PREPROCESSING TECHNIQUES FOR ONLINE SIGNATURE VERIFICATION AND IDENTIFICATION

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Abstract: Handwritten signature is a behavioral biometric that can be used for automatic signer verification and identification. Online signature, in addition to visual shape, incorporates dynamics of the writing process such as trajectory, velocity and additional characteristics such as pen pressure and angles. While there are many approaches to online signature verification proposed in the literature, only few works related to preprocessing and its effect on the system performance. In this work selected preprocessing techniques were investigated such as: normalization, noise filtering and resampling. The evaluation was carried out in verification and identification tasks based on DTW distance measure and signatures from SVC2004 database.

Keywords: online signature, signature preprocessing

1. Introduction

Handwritten signature is one of the behavioral biometric traits that is widely used in all parts of the world. Compared with physical traits such as finger veins or iris image it has drawbacks that include low permanence and ease of producing a forgery. However, due to its widespread usage it has been a subject of intensive research and gained a lot of interest in commercial institutions. The ongoing development of new algorithms and methods allowed to lower the error rates of automatic signature verification to levels comparable with the results obtained for physical biometrics and opened the way for potential applications [4].

During data acquisition handwritten signatures are collected for further processing. There are two ways in which data can be acquired: offline – where the input of the system are static images of handwritten signatures; online – registers the act of signing that includes both the image and dynamics of writing. Due to specified nature

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of data, offline and online signatures usually require different methods at each stage of the biometric system, however the stages of the system are similar.

The architecture of signature recognition system does not differ much from a typical biometric system. Its main stages are: data acquisition, preprocessing, feature extraction and classification (Fig. 1). Data acquisition is the process of registering data using particular type of input device . The preprocessing is responsible for preparing raw input to feature extraction process. Methods used at this stage may perform tasks such as: normalization, resampling, noise filtering.

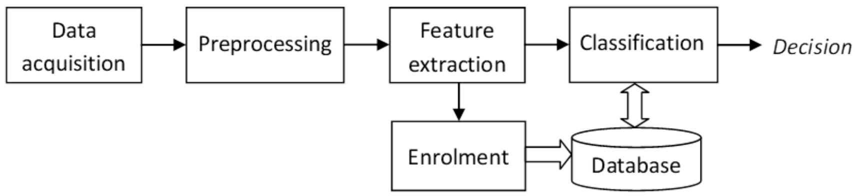

Fig. 1. Biometric signature verification and identification system

The feature extraction methods are responsible for constructing the feature vector that is passed to classification stage. The classification is used for one of the two tasks: identification and verification. The aim of verification is to decide whether the given biometric sample is genuine or forged. During the identification the systems finds individual whose signature best matches given sample.

While are there many approaches to automatic signature verification and identification proposed in the literature, few works related to signature preprocessing and its effect on system performance. To address it, this investigation is focused on preprocessing techniques and evaluation of their usefulness in signature verification and identification tasks. The evaluation is carried out using signature verification and identification system based on Dynamic Time Warping distance measure [9].

2. Online signature acquisition

In order to register online characteristics of the signing process a special input device is necessary. Dynamic data can be recorded by means of PC tablets [1], specialized signature pads [2] or cameras [8] where the trajectory of the signature is traced in video sequence. Some recent works investigate possibility of signature registration with mobile devices such as smartphones and mobile tables [6,7]. Widespread usage of these devices makes them interesting alternative for specialized signature pads. However, the lower quality of acquired data and lack of important features (ex. pressure) may lead to increased error rates [6] and needs to be addressed.

Basic dynamic data gathered at the time of signing can contain the following parameters (Fig. 2): X, Y coordinates, pressure (P), altitude (AL) and azimuth (AZ). The coordinates X and Y determine the position of the pen tip inside the controlled area where the signing process is being traced. The pressure parameter describes the pen pressure inflicted on the tablet surface. The altitude is the angle between the pen and the surface. The azimuth denotes the angle between the projection of the pen onto the writing surface and the X coordinate axis.

