R and r_i is the signature i in the training set.

We can use the same definitions to compute the distance between a test signature and a training set.

Table 2 shows the false accept and false reject errors in percentage terms. The Equal Error rate (EER) is the percentage where the false acceptance and the false rejection rates are equal. We see that we get the best results (the lowest EER), when we use $d_{\min}$ both for the training and the test set.

Table 2. Equal Error rates (EER) depending on the chosen distance on the reference set and the chosen distance between references and the sample. The values in brackets are the corresponding multipliers.

		Test distance		
		average	**maximum**	**minimum**
Training	**average**	14.50% (1.36)	23.50% (0.56)	18.00% (3.34)
	maximum	17.25% (2.02)	29.50% (0.84)	23.25% (4.82)
	minimum	15.50% (0.98)	23.25% (0.38)	13.00% (2.28)

4 Summary, Discussion and Conclusions

In this paper an online signature verification method was proposed for verifying human signatures. The proposed procedure was implemented and then tested. A test dataset was created using a special device fitted with an accelerometer. The dataset contained 600 signatures, where 400 signatures were genuine and 200 were forged. In the study we found we had to limit the 3d acceleration vector data to 1d acceleration vector data so as to make the verification task more manageable. Using a time series approach and various metrics we were able to place signature samples into two classes, namely those that are genuine and those that are forged. The results we got were instructive and the method looks promising.

The method outlined in [15], which used a similar device and neural networks to verify signatures, attained an overall accuracy ratio between 82.3% and 94.3%, depending on the author of the signatures (with an average of 87.88%). We attained an 88.50% overall accuracy ratio in the case of the minimum distance and choosing $m = 2.2$ as a multiplier. Thus our results compared to the above mentioned previous study is slightly better, despite the fact we used less data, as we did not use pressure data.

There are several ways that the work described here could be extended. First, other metrics than DTW could be included and the results compared. Second, our method just uses the magnitude of the acceleration, not the direction. Thus our verification method could be improved by extracting more useful information from the 3 dimensional signals. Third, we could compare other features (e.g. velocity, which can be computed from the acceleration data values) to learn which features are the most important in the signature verification process. A normalisation of the acceleration signals may be helpful too. Finally, we could adapt other sensors to make our signature-verifying tool more robust.

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