Some Handwritten Signature Parameters in Biometric Recognition Process

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Some Handwritten Signature Parameters in Biometric Recognition Process

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Abstract. *In this paper there is the off–line type signature analysis profoundly considered. The analysis consists of three stages which allow to define the features (weights) of the signature. Different influences of such features are tested and stated. In this paper personal signature is first pre-processed and then processed in the three-stage method. In proposed approach the Hough transform is introduced, the centre of signature gravity is determined, and the horizontal and vertical signature histograms are performed. Proposed approach gives good signature recognition level, hence described method can be used in many areas, for instance in biometric authentication, either as biometric computer protection or as a method of the analysis of person's behaviour changes.*

Keywords. Signature recognition, Hough transform, pre-processing , features extraction

1. Introduction

The signature recognition is the process aiming at writer's verification. During this process the samples of signatures are compared with the other ones gathered in the database records. The signature recognition is one of many biometric identification techniques which are used in practice. In the business world we sign different papers such as accounts and other official documents. Personal signature lends itself well to biometric verification in state–of–the–art electronic devices. Numerous methods and approaches are summarised in a number of survey articles [1,2,4]. Signature recognition can be realised by means of static or dynamic methods [1]. Static methods, based on bitmap image analysis, do not require specialised devices, for example pressure-sensitive pens and surfaces, hence are willingly used. Dynamic methods, where time, stroke, speed and signature pressure are additionally recorded, are expensive and signature capturing is very often uncomfortable. It should be stressed that dynamic methods are difficult to forge [1,4]. In our approach new signature parameters are also determined – where centre of signature's histogram was computed and proportion factor was established. Proposed method gives better results of recognition and verification comparing with methods described in [1,4]. Complete investigation results could not be included as over 800 signatures from database were tested.

One drawback of signature is that people do not sign in exactly the same manner. For example, the angle at which they sign may be different due to seating position or due to hand placement on the writing surface. For this reason, the original signature should be appropriately formatted and pre-processed. In our approach, the signature analysis process is composed of three main stages:

– pre–processing: where image binarization and its size standardization are performed,
– feature extraction: where the unique set of characteristics of the analysed signature is gathered,
– comparison: where personal signature is compared with the pattern from the signatures database.

2. Pre-processing

A wide variety of devices capturing signature causes the need to normalize an input image of signature (so called: pre-processing). The pre–processing procedure consists of three steps: –binarization, –cutting edges, –thinning.

2.1. Binarization

It allows us to reduce the amount of image information (removing colour and background), so the output image is black-white. The black-white type of the image is easier to further processing.

2.2. Cutting edges

Size of the image is reduced. In this procedure unnecessary signature areas are removed. In other words, we find the *max*/*min* value of the X and Y coordinates of the signature (Fig.1) and then the image is cut to the signature size. It allows to reduce the total number of the pixels in the analysed image (Fig. 2).

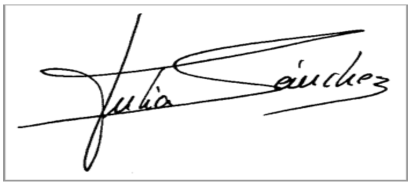


Figure 1. Input image

Figure 2. Reduced image size

2.3. Thinning

It allows us to form a region-based shape of the signature. It should be noticed that main features of the object are protected. After thinning, the 1-pixel shape of signature is obtained. Good results of image thinning can be achieved from so called Pavlidis algorithm [3].

3. Features extraction

During that step a gathering of characteristic data takes place. The output result is a set of the unique information about the signature. Actions occurring during that step supply:
–proportion factor, –vertical and horizontal projection, –centre of gravity, –the Hough transform.

3.1. Proportion factor

Proportion factor γ defines the relation between width w and height h of the different personal signatures, which are signed by the same person. Value of the proportion factor is calculated by the formulas:

$$\gamma = \frac{w}{h} \qquad \text{if} \quad w \geq h \tag{1}$$

$$\gamma = -\frac{h}{w} \qquad \text{if} \quad w < h \tag{2}$$

3.2. Vertical and horizontal projection

This method describes the vertical and horizontal signature pixels density (histogram). The histogram is obtained in two-passes algorithm, where the number of signature's pixels in each row and in each column is counted. Obtained results are stored in the two one-dimensional auxiliary tables T_v (for vertical part of the image) and T_h (for horizontal part of the image). After the data collecting, appropriate image projections are calibrated to resolution of 256×256 pixels. In the first stage the calibration coefficient δ is calculated:

$$\delta = \frac{\max\{X, Y\}}{256} \tag{3}$$

In the next stage two normalized projection arrays N_v i N_h are prepared:

$$N_v[i] = round(\frac{T_v[round(i * \delta)]}{\delta}), \; i = 0,...,255 \tag{4}$$

$$N_h[i] = round(\frac{T_h[round(i * \delta)]}{\delta}), \; i = 0,...,255 \tag{5}$$

