New Fast Algorithm for the Dynamic Signature Verification Using Global Features Values

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Abstract. Identity verification based on the dynamic signature is an important issue of biometrics. There are many effective methods to the signature verification which take into account the dynamic characteristics of the signature (e.g. velocity of the pen, the pen's pressure on the surface of the graphic tablet, etc.). Among these methods, the ones based on the so-called global features are very important. In our previous paper we have proposed new algorithm for evolutionary selection of the dynamic signature global features, which selects a subset of features individually for each user. Algorithm proposed in this paper is a faster version of the method proposed earlier. During development of the algorithm we resigned from using evolutionary selection of global features and standardized working of the classifier in the context of all users. The paper contains the simulation results for the BioSecure database of the dynamic signatures.

1 Introduction

Signature is a commonly used form of authentication. Its advantage is that the method of signature acquisition is not controversial, as in the case of certain biometric characteristics such as fingerprint or face image (see e.g. [47,48]).

In the literature there are two approaches to the signature verification. The first is based on the analysis of static features of the signature such as shape, size ratios, etc. (see e.g. [4,33]). The second approach is based on the analysis of the dynamics of signing process (see e.g. [12,28,39]). The dynamics of the signature is difficult to see and forge, so the use of the so-called dynamic signature brings much better results than the use of the so-called static signature. Moreover, the dynamic features of the signature are unique to the signer.

Approaches used to the dynamic signature verification can be divided into four main groups: **Global features based methods.** Some methods base on the global features which are extracted from signature and used during training and classification phase. Approach based on global features may be found in many research papers (see e.g. [14,37,39,79,75]). **Functions based methods.** Another approach commonly used in identity verification based on dynamic signature is functions-based approach. This approach bases on comparison of time

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functions, which contains information about changes of signature features over time (see e.g. [12,27,29]). **Regional based methods.** The literature contains also approaches relying on segmentation of signature into some regions, which are used during training and verification phase (see e.g. [9,10,13,26,28,77,78]). **Hybrid methods.** In the literature one can also find the hybrid methods which are based on combination of the described approaches (see e.g. [38,40]).

In this paper we focus on the approach based on global features. We use a set of global features proposed in [14], which contains extended collection of features from three other papers: [36,41,42]. It should be noted that the proposed fast algorithm is not dependent on the initial feature set, especially it is not sensitive to the wrong choice of this set. Moreover, the feature set can be practically arbitrarily reduced or extended. This is very important from the point of view of the flexibility of the proposed method and the possibility of its easy adaptation to the hardware used for the acquisition of features. The following conditions have prompted us to develop a method proposed in this work: **The proposed method does not require complex calculations, in particular machine learning.** Its characteristic feature is that a typical set of features describing the dynamics of the signature is considered for each user, without the need for features selection. As a result, the proposed algorithm does not require machine learning. The two following facts are also worth to note: (a) proposed algorithm does not depend on the used set of features, (b) the set of features selected in the previous paper (i.e. [79]) could depend on the specificity of used databases. **The proposed method uses in the classification process a hierarchy of features individually for each user.** In particular, it allows to determine for each user weights of importance of each feature. Values of weights are related to the similarity of features values (specifying stability of the reference signatures creation), taking into account all signatures created by the user in the acquisition phase of genuine signatures (training phase). **The proposed method takes advantage of the theory of fuzzy sets and neuro-fuzzy systems.** Neuro-fuzzy systems (see e.g. [30,31,43,44,45,52,70]) combine the natural language description of fuzzy systems (see e.g. [2,15,32,46]) and the learning properties of neural networks (see e.g. [34,35,50,51,69,73]). For the purposes of the proposed method, we have developed a new neuro-fuzzy one-class classifier, proposed by us earlier (see e.g. [9,78]). The proposed classifier is characterized the following properties: (a) it does not require supervised learning (what is crucial in the context of the considered sphere of application), (b) it has a uniform structure for all users and it is based on values of descriptors of the signature's features, (c) it does not require forged signatures, so called skilled forgeries, to proper work (what not always distinguish methods of signature verification, so it is definitely a positive property), (d) it is distinguished by the interpretability of rules included in the base of rules (also semantic). It is worth to note that many computational intelligence methods (see e.g. [1,11,17,18,19,21,68,49,64,65]) are succesfully used in pattern recognition (see e.g. [20,22,23,55,56,57,58]) and modelling (see e.g. [3,54,66]) issues.

