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SIGNATURES RECOGNITION METHOD BY USING THE NORMALIZED LEVENSHTEIN DISTANCES

This study examines the effectiveness of normalized Levenshtein metrics in the process of recognition of handwritten signatures. Three methods of normalization of the Levenshtein metric were taken into consideration. In addition, it was determined, which signature features are most important during their comparisons with the use of the aforementioned metric. The following signature features were examined: coordinates of signature points, pen pressure in successive points, and different types of pen speed. The influence of individual parameters of the Levenshtein algorithm on the obtained results was also determined, and the best method of normalization was selected.

1. INTRODUCTION

The methods of verifying people's identity based on biometric features are becoming some of the safest methods of authentication [4,11]. This results to a large extent from the fact that biometric data cannot be stolen or lost. Among various methods of verifying people's identity, the method based on recognition of handwritten signatures is one of the most popular. The use of a handwritten signature for confirming or determining people's identity has been practiced for a long time. The signature features such as shape, size of letters, spacing between letters, angle of writing, and manners of connecting characters characterize the signature and writing of each man. A reliable system of signature recognition and verification allows avoiding forgeries that cause material losses as well as a loss of confidence in a company or an institution. Signatures are also used in time and attendance systems as well as in the systems verifying whether a given person has an adequate access level for the data requiring special protection [2,8].

This study presents a method of comparing signatures with the use of the normalized Levenshtein metrics [6,7,10,12]. The effectiveness of these metrics in the process of signature recognition has not been examined so far.

2. FEATURE PREPARATION

A specialized device – a tablet, can be used for registration of signatures (fig. 1).

Fig. 1. Tablet SigLite LCD 4x3

Thanks to it, a signature can be recorded in the form of an *n*-point set [1,3]. Values of individual features are determined in each point. Up to now, about 40 different signature features have been identified [5]. Some of them are obtained directly from the tablet. The second group includes the features, the values of which are calculated on the basis of the features registered by a tablet in individual moments $T = \{t_1, t_2, ..., t_n\}$.

The following signature features were used in the presented study:

1. $X = \{x_1, x_2, ..., x_n\}$ – x coordinates of signature points,

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2. $Y=\{y_1,y_2,...,y_n\}$ – y coordinates of signature points,
3. $P=\{p_1,p_2,...,p_n\}$ – pen pressure on the tablet surface in successive signature points,
4. $Vh=\{vh_1,vh_2,...,vh_{n-1}\}$ – horizontal speed of the pen in successive signature points, where:

$$vh_i=\frac{x_{i+1}-x_i}{t_{i+1}-t_i},\ i=1,...,n-1$$

5. $Vv=\{vv_1,vv_2,...,vv_{n-1}\}$ – vertical speed of the pen in successive signature points, where:

$$vv_i=\frac{y_{i+1}-y_i}{t_{i+1}-t_i},\ i=1,...,n-1$$

6. $Vt=\{vt_1,vt_2,...,vt_{n-1}\}$ – general speed of the pen in successive signature points, where:

$$vt_i=\sqrt{vh_i^2+vv_i^2},\ i=1,...,n-1$$

7. $Pch=\{pch_1,pch_2,...,pch_{n-1}\}$ – change in the pen pressure in successive signature points:

$$pch_i=\frac{p_{i+1}-p_i}{t_{i+1}-t_i},\ i=1,...,n-1$$

The number of elements in the speed set and in the set of pen pressure changes is always lower by one than the number of signature points. This results from the fact that between n points, n-1 speeds can be determined.

3. LEVENSHTEIN DISTANCE

The Levenshtein distance is defined as a metric for measuring the similarity of two character strings [6]. It is used mainly for error correction, speech recognition, and for detection of plagiarisms. It has been described in detail in many studies.

As the final value of the Levenshtein distance calculated for two character strings is included in the $[0,\infty)$ interval, it is not possible on this basis to determine the percentage similarity of the strings being compared. This considerably hinders the evaluation of similarity of the strings being compared.

In this study, there was used the *Ned*1 (Normalized Edit Distance), *Ned*2, $d_{N\text{-}GLD}$ distance metrics, which are modifications of the standard Levenshtein distance [7,10,12]. The values of similarity of two character strings obtained with the use of these metrics are included in the [0,1] interval.

4. NORMALIZATION OF THE LEVENSHTEIN DISTANCE

The Levenshtein distance is the number of certain operations, called elementary operations, which must be performed to transform one character string into another one [7,10].

