Novel Algorithm for the On-Line Signature Verification Using Selected Discretization Points Groups

Marcin Zalasiński and Krzysztof Cpałka

Częstochowa University of Technology,
Institute of Computational Intelligence, Poland
{marcin.zalasinski,krzysztof.cpalka}@iisi.pcz.pl

Abstract. Identity verification based on on-line signature is a commonly known biometric task. Some methods based on the on-line signature biometric attribute used for identity verification use information from partitions of the signature. Efficiency of these methods is relatively high. In this paper we would like to present a new approach to signature trajectories partitioning, based on selection of the discretization points groups. The new method was compared to other methods, with use of the SVC2004 public on-line signature database.

1 Introduction

Signature is a biometric attribute commonly used in identity verification process. This attribute may be categorized into two groups - off-line (static) signature and on-line (dynamic) signature. Off-line signature contains only information about shape of the signature. Systems which use this type of signature may be used for example for verification identity of person who signed some kind of documents. On-line signature contains many additional information about dynamics of signing process. This kind of signatures are acquired with use of some digital input device, e.g. graphic tablet. Dynamic signatures are more reliable than static ones, because they are more difficult to forge (see e.g. [6]).

One of the most effective method of identity verification with use of dynamic signature is method based on signature trajectories partitioning (see e.g. [9], [11]). In [11] velocity signal is split into three bands and strokes which belong to the medium-velocity band are used for discrimination purposes. Method presented in [9] assumes division of velocity and pressure signals into two parts. After this process four partitions are created. Each partition contains template created from trajectories of training signatures which belong to the partition. Then selection of the most discriminative partition (called stable partition) is performed. Stable partition is selected on the basis of similarities between each training signature of the user and the template. The template from selected partition is compared to the test signature during verification process. Identity verification is performed on the basis of this comparison, signature is classified as genuine or forgery. Our approach to identity verification, presented in [31],

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also refers to partitioning of signature trajectories. In our method all partitions are considered during verification process, because we assume that all partitions may contain useful information about signer. All partitions have also weights of importance calculated individually for each signer, therefore partitions which are more characteristic for the user will be more important during verification process. During classification phase classifier based on the t-conorm with the weights of arguments is used (see [1]-[4], [23]). This approach is more effective than approach with use only one partition.

In this paper we present a new method of signature partitioning based on selection of discretization points groups. This method also divide signature trajectories into few partitions which are weighted by weights of importance and are used during classification process. Classification is performed with use a neuro-fuzzy system (see e.g. [2]-[3], [7], [12]-[15], [17]-[18], [22]-[28]).

This paper is organized into four sections. In Section 2 the new approach to signature trajectories partitioning with selection of the discretization points groups is presented. Simulation results are presented in Section 3. Conclusions are drawn in Section 4.

2 Signature Verification Based on discretization Points Groups

2.1 General Idea of the Algorithm

In this paper we propose a new method of signature partitioning. The method may be summarized as follows: (a)In our approach partitions are used during the training and classification phase. (b)Classification process is performed with use of weights of importance. Weights are calculated individually for each signer and for each partition. Partitions are created in a new way, so that the interpretation of weights is different from the weights considered in [31]. (c)Proposed classifier bases on flexible neuro-fuzzy system with weights of antecedents (see e.g. [2]-[3], [22]). The weights of importance are associated with the parts of the signatures. The conception of use of weights in triangular norms and neuro-fuzzy systems is described in [5], [22].

The algorithm is performed as follows:

- **Step 1. Partitioning of signatures.** Signatures are partitioned with use of the method which creates vertical partitions, selecting best discretization points groups. Each of vertical partitions has the same width. Number of vertical partitions is the same for each user (see Fig. 1).
- **Step 2. Template generation.** In this step templates for each partition are generated. Templates are created on the basis of signatures generated by signer during training data acquisition phase. Each template contains average values of signature signals. This step is performed only during training phase.