To test the proposed method we used the BioSecure Database (BMDB) distributed by the BioSecure Association (see [24]) which is admitted source of data used in this field.

This paper is organized into four sections. In Section 2 we present description of the new method for dynamic signature verification based on global features. In Section 3 simulation results are presented. Conclusions are drawn in Section 4.

2 Description of the New Method for Dynamic Signature Verification Based on Global Features

Idea of the proposed in this paper method can be summarized as follows: **(a)** It works on the basis of a set of features describing the dynamics of the signature which have been systematized, for example, in the paper [14] (in our simulations 78 features have been considered). As already mentioned, the proposed method does not depend on the base set of features. This set can be freely modified. We would like to emphasize that from the set of all features (i.e. 85) considered in the paper [14], we removed those which were not selected by the algorithm for automatic features selection proposed by us earlier (see e.g. [79]). **(b)** It uses (developed for the considered method) one-class classifier which is based on the capacities of the flexible fuzzy system (see e.g. [6,9,62,63,78]). It allows to take into account the weights of importance of individual features, selected individually for each user. **(c)** It works in two modes: learning and testing (operating mode). In the first mode descriptors of features and weights of importance of features are determined. They are needed for proper work of the classifier in the test phase. These parameters are stored in a database. In the second mode, mode of operation (verification of test signatures), the parameters stored for each user in the learning phase are downloaded from the database and then signature verification is realized on the basis of these parameters.

General description of the fast training phase for the user i (procedure `Training(`i`)`) can be described as follows: **Step 1.** Acquisition of J training signatures of user i. **Step 2.** Determination of matrix $\mathbf{G}_i$ of all considered global features, describing dynamics of signatures, for all available J training signatures of user i. **Step 3.** Determination of vector $\bar{\mathbf{g}}_i$ of average values for each global feature, determined in Step 2 for J training signatures of user i. **Step 4.** Selection of classifier parameters used in the test phase (procedure `Classifier Determination(`$i, \mathbf{G}_i, \bar{\mathbf{g}}_i$`)`). **Step 5.** Storing in a database the following information about user i: vector $\bar{\mathbf{g}}_i$, parameters of classifier $maxd_{i,n}$ and $w_{i,n}$ $(n = 1, \ldots, N)$.

It is worth noting that for each user the procedure described above is independent, although the number of features N for each user is the same. Later in this section steps 2 and 3 of the procedure `Training(`i`)` have been described in details.

Matrix $\mathbf{G}_i$, which contains all considered global features of all J training signatures of user i, has the following structure:

$$\mathbf{G}_i = \begin{bmatrix} g_{i,1,1} \; g_{i,2,1} \cdots g_{i,N,1} \\ g_{i,1,2} \; g_{i,2,2} \cdots g_{i,N,2} \\ \vdots \\ g_{i,1,J} \; g_{i,2,J} \cdots g_{i,N,J} \end{bmatrix} = \begin{bmatrix} \mathbf{g}_{i,1} \\ \mathbf{g}_{i,2} \\ \vdots \\ \mathbf{g}_{i,N} \end{bmatrix}^T, \tag{1}$$

where $\mathbf{g}_{i,n} = \left[g_{i,n,1} \; g_{i,n,2} \cdots g_{i,n,J} \right]$, $g_{i,n,j}$ is a value of the global feature n, $n = 1, 2, \ldots, N$, determined for the signature j, $j = 1, 2, \ldots, J$, created by the user i, $i = 1, 2, \ldots, I$, I is a number of the users, J is a number of the signatures created by the user in the acquisition phase, N is a number of the global features. As already mentioned, the detailed method of determining each of the considered features is described in [14].