Let's define an alphabet of characters $\sum$ and a set containing all character sub-strings from this alphabet $\sum'$. Then, let's define two character strings $A=\{a_1,a_2,...,a_n\}$ and $B=\{b_1,b_2,...,b_m\}$ belonging to $\sum'$, where n and m are the lengths of these strings. Let $T_{A,B}=T_1,T_2,...,T_l$ mean the transformation of the A character string into the B character string with the use of the finite number l of elementary operations.

Elementary operations are performed on the pair of characters (a,b), where $a,b\neq\lambda$, described more often as $(a\to b)$. λ represents here an empty character, which does not belong to the alphabet. Three elementary operations can be distinguished:

– D – deleting a character $(a\to\lambda),(b\to\lambda)$,
– I – inserting a character $(\lambda\to a),(\lambda\to b)$,
– R – replacing a character $(a\to b),(b\to a)$.

Each elementary operation has a specific cost of its performance, which is called a weight of a given elementary operation. The weighting function δ assigns a non-negative real number to the i-th elementary operation $(a\to b)$:

$$\delta(T_i)=\delta(a\to b) \tag{1}$$

The weight of the $T_{A,B}$ transformation can be calculated from the following formula:

$$\delta(T_{A,B})=\sum_{i=1}^{l}\delta(T_i) \tag{2}$$

The $T_{A,B}$ transformation can be defined for a specific path of transition from the *A* character string into the *B* character string. Let the $P_{A,B} = \left\{ P_{A,B}^{1}, P_{A,B}^{2}, ..., P_{A,B}^{h} \right\}$ set contain all possible paths of transitions from the *A* character string into the *B* character string, where *h* is the number of all possible transition paths.

Let $W\left(P_{A,B}\right)$ be a function calculating weights of individual paths from the $P_{A,B}$ set:

$$W\left(P_{A,B}\right) = \delta\left(T_{A,B}\right) \tag{3}$$

The General Levenshtein Distance (GLD) for the two character strings *A*, *B* being compared can be defined as follows:

$$GLD\left(A,B\right) = \min\left\{\delta\left(T_{A,B}\right)\right\} = \min\left\{W\left(P_{A,B}\right)\right\} \tag{4}$$

*Ned*1 metric is defined by the formula:

$$Ned1\left(A,B\right) = \min\left\{\frac{W\left(P_{A,B}\right)}{Ld\left(P_{A,B}\right)}\right\} \tag{5}$$

where:

$Ld\left(P_{A,B}\right) = \left|P_{A,B}\right|$ – the number of elementary operations in an individual path.

Another measure is the *Ned*2 metric described by the following formula:

$$Ned2\left(A,B\right) = \min\left\{\frac{W\left(P_{A,B}\right)}{|A|+|B|}\right\} = \frac{GLD\left(A,B\right)}{|A|+|B|} \tag{6}$$

where:

$|A|+|B|$ – is the sum of lengths of the *A* and *B* strings.

Another modification of the Levenshtein distance, used in this study, is the $d_{N\text{-}GLD}$ distance. This distance is expressed by the formula:

$$d_{N-GLD}\left(A,B\right) = \frac{2\cdot GLD\left(A,B\right)}{\max\left(D,I\right)\cdot\left(|A|+|B|\right)+GLD\left(A,B\right)} \tag{7}$$

where:

D – the cost of deleting a character,
I – the cost of inserting a character.

All presented metrics: *Ned*1, *Ned*2, $d_{N\text{-}GLD}$ return results from the [0,1] interval. If two strings being compared are the same, the metrics return the 0 value. For further assessment of their effectiveness with the use of EER, the metrics (5), (6) and (7) were adequately modified so that the result of the comparison of two identical strings was the value 1:

$$NED1\left(A,B\right) = 1 - Ned1\left(A,B\right) \tag{8}$$

$$NED2\left(A,B\right) = 1 - Ned2\left(A,B\right) \tag{9}$$

$$NGLD\left(A,B\right) = 1 - d_{N-GLD}\left(A,B\right) \tag{10}$$

5. THE USE OF NORMALIZED LEVENSHTEIN METRICS IN THE PROCESS OF RECOGNITION OF HANDWRITTEN SIGNATURES

The values of signature features were normalized to the [0,1] interval, so they can take indefinitely many values from this interval. So the probability of occurrence of two identical feature values in two strings being compared is near zero. In order to eliminate this situation, the ϑ parameter was introduced. It determines, to what maximum extent the two values being compared can differ from each other in order to be treated as equal. The *g* number is deemed to be equal to the *r* number, if it fulfils the following condition:

$$g \in \left\langle r-\vartheta, r+\vartheta\right\rangle$$

where:

ϑ – the maximum difference between the values of the features that allows recognizing them as equal, $0 < r - \vartheta \le r + \vartheta \le 1$.

