

# The effect of training data selection and sampling time intervals on signature verification

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**Abstract**—Based on an earlier proposed procedure and data, we extended our signature database and examined the differences between signature samples recorded at different times and the relevance of training data selection. We found that the false accept and false reject rates strongly depend on the selection of the training data, but samples taken during different time intervals hardly affect the error rates.

**Index Terms**—online signature; signature verification

## I. INTRODUCTION

In our earlier study [1], we investigated a procedure for signature verification which is based on acceleration signals. The necessary details about the method – applied in the earlier study and recent study – are explained in Section II. Previously we created a database with genuine and unskilled forgeries and used the dynamic time warping method to solve a two-class pattern recognition problem.

In our recent study we extended the database with fresh recordings of the signatures from former signature suppliers, thus we were able to compare signature samples recorded in different time periods. In addition, we examined how the selection of training data can affect the results of the verification process.

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 ways of recognizing signatures, namely the offline and the online. Offline signature recognition is based on the image of the signature, while the online case uses data related to 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 more sophisticated techniques.

The online signature recognition systems differ in their feature selection and decision methods. Some studies analyze the consistency of the features [2], while others concentrate

on the template feature selection [3]; some combine local and global features [4].

A key step in signature recognition was provided in the First International Signature Verification Competition [5], and reviews about the automatic signature verification process were written by Leclerc and Plamondon [6], [7], Gupta [8], Dimauro et al. [9] and Sayeed et al. [10].

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 [11], [12]; the F-Tablet was described in [13] and the Genius 4x3 PenWizard was used in [14]. In several studies (like ours), a special device (pen) was designed to measure the dynamic characteristics of the signing process.

In [15], 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 [16], they described the mathematical background of motion recovery techniques for a special pen with an embedded accelerometer.

Bashir and Kempf in [17] 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 recognize characters and PIN words, not signatures. Rohlik et al. [18], [19] 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 [18] they had two aims, namely signature verification and author identification, while in [19] the aim was just signature verification. Both made use of neural networks.

Many studies have their own database [12], [13], but generally they are unavailable for testing purposes. However some large databases are available, like the MCVT biometric database [20] and the database of the SVC2004 competition<sup>1</sup> [5].

<sup>1</sup>Available at <http://www.cse.ust.hk/svc2004/download.html>

## II. PROPOSED METHOD

### A. 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 [15], [17]. 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).

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 [21].

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 [22]. A 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.

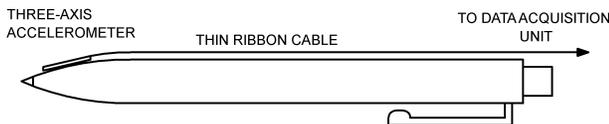


Fig. 1: The three-axis accelerometer is mounted close to the tip of the pen

### B. Database

The signature samples were collected from 40 subjects. Each subject supplied 10 genuine signatures and 5 unskilled forgeries, and 8-10 weeks later the recording was repeated with 20 subjects, so we had a total of  $40 \times 15 + 20 \times 15 = 900$  signatures. The signature forgers were asked each time to produce 5 signatures of another person participating in the study.

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). This 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 2 forged signature. Figures 3a and 3b show samples from the same author, and they appear quite similar. Figures 3c and 3d are the corresponding forged signatures, which differ significantly from the first two.

### C. 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 minimized. The DTW distance between the  $u = (u_1, \dots, u_n)$  and  $v = (v_1, \dots, v_m)$  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:

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

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

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

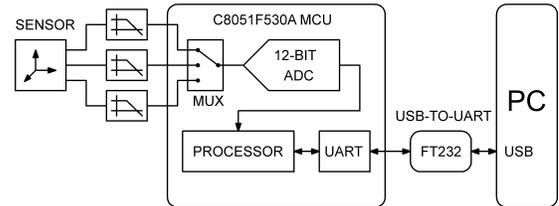


Fig. 2: Block diagram of the data acquisition system

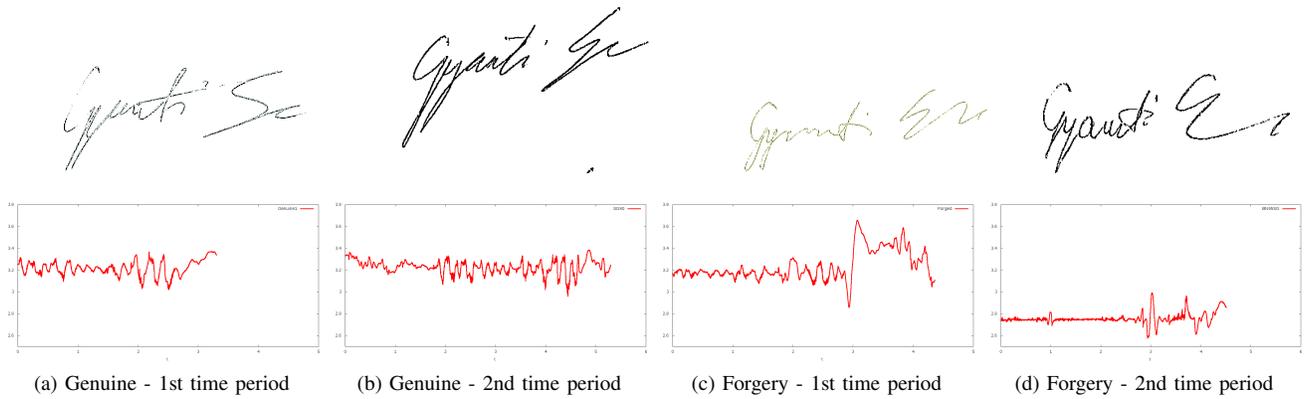


Fig. 3: The images and corresponding acceleration signals of two genuine signatures and two forged signatures

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.

### III. SELECTION OF REFERENCE SIGNATURES

First, we examined the  $40 \cdot 15 = 600$  signatures from the first time period. For each person, 5 genuine signatures were chosen first randomly as references, and included in 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 minimum distance between the five elements of the training set ( $D_{\min}$ ). Then, for each signature in the test set, the minimum distance of the signature from the training set's five signatures was found ( $D_{\text{dis}}$ ). Now, if for some  $t$  in the set

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

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

Besides the minimum we also used two other metrics, namely the maximum and average distances, but the minimum produced the lowest error rates.

The performance of a signature verification algorithm can be measured by the Type I error rate (false reject), when a genuine signature is labelled as a forgery and Type II error rate (false accept), when a forged signature is marked as genuine. After we analyzed the results, we observed that the Type I and II errors depend on how we choose the reference signatures, so we checked all the possible choices of reference signatures and compared error rates. For each person there were  $\binom{10}{5} = 252$  possible ways of how to choose the 5 reference signatures from the 10 genuine signatures.

False acceptance/rejection rates		
Type I	Type II	No of cases
0%	0%	39
20%	0%	135
40%	0%	68
60%	0%	7
80%	0%	3
<b>Total</b>		252
24.13%	0%	

TABLE I: A typical distribution of error rates

False acceptance/rejection rates		
Type I	Type II	No of cases
0%	0%	13
0%	20%	52
0%	60%	45
20%	0%	8
20%	60%	58
20%	20%	45
40%	20%	8
40%	60%	22
60%	60%	1
<b>Total</b>		252
13.81%	38.33%	

TABLE II: A different distribution of error rates

Based on our earlier studies [1], we set the multiplier  $m$  at 2.16 because we got the highest overall accuracy ratio (88.5%) with this value.

A typical distribution of Type I and Type II error rates is shown in Table I. The first two columns show the error rates, while the third one shows certain cases with the corresponding error rates. The last row shows the average error rate.

