Dynamic Signature Verification Using Selected Regions

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Abstract. Identity verification takes into account biometric attributes. Behavioral ones are particularly important. One of them is a dynamic signature. An analysis of such type of a signature uses signals describing the signing process. In this paper, we consider the velocity signal and propose a new method for dividing the dynamic signature into groups. In this case, a group is a subset of consecutive discretization points corresponding to similar velocity values. We have also assumed here that the signature fragments characterized by the highest pen velocity are the most characteristic of each user, therefore we reject partitions related to medium and low velocity values. As a result, we individually create a unique set of partitions of different sizes for each user. We do not use skilled forgeries, which is an additional advantage of our approach. The proposed method has been tested using the BioSecure dynamic signature database. The obtained results have confirmed the effectiveness of the proposed approach.

Keywords: Behavioral biometrics · Identity verification · Dynamic signature · Signature partitioning · Signature groups

1 Introduction

Identity verification takes into account biometric attributes, in which behavioral ones are particularly important, and one of them is the dynamic signature. Usually, a graphics tablet is used to create such a signature. The dynamic signature is represented by discrete waveforms describing how the pen is guided. They are, e.g., pen trajectory signals which can be used to determine pen velocity and acceleration. There are different approaches to analyzing dynamic signatures and they often use population-based algorithms [19,20,26,29,54,56], fuzzy systems [28,35], neural networks [7,8,15,31], and other methods of artificial intelligence and machine learning [21,32,47]. The most common approaches:

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- extract features from the waveforms describing the signing process [22,52]. Values of these features depend on the specificity of the user's signatures and are used in the verification of test signatures. The set of features can be additionally selected individually for each user and various metaheuristic methods can be used for the selection [53,55].
- divide signatures into partitions that may have different interpretations [16, 17]. Partitions are usually created by points similar to each other in the sense of the adopted similarity criterion. For example, they are related to a similar velocity value or the same time moment of signing. Moreover, partitions can be selectable, like features [51].
- select characteristic fragments of the signature and analyze them [34]. This selection can be made individually for each user.
- analyze the shape of the signature and its dynamics [24]. Thus, such approaches are hybrid in nature-they can use many different methods of shape and dynamics analysis, aggregating the results of the component methods.
- transform the waveforms describing the signature dynamics in order to select unique properties that increase the effectiveness of signature verification [1, 14].
- generate common properties of the real signatures of all available users. They most often use skilled forgeries [49], which reduces the verification of signatures to two-class classification and eliminates the problem of designing one-class classifiers. The disadvantage of such solutions is the use of skilled forgeries, which in practice are usually not available.

In this paper, we consider the discrete waveform of the signature velocity and propose a new method for dividing the signature into groups. By a group we mean a subset of successive discretization points corresponding to similar velocity values. In this paper we have assumed that the most characteristic of the user are the fragments of the signature written at the highest pen velocity, hence we discard the partitions related to the medium and low velocity. Therefore, for each user, we create an individual set of partitions with different sizes. We do not use skilled forgeries, which is an additional advantage of the proposed approach.

1.1 Motivation

The motivation for the preparation of the method considered in this paper can be summarized as follows:

- In our previous research on dynamic signature verification, we also created partitions and determined their importance. Partitions related to higher pen velocity were most often more important than others (see e.g. [17]). Therefore, in this work, we only focus on the partitions related to the high pen velocity and the signature areas related to them.
- In the proposed algorithm, the signature partitions have a different interpretation than in our previous work. Then, the partition associated with e.g. high velocity was a set of discretization points that did not have to be adjacent to

each other (see e.g. [17]). In this paper, a partition has a group of adjacent discretization points. Such groups of points are easier to interpret and relate to signature areas.

1.2 Contribution of the Paper

The elements of the novelty presented in this paper can be summarized as follows:

– We propose a new interpretation of the dynamic signature partitions. In our algorithm, a partition is a group of contiguous discretization points that are not distributed as they were in our previous methods.
– We propose a new method of dynamic signatures verification that focuses on the areas with the highest pen velocity. In our previous papers, we considered all the discretization points regardless of what velocity they were related to.

1.3 Structure of the Paper

In Sect. 2 we have described the proposed approach to the dynamic signature verification using selected regions. Section 3 contains sample simulation results. Section 4 presents a summary of the most important conclusions and plans for future research.

2 Description of the Proposed Method

The algorithm for the dynamic signature verification using selected regions implements partitioning in the domain of velocity. It searches for partitions for each user independently, so the number of partitions may consequently be different for each user. The proposed method requires a training phase which can be followed by a testing phase (practical use). A scheme of the training phase is shown in Fig. 1. The steps - for a single user - of this phase are as follows:

– Rejection of random discretization points. It consists in selecting and rejecting $Ndisprej$ (in %) discretization points associated with the highest and lowest pen velocity values. As a result, points corresponding to random pen movements are rejected and do not determine the signature verification procedure. Each user usually creates several reference signatures in the training phase, so this step is performed independently for each of the signatures.
– Averaging values of the corresponding discretization points from different reference signatures. Before this process, the points should be matched using the Dynamic Time Warping [25] algorithm in the context of reference signatures. As a result of this step, a template of reference signatures is created for each user. The template is processed in the subsequent steps of the training phase.
– Normalization of the signature template discretization points. It facilitates the partitioning of signatures and their classification.