- **Step 3. Calculation of signatures similarity in each partition.** In this phase similarities between each signature of the user and template are calculated. The similarities are calculated for each partition.
- **Step 4. Computation of the weights of importance.** During this step weights of importance for each partition are created. Values of weights are based on mean distance between training signatures and template and also on similarity in distances between training signatures and template. This step is performed only during training phase.
- **Step 5. Creation decision boundary for each partition.** During this step linear decision boundary between genuine signatures and forged signatures is created individually for the user (see [31]). This step is performed only during training phase. Genuine signatures of the other users may be used as forged signatures (see e.g. [29]).
- **Step 6. Determination of the fuzzy rules used in classification phase.** Fuzzy rules describe a way of test signature classification. The rules based on the fuzzy sets, which use decision boundaries determined in the step 5. Therefore they may be interpretable.
- **Step 7. Classification.** In this step signature is classified as genuine or forgery. Classification process is performed on the basis of distances between template and sample signature in the partitions. This step is performed only during test phase. In the verification process flexible neuro-fuzzy system of the Mamdani type is used. Each of the antecedents of this classifier is associated with the weight determined in Step 2.

We can see that steps 1-6 are performed during training phase, while steps 1,3,7 are performed during test phase.

2.2 Determination of Partitions and Weights of Partitions

First, partitioning of the signatures is performed. The new approach presented in this paper assumes partitioning based on selected time intervals of signing. This approach is possible to implement because lengths of the all signature signals are the same through the pre-processing. Pre-processing of the signatures is performed after the acquisition phase. Lengths of the signatures are fitted by the Dynamic Time Warping algorithm (see e.g. [16]) which use velocity or pressure signal. Next, each signal is divided into parts of the same width. Membership of the k-th sample of the j-th signature of the i-th user to the p-th partition is described as follows:

$$part_{i,j,k}^{\{s\}} = \begin{cases} 1 & \text{for} \quad 0 < k \leq \frac{K}{PN^{\{s\}}} \\ 2 & \text{for} \quad \frac{K}{PN^{\{s\}}} < k \leq \frac{2K}{PN^{\{s\}}} \\ \vdots & \\ PN^{\{s\}} & \text{for} \quad \frac{(PN^{\{s\}}-1)K}{PN^{\{s\}}} < k \leq K \end{cases}, \tag{1}$$

where s is a signal type (velocity or pressure) used during alignment phase, i is the user number ($i = 1, 2, \ldots, I$), j is the signature number ($j = 1, 2, \ldots, J$), K

is a number of samples, k is the sample number ($k = 1, 2, \ldots, K$) and $PN^{\{s\}}$ is a number of partitions. In this method we have assumed, that $PN^{\{v\}} = PN^{\{z\}}$. Partitioning method is shown in Fig. 1.

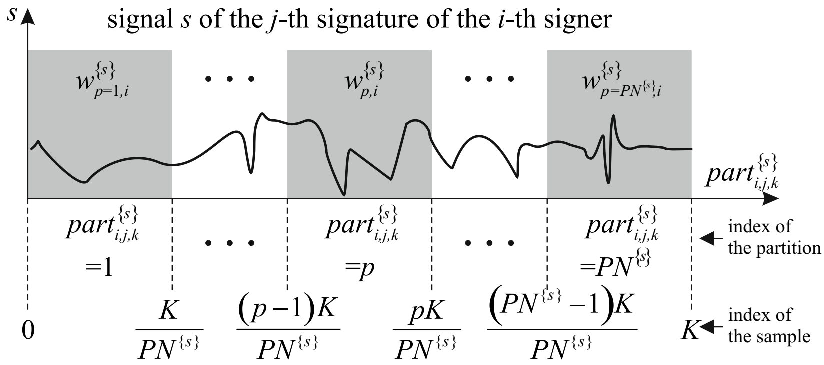

Fig. 1. Signature partitioning

After partitioning, templates of the signatures are generated. Generation of the templates is based on the training signatures. Templates are concerned with the user and assigned to the partition. Generation of an element of template $ta^{\{s\}}_{p,i,k}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $k = 1, 2, \ldots, K$, for the k-th time step of the p-th partition of the i-th signer for signatures aligned with use of s signal (v velocity or z pressure) and a trajectory (x or y) is calculated by the formula:

$$ta^{\{s\}}_{p,i,k} = \frac{1}{J} \sum_{j=1}^{J} a^{\{s\}}_{p,i,j,k}, \tag{2}$$

where $a^{\{s\}}_{p,i,j,k}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J$, $k = 1, 2, \ldots, K$, is trajectory (x or y) value in the k-th sample of the p-th partition of the j-th signature of the i-th signer. Template $\mathbf{ta}^{\{s\}}_{p,i}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, of the p-th partition of the i-th signer for signatures aligned with use of s signal (v velocity or z pressure) and a trajectory (x or y) is described by the following equation:

$$\mathbf{ta}^{\{s\}}_{p,i} = \left[ta^{\{s\}}_{p,i,1}, ta^{\{s\}}_{p,i,2}, ..., ta^{\{s\}}_{p,i,k} \right]. \tag{3}$$

Next, distances between each template and each signature trajectory are calculated. Distance $da^{\{s\}}_{p,i,j}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J$, between template of the p-th partition of the i-th signer generated for signatures aligned with use of s signal (v velocity or z pressure) and a trajectory (x or y), and the j-th signature of the i-th signer is described as follows:

$$da_{p,i,j}^{\{s\}} = \sqrt{\sum_{k=1}^{K} \left(ta_{p,i,k}^{\{s\}} - a_{p,i,j,k}^{\{s\}} \right)^2}, \tag{4}$$

where $a_{p,i,j,k}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J$, $k = 1, 2, \ldots, K$, is a a trajectory (x or y) value in the k-th sample of the p-th partition of the j-th signature of the i-th signer.

Next, distances between templates and signatures in two dimensional space are calculated. Distance $d_{p,i,j}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J$, between the j-th signature trajectory of the i-th signer and template of the i-th signer in the p-th partition generated for signatures aligned with use of s signal is calculated by the formula:

$$d_{p,i,j}^{\{s\}} = \sqrt{\left(dx_{p,i,j}^{\{s\}} \right)^2 + \left(dy_{p,i,j}^{\{s\}} \right)^2}. \tag{5}$$

Next, weights of importance for each partition are calculated. First step to compute weights of importance is calculation of mean distances between signatures and template in partitions. Mean distance between signatures of the i-th signer and template of the i-th signer in the p-th partition $\bar{d}_{p,i}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, related to signal s (v velocity or z pressure) is calculated by the formula:

$$\bar{d}_{p,i}^{\{s\}} = \frac{1}{J} \sum_{j=1}^{J} d_{p,i,j}^{\{s\}}. \tag{6}$$

Then, standard deviation of distances in each partition should be calculated. Standard deviation of signatures $\sigma_{p,i}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, of the i-th user from the p-th partition related to signal s (*velocity* or *pressure*) is calculated using the following equation:

$$\sigma_{p,i}^{\{s\}} = \sqrt{\frac{1}{J} \sum_{j=1}^{J} \left(\bar{d}_{p,i}^{\{s\}} - d_{p,i,j}^{\{s\}} \right)^2}. \tag{7}$$

Next, weights of importance are calculated. Weight $w_{p,i}^{'\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, of the p-th partition of the i-th user related to signal s (*velocity* or *pressure*) is calculated by the following formula:

$$w_{p,i}^{'\{s\}} = \bar{d}_{p,i}^{\{s\}} \sigma_{p,i}^{\{s\}}. \tag{8}$$

After that, weights should be normalized. Normalization of weight is used to simplify the classification phase. Weight $w_{p,i}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, of the p-th partition of the i-th user related to signal s (*velocity* or *pressure*) is normalized by the following equation:

$$w_{p,i}^{\{s\}} = 1 - \frac{0.9 \cdot w_{p,i}^{'\{s\}}}{\max\left\{w_{1,i}^{'\{s\}}, \ldots, w_{PN^{\{s\}},i}^{'\{s\}}\right\}}. \tag{9}$$

Use of coefficient 0.9 in formula (9) causes that partition with the lowest value of weight of importance is also used in classification process.