6. THE COURSE AND RESULTS OF THE STUDIES

The evaluation of the similarity of individual signatures was performed on the basis of an analysis of seven signature features. Thus, seven different values were obtained as the result of the comparison, and each of them described the similarity of a different signature feature. Then the F_i weight was assigned to each M_i value that determines the similarity of the *i*-th feature in two signatures being compared. This allowed determining, which of the analysed features were most important, and how considerable influence on the effectiveness of the signature recognition process they have. The formula for determining the *Sim* similarity value of two signatures S_1 and S_2, taking into account seven features, is as follows:

$$Sim(S_1, S_2) = \sum_{i=1}^{7} (M_i \cdot F_i), \text{ for } F_i \in [0,1], \sum_{i=1}^{7} F_i = 1 \quad (11)$$

It has been assumed that the weights of individual signature features will change within the range from 0.0 to 1.0 with the 0.2 increment and, that the sum of the weights of all features must equal 1.0.

In the course of the studies, the weights of elementary operations used in the Levenshtein algorithm were also changed. In the standard Levenshtein algorithm, all weights have the value 1. The studies allowed determining the influence of using non-standard values of weights of elementary operations on the signature recognition process. It was assumed that w_R corresponded to the weight of a character replacement operation *R*, w_D corresponded to the weight of a character deletion operation *D* while w_I corresponded to the weight of a character insertion operation *I*. It was also assumed that the weight of each elementary operation $w_R, w_D, w_I \in \{0.5, 0.75, 1\}$.

The tests were carried out on a set of 200 signatures put by 40 different people. The signatures being compared come from the SVC2004 database. Four original signatures and one professionally forged signature were analysed for each person. The signatures were compared using the “round-robin” method, however the forged signatures were not compared with each other. After generating all results, EER was determined for each of them.

The Table 1 presents 5 best results for individual metrics together with the values of the parameters, for which the results were obtained.

All the best results presented in Table 1 were obtained for the parameter ϑ=0.05. The analysis of the results shows that the least EER=0.80% was obtained for the *NGLD* metric. It can be also noticed that non-zero values of the *Y* weight indicate a considerable significance of this feature in the signature recognition process with the use of the metrics being examined. The *X* and *P* features show only a little lower significance. Whereas, the *Pch*, *Vv*, *Vt* features, the weights of which were 0 nearly in each analysed case, show the least significance.

Table 1. The best 5 results in individual metrics

	The weight of elementary operation			The weights of individual signature features				EER [%]
	w_R	w_D	w_I	*X*	*Y*	*P*	*Vh*	
*NED*1	1	1	0,75	0,2	0,4	0,4	0	1,16
	0,75	0,75	0,75	0	0,6	0,4	0	1,37
	0,75	1	0,75	0,2	0,4	0	0,2	1,40
	1	1	0,75	0,4	0,2	0,4	0	1,43
	0,5	1	0,5	0,4	0,4	0	0,2	1,43
*NED*2	1	0,75	0,75	0	0,6	0,4	0	1,16
	1	1	0,5	0,2	0,4	0,4	0	1,18
	0,5	0,75	0,5	0	0,4	0,2	0,2	1,25
	0,75	0,75	0,5	0,2	0,4	0,4	0	1,25
	1	0,75	0,5	0,2	0,4	0,4	0	1,27
NGLD	1	0,75	0,5	0,2	0,4	0,4	0	0,80
	1	1	0,5	0,2	0,4	0,4	0	0,80
	1	0,5	0,5	0,2	0,4	0,4	0	0,98
	1	0,75	0,75	0	0,6	0,4	0	1,16
	0,75	0,5	0,5	0,2	0,4	0,4	0	1,18

The studies demonstrated also that adequate selection of weights of elementary operations affected the effectiveness of the method. Adequate selection of values for weights of elementary operations can reduce EER as compared with the standard Levenshtein method, where the w_R, w_D, w_I values are the same.

7. CONCLUSIONS

This paper presents a method of comparing signatures with the use of the normalized Levenshtein metrics. The conducted studies confirm the usability of the presented metrics in the signature recognition process. The studies allowed determining the influence of the parameters of the method, such as weights of individual signature features and weights of elementary operations, on the result of signature recognition.

Next stages of the research will aim at comparing the results obtained from the tests with the results obtained with the use of other coefficients and methods known from the literature. In the course of the research work, various types of signature forgery will also be taken into consideration.

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