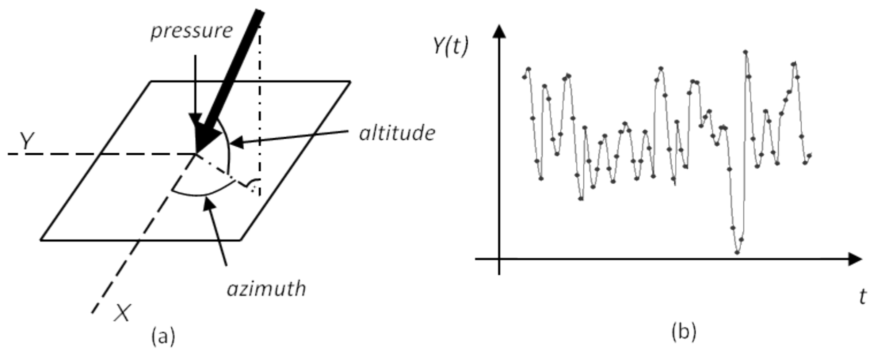

Fig. 2. Online signature parameters (a) and example of Y samples collected during the signing process (b)

Dynamic information acquired during online registration is very important because it allows to increase the system resistance to forgeries. Imitation of pen pressure, pen angles and dynamics of drawing signature is much more difficult than just copying a signature image. These dynamic parameters are also called hidden because it is impossible to precisely reconstruct their characteristics given only the image of a genuine signature. Another advantage when using online data compared to offline is that it is much easier to analyze – there is no need to extract a signature from complex background or deal with artifacts resulted from poor quality of scans.

3. Preprocessing techniques

There are various preprocessing techniques that may be used for online data. In this study the following types of preprocessing methods were investigated: normalization, filtering, resampling and component merging

3.1 Normalization

Raw data from acquisition device usually has range and precision dependent on a particular hardware. In addition, different characteristics have distinct units and scale. Signatures may be also given at arbitrary or fixed positions on writable surface depending on the constraints imposed by the application. In order to standardize ranges of values the normalization is applied to input data. However, the normalization process, may also result in loosing information important to distinguish genuine from forged signatures. In this work we experimented with the following techniques

Position scaling scales X and Y values according to equation (1).

$$x_i^N = K\frac{x_i}{M},\ y_i^N = K\frac{y_i}{M},\ M = \sqrt{\sum_{i=1}^{n} x_i^2 + y_i^2} \tag{1}$$

Position centroid translation translates centroid of a signature to the origin of coordinate system (2).

$$x_i^N = x_i - \bar{x},\ y_i^N = y - \bar{y},\ \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i,\ \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{2}$$

Position standarization translates centroid of a signature to the origin of coordinate system (3) and scales by standard deviation.

$$x_i^N = \frac{x_i - \bar{x}}{\sigma_x},\ y_i^N = \frac{y_i - \bar{y}}{\sigma_x} \tag{3}$$

During experiments we also performed centroid translation and standardization for complete set of input characteristics, namely for: X, Y, P, AL, AZ.

3.2 Filtering

The aim of filtering is to remove noise present in the signal. Main sources of such noise are instability of device during signing and noise introduced by input device. In this work we used three techniques for noise filtering [3].

Median filter replaces each sample with median value computed over window of length W as given by (4).

$$c_i^N = median(i - \lfloor W/2 \rfloor, ..., i + \lfloor W/2 \rfloor + 1) \tag{4}$$

Average filter replaces each value with the average computed over window of size W.

$$c_i^N = \frac{\sum_{j=i-\lfloor W/2 \rfloor}^{i+\lfloor W/2 \rfloor} c_j}{W}, \; i = \lfloor W/2 \rfloor + 1 ... n - \lfloor W/2 \rfloor \tag{5}$$

Gaussian filter replaces each value with weighted sum where weight coefficients are computed based on Gaussian distribution (6)

$$c_i^N = \sum_{j=-2\sigma}^{2\sigma} w_j c_{i+j}, \; w_k = \frac{e^{-\frac{k^2}{2\sigma}}}{\sum_{i=-2\sigma}^{2\sigma} e^{-\frac{i^2}{2\sigma}}} \tag{6}$$

3.3 Resampling

Resampling results in increasing or decreasing number of samples acquired by input device. Downsampling procedure may be implemented by selecting every k-th sample from input signal, resulting in reduction of frequency k times. The need for downsampling my may arise from Nyquist criteria. According to studies on dynamics of handwriting [5] the cut-off temporal frequency of the signing process is below 20Hz. This reduces the number of samples without losing information. Nyquist frequency in this case requires only 40 samples per second to retain all important components of writing parameters. Upsampling requires “inventing” new samples using interpolation. Upsamling may considered when the acquisition frequency of device is too low. For upsampling two interpolation techniques have been investigated.