Matrix $\mathbf{G}_i$ is used to determine value of the vector $\bar{\mathbf{g}}_i$ in the **Step 3**. Vector $\bar{\mathbf{g}}_i$ of average values of each global feature of all training signatures J of user i is described as follows:

$$\bar{\mathbf{g}}_i = \left[\bar{g}_{i,1}, \bar{g}_{i,2}, \ldots, \bar{g}_{i,N} \right], \tag{2}$$

where $\bar{g}_{i,n}$ is average value of n-th global feature of training signatures of user i, computed using the following formula:

$$\bar{g}_{i,n} = \frac{1}{J} \sum_{j=1}^{J} g_{i,n,j}. \tag{3}$$

2.1 Determination of Classifier

In the procedure described in this section all available global features of the dynamic signature are considered. It causes that matrix $\mathbf{G}_i$ and vector $\bar{\mathbf{g}}_i$ are taken into account during determination of classifier parameters. General form of the procedure `Classifier Determination(`$i, \mathbf{G}_i, \bar{\mathbf{g}}_i$`)`, which determines parameters of the our classifier, can be presented as follows: **Step 1.** Determination of Euclidean distances $d_{i,n,j}$ between each global feature n and average value of the global feature for all J signatures of user i. **Step 2.** Selection of maximum distance for each global feature n from distances determined in Step 1. It should be emphasized that the maximum distance (labelled as $maxd_{i,n}$, $i = 1, 2, \ldots, I$, $n = 1, 2, \ldots, N$) are individual for each user i. They will be used in the classification phase of the signature (verification of the authenticity). Therefore, they must be stored in the database (in addition to vector $\bar{\mathbf{g}}_i$). **Step 3.** Computation of weights of importance $w_{i,n}$, $i = 1, 2, \ldots, I$, $n = 1, 2, \ldots, N$, associated with the feature number n of the user i and used in the classification phase. It should be emphasized that the weights also have individual character for the user i and they will be used in the classification process of the signature. Therefore, they must be stored in the database (in addition to vector $\bar{\mathbf{g}}_i$ and distances

$maxd_{i,n}$). **Step 4.** Creation of parameters of the flexible neuro-fuzzy system (see e.g. [60,61,76]) using values determined in Step 2 and Step 3.

In the **Step 1** distances $d_{i,n,j}$ between each global feature n and average value of the global feature for all J signatures of user i is computed using the following formula:

$$d_{i,n,j} = \left|\bar{g}_{i,n} - g_{i,n,j}\right|. \tag{4}$$

Next, maximum distance for each global feature is selected (**Step 2**):

$$maxd_{i,n} = \max_{j=1,\ldots,J}\left\{d_{i,n,j}\right\}. \tag{5}$$

Please note that distance $maxd_{i,n}$ is associated with the global feature n of the user i and determines instability of the signature in the context of the feature n. Value of the distance $maxd_{i,n}$ is also dependent on the variability of feature and it has an impact on the work of the signature classifier (see Fig. 1).

In the **Step 3** weights of importance of features $w_{i,n}$ for each global feature n of user i are determined. Weight of n-th global feature of the user i is computed on the basis of standard deviation of n-th global feature of the user i and average value of distances for n-th feature of the user i (computed in the **Step 2**). This process is described by the following formula:

$$w_{i,n} = 1 - \frac{\sqrt{\frac{1}{J}\sum\limits_{j=1}^{J}\left(\bar{g}_{i,n} - g_{i,n,j}\right)^2}}{\frac{1}{J}\sum\limits_{j=1}^{J} d_{i,n,j}}. \tag{6}$$

It should be noted that the larger value of the weight $w_{i,n}$, the corresponding feature is more important in the verification of the signature (as described in the next subsection).