According this table, in 39 cases (out of 252) the Type I and Type II error rates are equal to 0. The average type error rate of 252 possibilities is 24.13%, while the average Type error rate is 0. For 27 authors (out of 40) and for each case, the false reject rates were 0%. A much worse, but very rare case is shown in Table II.

The average false accept rate was 14.34%, with a standard deviation of 13.62%; the average false reject rate was 12.89%,

DTW	AE50	AE51	AE52	AE53	AE54	AE55	AE56	AE57	AE58	AE59	ME60	ME61	ME62	ME63	ME64
AE50	0														
AE51	63	0													
AE52	98	64	0												
AE53	125	71	105	0											
AE54	116	65	67	101	0										
AE55	63	113	136	167	157	0									
AE56	114	80	76	127	67	155	0								
AE57	104	68	76	115	73	147	63	0							
AE58	74	66	63	111	59	105	37	49	0						
AE59	233	173	86	177	82	317	165	152	122	0					
ME60	344	239	254	281	386	332	333	202	234	372	0				
ME61	274	232	252	285	441	450	402	239	246	501	135	0			
ME62	237	177	175	231	255	350	222	179	158	316	70	107	0		
ME63	318	259	260	304	410	494	334	221	227	372	50	83	67	0	
ME64	710	677	697	716	875	854	796	670	684	977	260	198	395	269	0

TABLE III: Sample distance matrix – First time period

DTW2	AE80	AE81	AE82	AE83	AE84	AE85	AE86	AE87	AE88	AE89	ME90	ME91	ME92	ME93	ME94
AE80	0														
AE81	34	0													
AE82	34	41	0												
AE83	50	63	47	0											
AE84	52	58	43	49	0										
AE85	217	213	179	227	206	0									
AE86	139	130	152	150	145	325	0								
AE87	117	103	144	154	147	339	81	0							
AE88	55	52	52	91	82	140	154	121	0						
AE89	65	63	60	71	65	233	105	125	92	0					
ME90	293	245	270	355	310	236	336	302	228	328	0				
ME91	227	198	208	295	252	245	275	262	165	259	54	0			
ME92	339	298	322	419	387	288	393	348	273	413	45	106	0		
ME93	617	625	569	617	699	473	518	415	473	770	202	260	117	0	
ME94	388	425	492	540	582	293	469	376	395	582	67	150	40	100	0

TABLE IV: Sample distance matrix – Second time period

DTW	AE50	AE51	AE52	AE53	AE54	AE55	AE56	AE57	AE58	AE59	AE80	AE81	AE82	AE83	AE84	AE85	AE86	AE87	AE88	AE89
AE50	0																			
AE51	63	0																		
AE52	98	64	0																	
AE53	125	71	105	0																
AE54	116	65	67	101	0															
AE55	63	113	136	167	157	0														
AE56	114	80	76	127	67	155	0													
AE57	104	68	76	115	73	147	63	0												
AE58	74	66	63	111	59	105	37	49	0											
AE59	233	173	86	177	82	317	165	152	122	0										
AE80	74	51	47	95	75	112	65	67	50	168	0									
AE81	75	51	50	102	69	119	64	59	47	179	34	0								
AE82	67	40	48	96	54	104	74	66	57	179	34	41	0							
AE83	94	63	58	94	58	121	78	75	68	129	50	63	47	0						
AE84	90	54	57	87	44	120	65	53	49	124	52	58	43	49	0					
AE85	84	238	265	259	251	147	352	303	268	453	217	213	179	227	206	325	0			
AE86	223	145	111	192	141	306	128	145	110	92	139	130	152	150	145	325	0			
AE87	179	126	126	190	170	252	84	108	96	203	117	103	144	154	147	339	81	0		
AE88	45	63	77	132	105	82	87	83	64	217	55	52	91	82	140	154	121	121	0	
AE89	133	70	55	120	52	185	67	77	65	109	65	63	60	71	65	233	105	125	92	0

TABLE V: Distances between genuine signatures from both time periods

with a standard deviation of 24.33%.