Linear interpolation in time domain with samples interpolated at equal intervals in time to preserve time characteristics of signal (7).

$$L = \left\lfloor \frac{f_{req}}{f_{act}} \right\rfloor - 1 \tag{7}$$

where L is number of points to be added to the signal between consecutive samples, f_{req} is required frequncy, f_{act} is actual frequency.

Linear interpolation in space domain adds additional points based on position. It does not preserve time characteristics (8).

$$LP = \left\lfloor \frac{d}{D} \right\rfloor \tag{8}$$

where LP is number of points required to be added to signal between consecutive samples, d is distance between those points, D is threshold distance above which proportional number of points will be added.

3.4 Component merging

The signature may be splitted into separate curves that are separated by pen-up and pen-down events. This happens due to the signer lifting pen between drawing different parts of the signature. Similarly to upsampling techniques, two methods for adding artificial samples between up/down events were investigated – *merging in time domain* and *merging in space domain*. The interpolation method is the same as previously described approach, but in this case it is only used to add points between samples corresponding to pen-up/down events.

4. Classification

In order to evaluate different preprocessing techniques a signature recognition system was implemented. In the literature one may find many approaches to signature classification, among them some of the most successful techniques are based on Dynamic Time Warping (DTW) distance measure [4]

DTW method allows for modeling the time-axis fluctuation with nonlinear warping function [9]. The timing differences are eliminated by warping the characteristics of the signatures in such a way that the optimal alignment is achieved. DTW algorithm defines a measure $D'(R',S')$ between two sequences $R^{'}$ and $S^{'}$ (9):

$$R' = < r'_1, r'_2, ..., r'_M >, \; S' = < s'_1, s'_2, ..., s'_N > \tag{9}$$

The distance D' is defined using the following (10) and (11):

$$D'(R', S') = D^R(N, M) \tag{10}$$

$$D^R(i,j) = \min \left\{ \begin{array}{c} D(i,j-1) \\ D(i-1,j) \\ D(i-1,j-1) \end{array} \right\} + d(r'_i, s'_j) \tag{11}$$

where $i = 1..M, j = 1..N$. $d(r'_i, s'_j)$ can be distance measure such as Euclidian.

The calculations are carried out using dynamic programming. The key part of this algorithm is forming the so called cost matrix g. Its elements are cumulative distances computed as the sum of distances with one of the cumulative distances being found in earlier iterations (12).

$$g(i,j) = d(r'_i, s'_j) + \min\{g(i-1,j), g(i,j-1), g(i-1,j-1)\} \tag{12}$$

The cost matrix enables to find a warping path that represents the best alignment and minimizes the overall distance given by the recursive function of (11).

5. Evaluation procedure

In this investigation we used SVC2004 signatures database [10] publicly available for research. There two datasets available:

- Task1 – samples in this category have only trajectory data : X,Y, pen up/down state.
- Task2 – samples contain all characteristics: X,Y,P,AL,AZ, pen up/down state.

Both sets contain genuine and forged signatures of 40 individuals. All signatures were collected using Intuos tablet with sampling frequency of 100Hz. In this study the signatures from Task2 dataset were used.

During experiments two classification tasks were considered: identification and verification. The experiments were repeated 10 times using cross-validation scheme. The final results are the average values over 10 trials. During each repetition both the training and testing sets were selected at random.

Identification task was carried out using DTW distance measure with k-NN algorithm. The training set contained three genuine signatures per individual, the test set consisted of 12 genuine signatures per individual. Final evaluation was based on percent of properly classified signatures.

In the verification, the minimal distance between tested and reference signatures from training set for particular individual was computed, and the final decision (accept or reject) was based on comparison with threshold value. The training (reference) set consisted of four genuine examples per individual. The test set was constructed from 10 genuine and forged examples per subject. The verification was performed separately for simple forgeries (signatures of other users used as forgeries) and skilled forgeries (attempts to forge user signature by individuals who had access to genuine samples and time to train). Equal Error Rate (EER) was used as a performance measure.