Next, selection of location of decision boundary and determination of the value $dlrnmax_{p,i}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $s \in \{v, z\}$ is performed (see [31]). The determined values have an impact on spacing of fuzzy sets, which represent values $\{\text{low}, \text{high}\}$ assumed by the $PN^{\{v\}} + PN^{\{z\}}$ linguistic variables "the truth of the i-th user signature from p-th partition of s signal" ($p = 1, 2, \ldots, PN^{\{s\}}$, $s \in \{v, z\}$).

2.3 Signature Classification

In the last step signature verification is performed. In this step flexible Mamdani-type neuro-fuzzy system is used (see e.g. [2]-[3], [22]). Our system works on the basis of two fuzzy rules presented as follows:

$$\begin{cases} R^1 : \left[\begin{array}{c} \text{IF}\left(dtst_{1,i}^{\{s\}} \text{is} A_{1,i}^{1\ \{s\}}\right) \Big| w_{1,i}^{\{s\}} \text{ OR} \ldots \\ \left(dtst_{PN^{\{s\}},i}^{\{s\}} \text{is} A_{PN^{\{s\}},i}^{1\ \{s\}}\right) \Big| w_{PN^{\{s\}},i}^{\{s\}} \text{ THEN} y_i \text{is} B^1 \end{array}\right] \\ R^2 : \left[\begin{array}{c} \text{IF}\left(dtst_{1,i}^{\{s\}} \text{is} A_{1,i}^{2\ \{s\}}\right) \Big| w_{1,i}^{\{s\}} \text{ OR} \ldots \\ \left(dtst_{PN^{\{s\}},i}^{\{s\}} \text{is} A_{PN^{\{s\}},i}^{2\ \{s\}}\right) \Big| w_{PN^{\{s\}},i}^{\{s\}} \text{ THEN} y_i \text{is} B^2 \end{array}\right] \end{cases}, \tag{10}$$

where

- $dtst_{p,i}^{\{s\}}$, $s \in \{v, z\}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, are input linguistic variables, whose numeric value is a distance between the test signature trajectory of the i-th signer and decision boundary in the p-th partition for signatures aligned with use of s signal.
- $A_{p,i}^{1\ \{s\}}$, $A_{p,i}^{2\ \{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, are input fuzzy sets related to the signal $s \in \{v, z\}$ shown in Fig. 2.
- y_i, $i = 1, 2, \ldots, I$, is input linguistic variable interpreted as reliability of signature.
- B^1, B^2 are output fuzzy sets shown in Fig. 2.
- $w_{p,i}^{\{s\}}$, $p = 1, 2, \ldots, PN^{\{s\}}$, $i = 1, 2, \ldots, I$, $s \in \{v, z\}$, are weights of the p-th partition of the i-th user related to signal s.

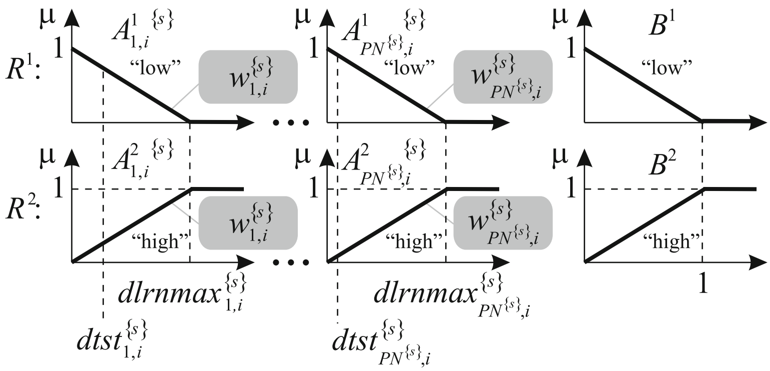

Fig. 2. Input and output fuzzy sets of the flexible neuro-fuzzy system of the Mamdani type for signature verification