Applying the size–normalized calibration approach allows to compare the image's projections for different size of signatures.

3.3. Centre of gravity

It supplies information about the layout of pixels' density. It is a point $G(x_g, y_g)$ where appropriate lines A and B are crossing, what presents Fig. 3. These lines divide the signature image into vertical and horizontal regions so that the number of pixels was the same in each region. The coordinates (x_g, y_g) are obtained basing on analysis of the vertical and horizontal projection arrays N_v and $N_{h.}$, respectively. The value of the coordinate x_g is equal to such index k_x of the cell of the N_v array, for which the next condition is fulfilled:

$$\sum_{i=0}^{k_x - 1} N_v[i] < \frac{\sum_{i=0}^{255} N_v[i]}{2} \;\wedge\; \sum_{i=0}^{k_x} N_v[i] \geq \frac{\sum_{i=0}^{255} N_v[i]}{2} \tag{6}$$

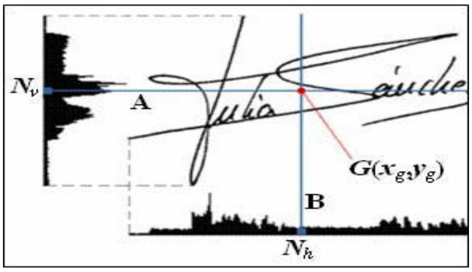


Figure 3. Signature centre of gravity

The value of the coordinate y_g is equal to such index k_y of the cell of the N_h array, for which the next condition is fulfilled:

$$\sum_{i=0}^{k_y-1} N_h[i] < \frac{\sum_{i=0}^{255} N_h[i]}{2} \wedge \sum_{i=0}^{k_y} N_h[i] \geq \frac{\sum_{i=0}^{255} N_h[i]}{2} \quad (7)$$

3.4. The Hough Transform

In the last stage the Hough Transform (HT) is used [1]. This algorithm searches a set of straight-lines, which appear in the analyzed signature. The classical transformation identifies straight-lines in the signature image but it has also been used to identifying the signature shapes. In the first step the HT is applied, where appropriate straight-lines are found (Fig.4). The analyzed signature consists of large number of straight-lines, which were found by the HT, hence reduction of the unnecessary lines should be carried out. For this reason additional straight-line selection algorithm is applied [4]. In this algorithm some lines are removed and the set of reduced straight-lines can be performed. It can be observed (Fig. 4) that a lot of straight-lines are related very close to each other and are quite similar (slightly different at angles and positions). The straight-line selection algorithm removes such lines. The range of the lines reduction by experiments is matched, where thresholding procedure is applied [1,4,6]. A result of the straight-line reduction presents Fig.5.

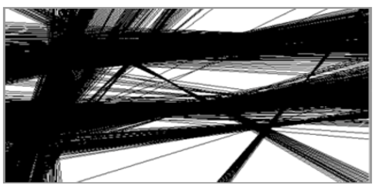


Figure 4. Straight-lines extracted from the image (Fig.2) by means of the HT

The Hough Transform is well known in the research community, therefore their details will be omitted. In the next step, the set of the reduced straight–lines is exchanged for appropriate sections by means of the back-propagation algorithm [5,6]. The set of the sections (Fig.6) is analyzed again and the sections lying along the same direction are connected (Fig. 7). Such step allows to reduce number of signature features.

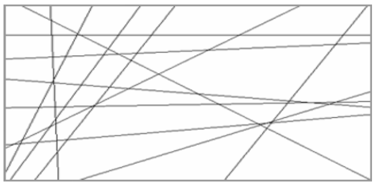


Figure 5. The reduced number of the lines

The result of the changes presents Fig. 6.