6. Results

As a baseline for comparison, first the verification and identification performance was computed without using preprocessing techniques. Table 1. presents obtained results.

Table 1. Baseline results without preprocessing

Verification EER [%]		Identification [%]
Skilled forgeries	Simple forgerie	
17.82	8.45	91.5

As could be expected, verification of skilled signatures has higher error than simple forgeries. It is important to note that in this investigation our aim was not to develop complete system with lowest error, but to compare different preprocessing techniques.

6.1 Normalization

Table 2 presents impact of selected normalization techniques on system performance. As can be seen normalization techniques may significantly improve verification and identification rates (improvement over baseline given in Table 1 is grayed out). For identification the highest result was achieved for position centroid translation. This method also resulted in lower error for skilled and simple forgeries verification as compared to baseline system. Best performance for skilled signature was obtained for position standarization, however for other task this technique performed worse than baseline.

Table 2. Results of normalization preprocessing techniques

Method	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
Position scaling	12.86	10.56	86.75
Position centroid translation	16.38	**5.70**	**99.81**
Centroid translation (for all parameters)	22.23	6.02	99.65
Position standarization	**12.69**	10.61	86.73
Standarization (for all parameters)	18.26	9.03	98.06

6.2 Filtration

The results of preprocessing using filters are given in Tables 3, 4 and 5.

Table 3. Results of median filtering

Window size	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
3	17.62	**8.18**	90.38
4	17.71	8.73	90.56
6	17.36	9.00	90.25
8	**16.69**	9.85	88.87
10	17.00	10.59	87.96
20	17.62	9.76	86.85
40	19.82	9.46	88.42

As can be seen from presented data, improvement over unfiltered input has been achieved mostly for skilled forgery verification but is less significant compared to normalization. Best result with median filtering was obtained for window of size 8. The average filter reported highest improvement with window size equal 6. In Gaussian the lowest error occurred for mask size of 14. In case of simple forgeries minor improvement occurred only with median at filter size of 3 and average filter of sizes 5 and 6. There were no enhancement for identification task under any of the investigated configurations. As a conclusion the application of filtering should be considered carefully, because it may decrease system performance depending on the type of task.

Table 4. Results of average filtering

Window size	Verification EER %		Identification [%]
	Skilled forgeries	Simple forgeries	
2	17.08	8.86	90.35
3	17.71	9.88	90.23
4	17.13	9.10	90.60
5	16.80	8.44	88.67
6	**15.26**	**7.71**	86.92
8	16.96	9.60	88.65
20	17.86	9.78	88.71
40	20.10	9.98	88.77

Table 5. Results of Gaussian filtering

Window size	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
2	17.14	9.08	90.04
3	16.90	9.09	90.73
4	17.05	9.78	88.38
5	16.80	9.80	87.10
6	16.94	9.27	87.29
7	16.24	10.36	87.35
14	**15.80**	11.58	81.00
15	16.49	10.84	79.54
20	17.07	11.52	78.71
30	18.03	11.85	72.23

6.3 Resampling

The effects of resampling in time domain by downsampling and upsampling using linear interpolation are shown in Table 6. The input frequency of acquired data is

Table 6. Results of resampling in time domain

Requested frequency [Hz]	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
50 (downsampling)	**16.75**	8.80	91.08
25 (downsampling)	18.63	8.37	**92.00**
20 (downsampling)	18.58	9.16	91.67
10 (downsampling)	21.80	10.39	89.36
200 (upsampling)	17.53	**8.07**	89.40

100Hz. As can be seen, downsampling to 50 or 25 Hz does not significantly decrease system performance. Moreover, for identification and verification slight improvement over raw input can be noticed. This may be attributed to the fact that 40Hz sampling is sufficient to reconstruct most of the frequencies present in handwriting, therefore part of the samples at higher frequencies are redundant. Reduction of frequency also decreases amount of computations required to process a signature. However, as can be seen in Table 6, reducing frequency below certain limit increases verification and identification errors. Upsampling to 200Hz gives slight improvement in verification process but also increases computational cost.