Next, a classifier is created (**Step 4**). We use flexible neuro-fuzzy system of the Mamdani type (see e.g. [6,7,5,8]). This system is based on the rules in the form if-then. The fuzzy rules contain fuzzy sets which represent the values, e.g. "low" and "high", of the input and output linguistic variables. In our method the input linguistic variables are dependent on the similarity between the global features of test signature and average values of global features computed on the basis of training signatures. The system uses N features. Output linguistic variables describe the reliability of the signature. In our method parameters of input fuzzy sets are individually selected for each user (**Step 2** of the procedure `Classifier Determination(`$i, \bar{\mathbf{g}}_i$`)`). Please note that if training signatures are more similar to each other, the tolerance of our classifier is lower ($maxd_{i,n}$ takes smaller values).

The flexibility of the classifier results from the possibility of using in the classification the importance of global features, which are selected individually for each user (**Step 3** of the procedure `Classifier Determination(`$i, \mathbf{G}_i, \bar{\mathbf{g}}_i$`)`).

Taking into account the weights of importance of the global features is possible thanks to the use of proposed by us earlier (see e.g. [7,62,67]) aggregation operators named the weighted triangular norms.

Our system for the signature verification works on the basis of two fuzzy rules presented as follows:

$$\left\{\begin{array}{l} R^{(1)}: \left[\begin{array}{c} \text{IF } \left(dtst_{i,1} \text{is} A^1_{i,1}\right)\middle| w_{i,1} \text{ANDIF } \left(dtst_{i,2} \text{is} A^1_{i,2}\right)\middle| w_{i,2} \text{AND} \\ \vdots \\ \text{IF } \left(dtst_{i,N} \text{is} A^1_{i,N}\right)\middle| w_{i,N} \text{THEN} y_i \text{is} B^1 \end{array}\right] \\ R^{(2)}: \left[\begin{array}{c} \text{IF } \left(dtst_{i,1} \text{is} A^2_{i,1}\right)\middle| w_{i,1} \text{ANDIF } \left(dtst_{i,2} \text{is} A^2_{i,2}\right)\middle| w_{i,2} \text{AND} \\ \vdots \\ \text{IF } \left(dtst_{i,N} \text{is} A^2_{i,N}\right)\middle| w_{i,N} \text{THEN} y_i \text{is} B^2 \end{array}\right] \end{array}\right. , \tag{7}$$

where: **(a)** $dtst_{i,n}$, $i = 1, 2, \ldots, I$, $n = 1, 2, \ldots, N$, $j = 1, 2, \ldots, J$, are input linguistic variables in the system for the signature verification. **(b)** $A^1_{i,n}$, $A^2_{i,n}$, $i = 1, 2, \ldots, I$, $n = 1, 2, \ldots, N$, are input fuzzy sets related to the global feature number n of the user i represent values "high" assumed by input linguistic variables. Analogously, fuzzy sets $A^2_{i,1}, A^2_{i,2}, \ldots, A^2_{i,N}$ represent values "low" assumed by input linguistic variables. Thus, each rule contains N antecedents. In the fuzzy classifier of the signature used in the simulations we applied a Gaussian membership function (see Fig. 1) for all input fuzzy sets. **(c)** y_i, $i = 1, 2, \ldots, I$, is output linguistic variable interpreted as reliability of signature considered to be created by the i-th signer. **(d)** B^1, B^2 are output fuzzy sets shown in Fig. 1. Fuzzy set B^1 represents value "high" of output linguistic variable. Analogously, fuzzy set B^2 represents value "low" of output linguistic variable. In the fuzzy classifier of the signature used in the simulations we applied the membership function of type γ (see e.g. [59]) in the rule 1 and the membership function of type L (see e.g. [59]) in the rule 2. Please note that the membership function of fuzzy sets B^1 and B^2 are the same for all users (their parameters do not depend on the chosen global features of the dynamic signature and their values). **(e)** $maxd_{i,n}$, $i = 1, 2, \ldots, I$, $n = 1, 2, \ldots, N$, can be equated with the border values of features of individual users (see formula (5)). **(f)** $w_{i,n}$, $i = 1, 2, \ldots, I$, $n = 1, 2, \ldots, N$, are weights of importance related to the global feature number n of the user i (see formula (6)).