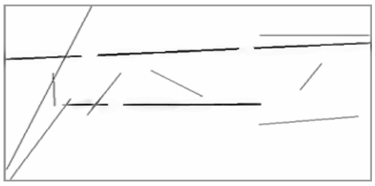


Figure 6. The sections extracted from lines

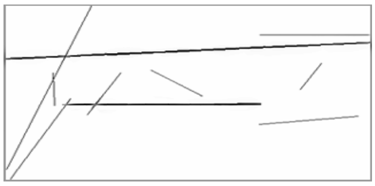


Figure 7. Joined sections

Additionally, for every section l_i their (x_i,y_i) coordinates are stored in auxiliary table. Finally, the sections image is calibrated to 256×256 the pixel-size image. It allows to compare signatures, which originate from different sources and have different sizes (Fig.8)

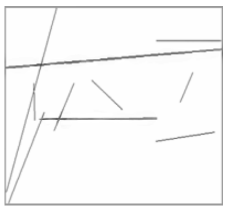


Figure 8. The normalized size of the image from the Fig. 7

The reduced set of sections is the most unique feature, which describes the signature. It will be shown in the conclusive investigations.

4. Determining of the pattern signature

For recognition process, the input and genuine signatures should be known. In this process, the unique features (patterns) of each signature are compared with analyzed input sign. For this reason, the patterns of the genuine signature are stored in a database. These patterns would contain all characteristic features of signature. Unfortunately, signatures of the same person have some differences. So it is needed to build a pattern, which covers these differences.

In proposed approach, a procedure that determines similarity between signatures S_1 and S_2 was implemented. As an input data the two sets of unique features of the signatures S_1 and S_2 are analyzed. The first set Ω_{S1} includes all straight-lines, which were found in the signature S_1(person signature). The second set Ω_{S2} includes all straight-lines, which were found in the signature S_2 (from database). The result of the comparison is the global signature similarity coefficient s. During the first step the straight-line similarity coefficient is determined. Each line *i-th* from the first set Ω_{S1} is compared with the adequate *j-th* line with the most appropriate coordinates in the second set Ω_{S2}. The basic principle of the lines comparison presents Fig. 9. From this figure follows, that the *i-th* straight-line has coordinates $(B_1, E_1) \triangleq B_1(x_{b_1}, y_{b_1}), E_1(x_{e_1}, y_{e1})$. The appropriate *j-th* straight-line has coordinates $(B_2, E_2) \triangleq B_2(x_{b_2}, y_{b_2}), E_2(x_{e_2}, y_{e_2})$. Hence, the partial similarity coefficient ε_i can be calculated from the formula:

$$\varepsilon_i = 1 - \frac{\Delta B + \Delta E}{2\sqrt{256^2 + 256^2}} \tag{8}$$

$$\Delta B = \sqrt{(x_{b_1} - x_{b_2})^2 + (y_{b_1} - y_{b_2})^2} \tag{9}$$

$$\Delta E = \sqrt{(x_{e_1} - x_{e_2})^2 + (y_{e_1} - y_{e_2})^2} \tag{10}$$

where:

ΔB – distance between beginning of the *i-th* and *j-th* straight-line coordinates,

ΔE – distance between end of the *i-th* and *j-th* straight-line coordinates

In the next stage the *j-th* straight-line is removed from the second set and the next straight-line from the first set is analyzed. After that, the algorithm is repeated in just opposite way (the lines from second set are compared to line from the first set) and we receive ε_j coefficient.

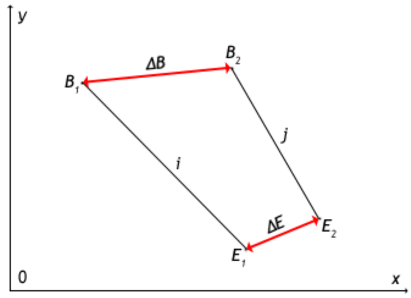


Figure 9. Basic principles of the comparison of the two different straight-lines

All partial coefficients are summarized and the mean value is calculated:

$$s_s = \frac{\sum_i \varepsilon_i + \sum_j \varepsilon_j}{2} \tag{11}$$

where $i = card(\Omega_{S1})$ and $j = card(\Omega_{S2})$.