Table 7. Results of resampling in space domain

Method	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
interpolation with D=50	21.01	9.34	**92.19**
interpolation with D=100	19.74	**8.36**	90.79
downsampling to 50Hz and interpolation with D=100	20.49	8.68	91.69
downsampling to 25Hz and interpolation with D=100	20.90	9.57	90.25

Table 7 shows the results of resampling that is based on distance between points that removes time dependencies between samples. In the last two rows the interpolation process was preceded by downsampling to replace removed samples with distance based interpolated points. By comparison with baseline one can notice small improvement in identification and simple forgeries verification. However, the verification of skilled forgeries worsened in all cases.

6.4 Component merging

Evaluation of component merging method with interpolation in space domain is given by Table 8. As can be seen, both the verification and identification may benefit from this technique. The parameter D denotes required distance between interpolated points, therefore controls the number of synthetic points added through interpolation. If D is small (number of added points is larger) the system performance decreases in all of the tasks. However starting from D=200, improvements start to be visible. Most of the positive effects happen in identification and skilled forgery verification.

Table 8. Results of component merging in space domain

D	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
25	22.53	12.64	87.41
50	19.49	9.64	89.41
100	18.80	9.21	90.85
200	18.38	8.65	91.52
300	17.73	8.26	91.42
600	**17.34**	8.80	91.52
650	17.80	8.91	90.60
800	17.58	8.60	**92.44**
900	17.50	**8.07**	91.79
1000	17.83	8.50	91.29

Table 9. Results of component merging in time domain

Requested frequency [Hz]	Verification EER [%]		Identification [%]
	Skilled forgeries	Simple forgeries	
200	20.01	12.34	90.71
100	18.37	10.15	91.08
50	17.85	8.49	90.92
33	17.49	9.20	91.73
20	17.22	8.77	91.06
16.67	**17.07**	8.53	**92.35**
14.26	17.47	**8.37**	92.02
11.11	17.20	8.73	90.83

Table 9 shows output of the system for component merging based on interpolation in the time domain. In this case the number of added points is controlled through requested frequency. Similarly to previous method if the number of generated points is high (frequency is high) the performance drops in both tasks. For lower interpolation frequencies the system performance may improve.

7. Conclusions

In this work we have assessed selected preprocessing techniques in online signature verification and identification tasks. As the results show, the preprocessing techniques can have significant influence on verification error and identification accuracy. The normalization techniques that may be recommend are position scaling, position centroid substraction and standarization. As for the filtering the investigated methods performed slightly better for skilled forgeries verification, however in other tasks they had negative effect. One may also consider downsampling data to 50Hz or even 25Hz to benefit from reduced computational cost. Merging components also seem to be promising. However, if too many samples will be interpolated the system accuracy may decrease. The results have been obtained for DTW based system. Further investigation may include assessment with different classifiers and combining different preprocessing techniques.

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METODY WSTĘPNEGO PRZETWARZANIA DLA WERYFIKACJI I IDENTYFIKACJI PODPISU DYNAMICZNEGO

Streszczenie Podpis odręczny jest behawioralną cechą biometryczna która umożliwia automatyczną weryfikację i identyfikację autora podpisu. Podpis dynamiczny, oprócz informacji o kształcie, zawiera również dane dotyczące dynamiki składania podpisu takie jak trajektoria kreślenia, prędkość, zmiana nacisku i kątów nachylenia pióra. W literaturze można znaleźć wiele podejść do automatycznej weryfikacji podpisu, brakuje jednak prac z szerszą analizą metod wstępnego przetwarzania i oceną ich wpływu na poprawność pracy całego systemu. W niniejszej pracy zbadano wybrane techniki wstępnego przetwarzania takie jak: normalizacja, filtracja, próbkowanie oraz oceniono ich użyteczność w procesie weryfikacji i identyfikacji podpisu. W badaniach wykorzystano system bazujący na mierze odległości Dynamic Time Warping. Eksperymenty przeprowadzono na podpisach dynamicznych z bazy SVC2004.

Słowa kluczowe: podpis dynamiczny, wstępne przetwarzanie

Artykuł zrealizowano w ramach pracy badawczej S/WI/2/2018.