Please note that regardless of the set of features chosen individually for the user, the interpretation of the input and output fuzzy sets is uniform. Moreover, the way of the signature classification is interpretable (see [16])

2.2 Identity Verification Phase

Formal notation of the process of signature verification (`SignatureVerification(i)`) is performed in the following way: **Step 1.** Acquisition of test signature of the user which is considered as user i. **Step 2.** Download of information about average values of global features of user i computed during training phase ($\bar{\mathbf{g}}_i$) and classifier

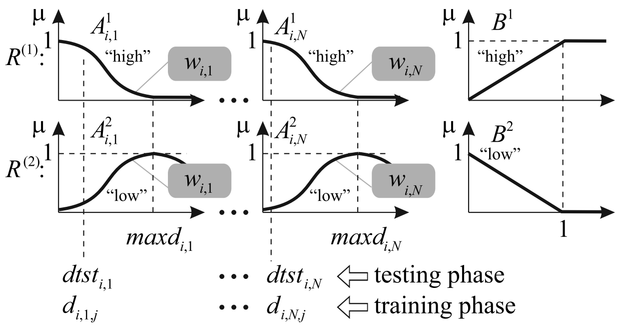

Fig. 1. Input and output fuzzy sets of the flexible neuro-fuzzy system of the Mamdani type for verification signature of user i

parameters of user i from the database $(maxd_{i,n}, w_{i,n})$. **Step 3.** Determination of values of global features which have been selected as the most characteristic for user i in training phase. **Step 4.** Verification of test signature using of one class flexible neuro-fuzzy classifier.

The purpose of the signature verification phase is therefore to determine whether the tested signature which belongs to the user claiming to be user i in fact belongs to the user i. For such a signature values of global features are calculated. Next, they are put on the input of the classifier described by the rules (7). Parameters of the classifier are loaded from the database.

In the **Step 1** user which identity will be verified creates one test signature. In this step user claims his identity as i. Next, information about average values of global features of user i computed during training phase ($\bar{\mathbf{g}}_i$) and parameters of the classifier of user i created during training phase $(maxd_{i,n}, w_{i,n})$ are downloaded from the database (**Step 2**). In the **Step 3** system determines global features of the test signature. Finally, verification is performed using flexible one-class neuro-fuzzy classifier of Mamdani type (**Step 4**). In the last step of the algorithm, the result of identity verification is presented. A signature is true if the following assumption is satisfied:

$$\bar{y}_i = \frac{T^* \left\{ \begin{array}{c} \mu_{A^1_{i,1}}\left(dtst_{i,1}\right), \ldots, \mu_{A^1_{i,N}}\left(dtst_{i,N}\right); \\ w_{i,1}, \ldots, w_{i,N} \end{array} \right\}}{\left(\begin{array}{c} T^* \left\{ \begin{array}{c} \mu_{A^1_{i,1}}\left(dtst_{i,1}\right), \ldots, \mu_{A^1_{i,N}}\left(dtst_{i,N}\right); \\ w_{i,1}, \ldots, w_{i,N} \end{array} \right\} + \\ T^* \left\{ \begin{array}{c} \mu_{A^2_{i,1}}\left(dtst_{i,1}\right), \ldots, \mu_{A^2_{i,N}}\left(dtst_{i,N}\right); \\ w_{i,1}, \ldots, w_{i,N} \end{array} \right\} \end{array} \right)} > cth_i, \tag{8}$$

where $T^*\{\cdot\}$ is the algebraic weighted t-norm (see [7,62]), $\mu_A(\cdot)$ is a Gaussian membership function (see e.g. [59]), $\mu_{B^1}(\cdot)$ is a membership function of class L (see e.g. [59]), $\mu_{B^2}(\cdot)$ is a membership function of class γ (see e.g. [59]), $\bar{y}_i$, $i = 1, 2, \ldots, I$, is the value of the output signal of applied neuro-fuzzy system described by rules (7), $cth_i \in [0,1]$ - coefficient determined experimentally for each user to eliminate disproportion between FAR and FRR error (see e.g. [74]).