The next stage of our algorithm determines the projection similarity coefficient. Data about horizontal and vertical projection are stored in two one-dimensional 1×256 arrays: N_v and N_h. Usually projections of two images are slightly shifted to each other. For this reason projections are compared to each other many times with some deviation $\Delta d = \pm 10$ pixels. The results are stored in the arrays T_v and T_h for the vertical and horizontal projection, respectively:

$$\begin{aligned} T_v[i] &= \left| N_{2,v}[i] - N_{1,v}[i] \right|, \; i = 0, \ldots, 255 \\ T_h[i] &= \left| N_{2,h}[i] - N_{1,h}[i] \right|, \; i = 0, \ldots, 255 \end{aligned} \tag{12}$$

where:

$N_{1,v}, N_{1,h}$ – vertical and horizontal projection arrays, for the signature S_1,

$N_{2,v}, N_{2,h}$ – vertical and horizontal projection arrays, for the signature S_2 from the database.

and then the partial similarity coefficients (σ_v and σ_h) are determined for each table:

$$\sigma_v = \sum_{i=0}^{255} \left(1 - \frac{T_v[i]}{256} \right) \tag{13}$$

$$\sigma_h = \sum_{i=0}^{255} \left(1 - \frac{T_h[i]}{256} \right) \tag{14}$$

The global projection similarity coefficient is calculated by the formula:

$$s_p = \frac{\max\{\sigma_{-d,v}, \ldots, \sigma_{d,v}\} + \max\{\sigma_{-d,h}, \ldots, \sigma_{d,h}\}}{2} \tag{15}$$

In the last stage the proportion similarity coefficient s_r is calculated:

$$s_r = 1 - \frac{|\gamma_2 - \gamma_1|}{2} \qquad (16)$$

and centre of gravity similarity coefficient s_g:

$$s_g = 1 - \frac{\Delta G}{\sqrt{256^2 + 256^2}} \qquad (17)$$

where ΔG – distance between coordinates of centre of gravity $G_1(x_{g1},y_{g1})$ for signature S_1 and centre of gravity $G_2(x_{g2},y_{g2})$ for the signature S_2 from the database, respectively. Finally, the global similarity coefficient is calculated by using the following formula:

$$s = s_s p_s + s_p p_p + s_r p_r + s_g p_g \qquad (18)$$

where :
s_s – sections similarity coefficient,
s_p – projection similarity coefficient,
s_r – proportion similarity coefficient,
s_g – centre of gravity similarity coefficient.

Above mentioned coefficients are formed by comparing each feature from one set with corresponding feature from the other set. Finally, the appropriate similarity coefficients are calculated. For every similarity coefficient s, appropriate feature weight p_s, p_p, p_r, p_g is selected and additionally, the condition $p_s+p_p+p_r+p_g=1$ has to be fulfilled. The weights values were empirically determined. It was established, that weights, where the best participation of the features were performed, have values: $p_s=0.54$, $p_p=0.32$, $p_r=0.02$ and $p_g=0.12$. When the similarities procedure is already implemented, it is possible to build a signature patterns. The patterns are determined on the basis of a few (say three) signatures of the same person. Such signatures should be collected at different day–time, during the whole week. At the next stage, features of the three signatures are compared with each other. As the pattern is chosen this signature that has the highest global similarity ratio (i.e. that is the most similar to others signature), that pattern and its characteristic features, are stored in the database. Using that pattern can be performed for all future comparisons. About 800 signatures were collected in our own database. All signatures were stored as bitmaps. From database, 28 signatures were randomly chosen. Each signature was collected four times (2 signatures × 2 session with an interval of two weeks). On the basis of 28×4=112 signatures efficiency of the proposed method were tested. From 4 signatures of the same person global features were extracted and stored in the database.

5. Signature verification and identification

There are two areas of application for signature recognition systems:
Verification – where the input signature (and its characteristic features) is compared with one pattern from the database and judging if these signatures are the same or not.
Identification – where the corresponding pattern in database is searched until the one matches the input signature.
Both methods above use global similarity coefficient and global threshold value [2,5]. The verification and identification are successful if the similarity for a tested signature is greater or equal to global threshold value. The global threshold value bases on the formula:

$$t_\psi = (1-\psi)(t_s p_s + t_p p_p + t_r p_r + t_g p_g) \qquad (19)$$

where:
t_s, t_p, t_r, t_g – partial thresholds for the elements of the pattern (set of sections, projection, proportion factor, centre of gravity)
p_s, p_p, p_r, p_g – importance (weight) for each feature
ψ – tolerance coefficient

The global tolerance coefficient ψ decreases (increases) all partial thresholds t_s, t_p, t_r, t_g of k %. For example if $\psi=k\%$ then $t_s= t_p=t_r= t_g =k\%$. The tolerance coefficient has some considerable influence on the final result of verification or identification. If condition $s \geq t_\psi$ is fulfilled then signatures identification process is positive, otherwise if $s < t_\psi$ identification is negative – compared signatures belong to different persons.