- Rejection of the signature template discretization points corresponding to the pen velocity lower than V_{LimHi}. It is a parameter of the algorithm that is common to all users. The reduction of discretization points results in the creation of discretization points groups of the signature template.
- Rejection of discretization points groups containing less than $Ndisppar$ points. This step allows you to eliminate the signature groups associated with short (random) moments of increased pen velocity. This is especially important in the context of recognizing skilled forgeries.
- Determination of the weights corresponding to the selected points groups. These weights are created by product-type aggregation of two components. The first is the average velocity in the group of points (its greater value means a greater weight value). The second component is the size of the group (its greater value means a greater weight value).
- Determination of the remaining parameters of the one-class signature classifier (in addition to partition groups weights). The operation of the classifier and the procedure for determining its parameters were described in our previous work [17].

The discrete test signature verification phase begins with matching its discretization points to the template points determined in the learning phase. Then, the test signature is normalized and its similarity to the template is determined. The determination of this similarity is based on the determination of absolute errors for each partition independently. The values of these errors are then given to the inputs of the classifier, which determines the fuzzy similarity of signatures. It is the basis for the test signature verification [50].

3 Simulations

The proposed method has been tested for the dynamic signature database BioSecure DS2 distributed by the BioSecure Association [23]. It contains the signatures of 210 users. In the training phase, we used 5 randomly selected genuine signatures of each signer and in the test phase, we used 10 genuine signatures and 10 skilled forgeries of each signer. Value of $Ndisprej$ was set to 10%, value of V_{LimHi} was set to average velocity signal value of the base signature multiplied by 1.15, and value of $Ndispar$ was set to 3% of the total number of the signature discretization points. The obtained results are presented in Table 1.

The simulation conclusions can be summarized as follows:

- The method proposed in this paper works correctly (see Table 1). The adopted interpretation of the discretization points group and the concept of focusing on the areas of the signature corresponding to the high velocity of the pen are correct.
- The proposed method works with an accuracy comparable to other partitioning methods (see Table 1). However, the accuracy of the method proposed in this paper was obtained for a reduced subset of partitions (selected fragments of the signature), which reduces its computational complexity.

Table 1. Comparison of the results for selected dynamic signature verification methods using partitioning.

Id.	Method	Average FAR	Average FRR	Average error
1.	Method using vertical partitioning presented in [16]	3.13 %	4.15 %	3.64 %
2.	Method using horizontal partitioning presented in [17]	2.94 %	4.45 %	3.70 %
3.	Method using hybrid partitioning presented in [18]	3.36 %	3.30 %	3.33 %
4	Our method	**3.78 %**	**5.26 %**	**4.52 %**

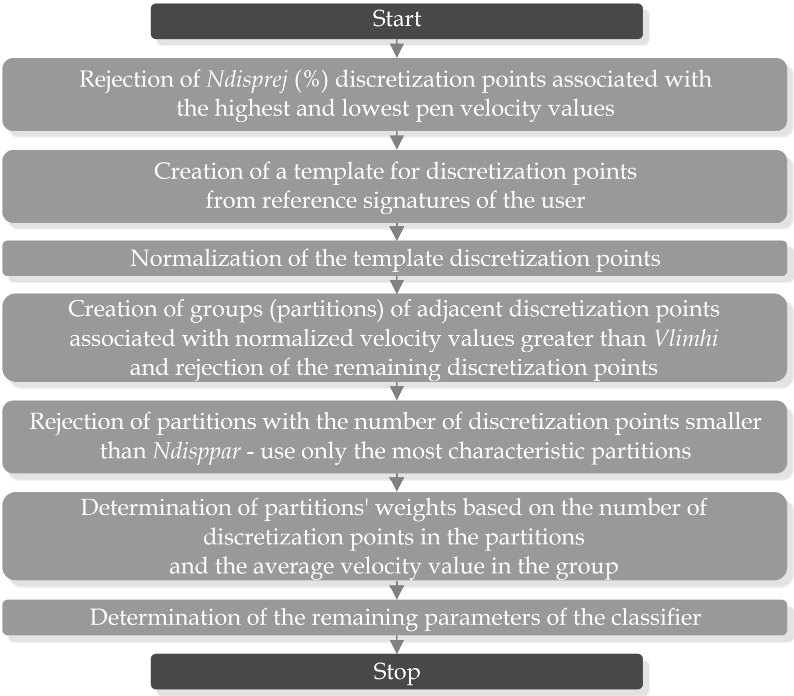

Fig. 1. The training phase scheme for a single user.

– Looking at the simulation results, one can get the impression that focusing only on the areas related to high pen speed is not the optimal solution for typical use cases of the method. Probably, this solution can only work for tests involving a large number of skilled forgeries. Therefore, no significant increase in accuracy was observed for the signature database used in the simulations.

4 Conclusions

In this paper, we have proposed an original method for dynamic signature verification. It uses signature partitioning and a new partition formula. The method was tested with the use of BioSecure DS2-an authentic signature database. The obtained results confirm that focusing on the areas of performance related to the highest pen velocity is the correct approach. This was confirmed by the simulation results. The resulting accuracy is similar to that obtained by other partitioning methods but was achieved with a reduced set of partitions.

Our plans for the dynamic signature verification include the use of population based algorithms [33,40–46], fuzzy systems [36–39,48], neural networks and deep learning methods [2–13,27,30] to determine the impact of skilled forgeries on the effectiveness of the signature partitioning procedure.

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