Formula (8) was created by taking into account in the description of system simplification resulting from the spacing of fuzzy sets, shown in Fig. 1. The simplifications are as follows: $\mu_{B^1}(0) = 0$, $\mu_{B^1}(1) \approx 1$, $\mu_{B^2}(0) \approx 1$, $\mu_{B^2}(1) = 0$.

3 Simulations

Simulations were performed using the commercial BioSecure DS2 Signature database which contains signatures of 210 users. The signatures was acquired in two sessions using the digitizing graphic tablet. Each session contains 15 genuine signatures and 10 skilled forgeries per person.

Test procedure proceeded as follows for signatures of each signer available in the database. During training phase we used 5 randomly selected genuine signatures of each signer. During test phase we used 10 remaining genuine signatures and all 10 skilled forgeries of each signer. The process was performed five times, and the results were averaged. The described method is commonly used in evaluating the effectiveness of methods for dynamic signature verification, which corresponds to the standard crossvalidation procedure. The test was performed using the authorial testing environment implemented in C# language.

3.1 Simulation Results

Table 1 contain a set of accuracies obtained using different methods in the field of the dynamic signature verification for the BioSecure database. The table contains values of FAR (False Acceptance Rate) and FRR (False Rejection Rate) errors which are commonly used in the literature to evaluate the effectiveness of identity verification methods (see e.g. [12,29]). Table 2 contains information on the computational complexity of the proposed method.

Table 1. Comparison of the results for the dynamic signature verification methods for the database BioSecure

Method	Average FAR	Average FRR	Average error
Methods of other authors [25]	-	-	3.48 % - 30.13 %
Horizontal partitioning [10]	2.94 %	4.45 %	3.70 %
Vertical partitioning [9]	3.13 %	4.15 %	3.64 %
Evolutionary selection with PCA [75]	5.29 %	6.01 %	5.65 %
Evolutionary selection [79]	2.32 %	2.48 %	2.40 %
Our method	**3.29 %**	**3.82 %**	**3.56 %**

It may be seen that the proposed method works with a very good accuracy for the BioSecure database taking into account all methods considered in the Table 1. Moreover, it seems that the method proposed by us deserves attention

Table 2. The computational complexity of the proposed algorithm for dynamic signature verification based on global features

	Step				
Procedure	1	2	3	4	5
`Training`(i)	J	$J\sum_{n=1}^{N} c_n$	JN	$4JN$	$4N$
`Signature Verification`(i)	1	-	$\sum_{n=1}^{N} c_n$	$2N+1$	-

c_n is computational complexity of feature n determination, "-" means the reading or the writing to the database

both in the aspect of accuracy and additional advantages, such as taking into account a hierarchy of importance of global features in the classification process and interpretability of the fuzzy system rules used for the classification of signatures.

4 Conclusions

In this paper we propose a new method for the dynamic signature verification based on the so called global features. Proposed method works without access to the so-called skilled forged signatures, it implements individual (created individually for each user) hierarchy of features and it uses a dedicated flexible fuzzy one-class classifier. Efficiency of the proposed method has been tested with use of the BioSecure. The proposed algorithm worked with a very good accuracy. Moreover, our algorithm does not require high complexity computation (see Table 2). This is due to the fact that the algorithm does not use gradient or evolutionary (see e.g. [53,71,72]) machine learning. As a result, the proposed method can be used everywhere where speed of operation is crucial.

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