6. Investigation results

In the investigations, characteristic features (set of sections, projection, proportion coefficient, centre of gravity) have been tested separately and the influence of the each feature has been observed. The test gives information about changes coefficients FAR (False Accept Rate) and FRR (False Reject Rate). The FAR typically is stated as the ratio of the number of false acceptances (N_{FAR}) divided by the number of total identification attempts T. The FRR is stated as the ratio of the number of false rejections (N_{FRR})divided by the number of total identification attempts T.

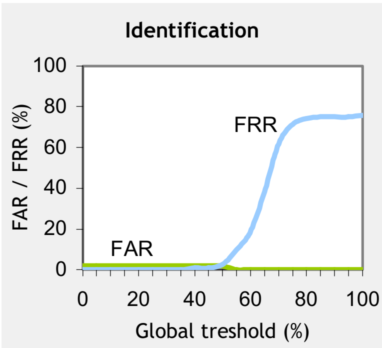
For identification mode T=112 signatures were analyzed and N_{FAR}= 2, N_{FRR}=6. For verification mode, for FAR we have T_1=4×27×28=3024, N_{FAR}=119. For FRR, T_2=112, N_{FRR}=6. T=T_1+T_2=3136. Hence:

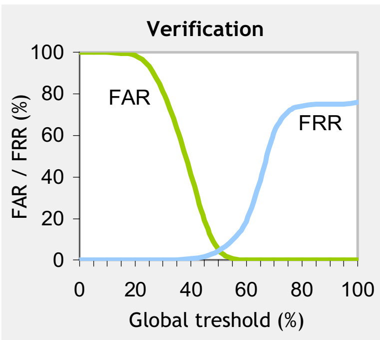
$$Efficiency = \frac{T-(N_{FAR}+N_{FRR})}{T}\times 100\% \qquad (20)$$

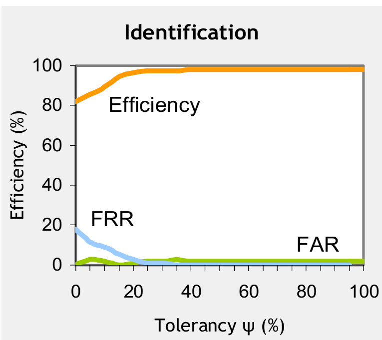
Experiments are carried out to estimate the performance of utilizing proposed approach in a combined matching system. Obtained results have been shown in Table 1. Retrieving time for one signature is 329*ms* for identification mode, and 299*ms* for verification mode (PC AMD Athlon 1.91GHz, RAM 512MB).

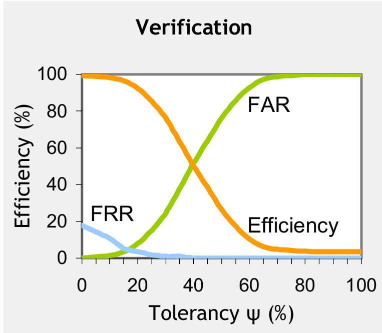
Table 1. Comparison of the two modes of the signature recognition

Identification (%)			Verification (%)		
FAR	FRR	Efficiency	FAR	FRR	Efficiency
1,79	3,57	94,60	3,94	5,36	96,00









7. Conclusions

A fundamental problem in the field of off-line signature verification is the lack of any pertinent shape factors. The main difficulty in the definition of pertinent features lies in the local variability of the signature line, which is closely related to the intrinsic characteristic of human beings. In this paper a new combined method of signature analysis has been proposed, where extraction of signature sections, its proportion, histograms and the centre of gravity are stated. Experimental evaluation of this scheme has been made using a signature database, which included 800 genuine signatures. This experiment confirmed that the proposed method is efficient and its effectiveness level is very attractive.

8. References

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