#### IV. DIFFERENT TIME PERIOD

Since a signature can change over time, we decided to examine how this affects the DTW distances of the acceleration signals of signatures. We recorded genuine and forged signatures from 20 authors in two time periods this year: between January and April and between May and June.

Table III and IV are two (DTW) distance matrices calculated for the same subject in the two time periods.

The intersection of the first 10 columns and 10 rows shows the distance values between the genuine signatures (obtained 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 corresponding forged signatures.

In Table III [Table IV] the distance between the genuine signatures varies from 60 to 317 with an average of 108 and a standard deviation 53 [from 34 to 334 with an average value of

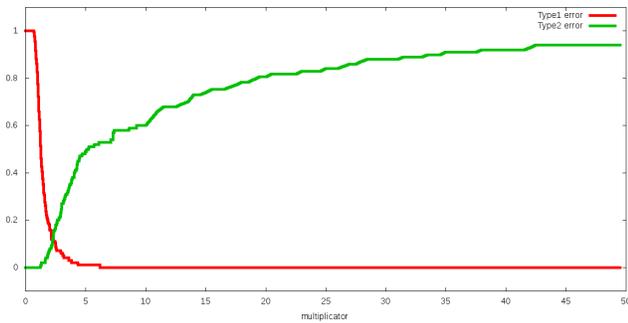
117 and a standard deviation 73], but between a genuine and a forged signature it varies from 158 to 977 with an average of 393 and a standard deviation of 211 [from 165 to 770 with an average value of 382 and a standard deviation of 142]. The distance matrices for other persons are similar to those given above.

In most cases there were no significant differences between distance matrices calculated for different time periods (and from the same author). Table V shows the DTW distance between genuine signatures taken from the same author for the different time periods. AE50-59 are from the first period, while AE80-89 are from the second. The average distance is 114, the minimum is 34, the maximum is 453 and the standard deviation of the distances is 70.3.

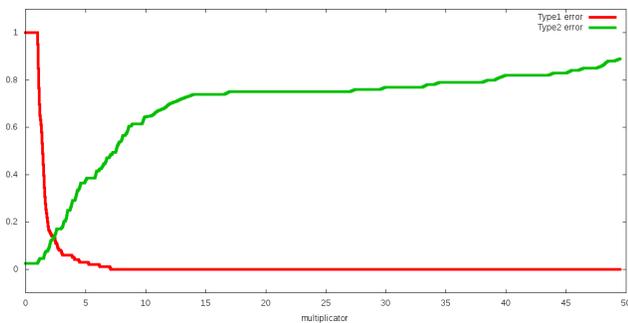
Figures 4a and 4b show the false reject and false accept rates as a function of the constant multiplier  $m$  of the minimum distance got from the training dataset.

We can see that in both time intervals we get a zero false accept rate when  $m = 7$ . The curves decrease quite quickly, while the increase of the false reject rate is less marked. The

main difference between the two time intervals and the false reject rate curves is that in the first time interval it increases faster than in the second. The reason is probably that in the second time interval the acceleration signals were quite similar (see tables III and IV).



(a) 1st time period



(b) 2nd time period

Fig. 4: False acceptance and false rejection rates

## V. CONCLUSIONS

In this paper an online signature verification method was proposed for verifying human signatures. The new procedure was implemented and then tested. First, a test dataset was created using a special device fitted with an accelerometer. The dataset contained  $600 + 300 = 900$  signatures, where 600 signatures were genuine and 300 were forged. By applying a time series approach and various metrics we were able to place signature samples into two classes, namely those that are probably genuine and those that are probably forged.

Based on our earlier experiments, we examined how the training set selection varies over a period of weeks (in most cases it was a few months) and how time influences the false acceptance and false rejection rates. We found that a person's signature does not vary much over a period of weeks or months, but it could vary more over longer periods.

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