Signature is considered true if the following assumption is satisfied:

$$\bar{y}_i = \frac{S^*\left\{\begin{array}{c}\mu_{A^2_{1,i}{}^{\{s\}}}\left(dtst^{\{s\}}_{1,i}\right),\ldots,\\ \mu_{A^2_{PN^{\{s\}},i}{}^{\{s\}}}\left(dtst^{\{s\}}_{PN^{\{s\}},i}\right);w^{\{s\}}_{1,i},\ldots,w^{\{s\}}_{PN^{\{s\}},i}\end{array}\right\}}{\left(\begin{array}{c}S^*\left\{\begin{array}{c}\mu_{A^2_{1,i}{}^{\{s\}}}\left(dtst^{\{s\}}_{1,i}\right),\ldots,\\ \mu_{A^2_{PN^{\{s\}},i}{}^{\{s\}}}\left(dtst^{\{s\}}_{PN^{\{s\}},i}\right);w^{\{s\}}_{1,i},\ldots,w^{\{s\}}_{PN^{\{s\}},i}\end{array}\right\}+\\ S^*\left\{\begin{array}{c}\mu_{A^1_{1,i}{}^{\{s\}}}\left(dtst^{\{s\}}_{1,i}\right),\ldots,\\ \mu_{A^1_{PN^{\{s\}},i}{}^{\{s\}}}\left(dtst^{\{s\}}_{PN^{\{s\}},i}\right);w^{\{s\}}_{1,i},\ldots,w^{\{s\}}_{PN^{\{s\}},i}\end{array}\right\}\end{array}\right)} > cth_i, \tag{11}$$

where

- $S^*\{\cdot\}$ is a weighted t-conorm of the algebraic type (see [2]).
- $\bar{y}_i$, $i = 1, 2, \ldots, I$, is the value of the output signal of applied neuro-fuzzy system described by rules (10). Detailed description of the system can be found in [2]. Formula (11) is the result of the general relationship describing the transformation of the input signal of Mamdani-type system.
- $cth_i \in [0, 1]$ - coefficient determined experimentally during training phase for each user to eliminate disproportion between FAR and FRR error (see [29]). The parameters $cth_i \in [0, 1]$, computed individually for the i-th user, $i = 1, 2, \ldots, I$, are used during verification process in the test phase.

In future research we plan to use probabilistic neural networks for classification of dynamic signature ([8], [19]-[21]).

3 Simulation Results

Public SVC 2004 database (see [29]) was used during simulation. The database contains 40 signers and for each signer 20 genuine and 20 forgery signatures. The test was performed five times, every time for all signers stored in the database. During training phase 5 genuine signatures (numbers 1-10) of each signer were used. During test phase 10 genuine signatures (numbers 11-20) and 20 forgery signatures (numbers 21-40) of each signer were used. All the methods were implemented in the authorial testing environment to compare the results.

In the Table 1 we present simulation results. FAR (False Acceptance Rate) and FRR (False Rejection Rate) values are commonly used in biometrics (see e.g. [10]). It should be noted, that method based on vertical partitions achieves the best results.

Table 1. Results of simulation performed by our system

Method	**Average FAR**	**Average FRR**	**Average error**
Khan et al. [9]	12.30 %	13.90 %	13.10 %
Zalasiński and Cpałka [31]	11.13 %	11.45 %	11.29 %
Our method	**11.35 %**	**9.80 %**	**10.57 %**

4 Conclusions

In this paper a new method of signature partitioning is presented. The method assumes division of signals on the basis of discretization points time index values. All partitions are used during training and verification process. They are described by weights of importance which contain information about reliability of the partition. Achieved high accuracy of signature verification proves the correctness of the proposed method.

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