Online Signature Verification Using Single-Template Matching Through Locally and Globally Weighted Dynamic Time Warping

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SUMMARY In this paper, we propose a novel single-template strategy based on a mean template set and locally/globally weighted dynamic time warping (LG-DTW) to improve the performance of online signature verification. Specifically, in the enrollment phase, we implement a time series averaging method, Euclidean barycenter-based DTW barycenter averaging, to obtain a mean template set considering intra-user variability among reference samples. Then, we acquire a local weighting estimate considering a local stability sequence that is obtained analyzing multiple matching points of an optimal match between the mean template and reference sets. Thereafter, we derive a global weighting estimate based on the variable importance estimated by gradient boosting. Finally, in the verification phase, we apply both local and global weighting methods to acquire a discriminative LG-DTW distance between the mean template set and a query sample. Experimental results obtained on the public SVC2004 Task2 and MCYT-100 signature datasets confirm the effectiveness of the proposed method for online signature verification.

key words: signature verification, dynamic time warping (DTW), Euclidean barycenter-based DTW barycenter averaging (EB-DBA), local stability-weighted DTW (LS-DTW), locally and globally weighted DTW (LG-DTW)

1. Introduction

PAPER

For many years, signatures have been accepted as a means of individual authentication based on their behavioral characteristics that are unique for each person. Owing to the recent advance of artificial intelligence and machine learning technologies, automated signature verification has progressed significantly, particularly in the fields of biometrics [1], [2] and forensics [3]–[5].

Data acquisition methods for automated signature verification can be categorized into offline and online ones. Offline methods are used to compare ink-on-paper signatures through optical and image analysis techniques [3], [6]– [9]. In contrast, online methods analyze the dynamic information related to the act of signing, such as pen pressure and pen inclination angle; consequently, online methods have generally better performance compared with offline ones [1], [2].

Online signature verification systems usually consist of two phases: enrollment and verification. In the enrollment phase, users provide their own reference signatures to be inputted into a system using feature extraction techniques.

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In the verification phase, the system compares a query signature with the reference ones, and then, applies matching methods to accept or reject it.

Feature extraction techniques utilized for online signature verification can be classified into parameter-based and function-based approaches. The parameter-based approach employs the global information represented by parameters or vectors (for example, signature duration, number of pen ups/downs, and aspect ratio) [10], [11]. The function-based approach is based on analyzing signature time series in terms of time functions (for example, pen position trajectory, pressure, and velocity) [12]–[18]. Generally, the systems based on the function-based approach achieve better verification performance compared with those relying on the parameter-based approach [10]–[12]. Both methods incorporate a widely adopted comparison method named template matching that applies distance measurements, such as dynamic time warping (DTW) [19], to signature data.

The template matching method includes multiple- and single-template strategies [14], [17]. The multiple-template strategy is used to calculate the respective distances between a test sample and each of the reference ones and to compare them in terms of descriptive statistics (for example, min, max, mean, or median). The single-template strategy focuses on a representative sample directly selected from a reference set or a mean template generated based on the reference set. Consequently, the single-template strategy has advantages over the multiple-template one, such as higher speed, security, and tolerance [15]–[18]. However, it is considered that the single-template strategy does not perform as good as the multiple-template one being applied to the function-based approach [14].

To improve the verification performance while addressing the limitation of the single-template strategy, recent studies aimed to construct online signature verification systems based on the single-template strategy. In the research work presented in [17], time series averaging based on Euclidean barycenter-based DTW barycenter averaging (EB-DBA) was proposed to obtain an effective single/mean template while considering intra-user variability in reference signatures. Additionally, this method using EB-DBA has advantages in security because we do not need to directly submit the original signature data to the system. The studies [15], [16], [18] introduced the single-template strategies utilizing mean templates obtained by performing time series averaging with EB-DBA and a weighted DTW distance defined as a weighted sum of multiple DTW distances

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using gradient boosting (GB). However, the recent studies, presented in [20], [21], were aimed at extending DTW itself and proposed a local stability-weighted DTW (LS-DTW) using multiple matching points (MMPs) to reduce the influence of local fluctuations in signatures. These studies addressed the limitations of the single-template strategy. However, this approach still has room in terms of performance improvement in real scenarios, such as forensic document examiners (FDEs) that need to investigate various types of signatures obtained under different writing conditions [4], [5].

A promising approach is to incorporate both local and global weighting estimates to fully exploit the complementary effects of the corresponding weighting approaches, which have been inspired by two basic factors, respectively: *within-feature variation* and *between-feature variation* for each user, described in detail as follows.

• Local weighting:

Local weighting relies on *within-feature variation* associated with discriminative local parts in each feature represented in different ways for various writers. In fact, FDEs typically analyze writing variations that provide an important indicator for writer characterization [4], [5]. Particularly, local stable parts in a signature prevent forgers from imitating it perfectly [5], [13].

• Global weighting:

Global weighting is based on *between-feature variation* corresponding to the discriminative combination of multiple features represented in different ways for various writers. The selection/weighting methods relying on discriminative features can be used effectively to reduce the influence of fluctuations caused by internal/external changes so that systems can achieve better verification performance [22], [23].

Therefore, the combined use of the local and global weighting methods for DTW calculation in the single-template strategy can facilitate analyzing inter-user variability while considering intra-user variability among reference samples through the use of mean templates. Consequently, it can allow improving the performance of online signature verification.

To effectively incorporate both local and global weighting estimates into the single-template strategy, in this paper, we propose a novel single-template strategy that is based on a mean template set and locally/globally weighted DTW (LG-DTW) aiming to improve the performance of online signature verification providing higher speed, security, and tolerance.

Specifically, in the enrollment phase, we adopt EB-DBA to obtain a suitable mean template set while considering intra-user variability among reference samples. Then, we derive a local weighting estimate based on a local stability sequence that is acquired analyzing MMPs of an optimal match between the mean template and reference sets. In the next step, we calculate a global weighting estimate based on the variable importance obtained through the GB model. Finally, in the verification phase, we apply both local and global weighting estimates to obtain the discriminative LG-DTW distance between the mean template set and a query sample.

The remainder of the paper is organized as follows. In Sect. 2, we present the proposed signature verification method. In Sect. 3, we discuss experimental methods and results, and Sect. 4 outlines the conclusions.

2. Proposed Online Signature Verification Method

2.1 Outline

Figure 1 represents an outline of the proposed method. Specifically, after obtaining online signature samples, we apply a preprocessing step to improve signature quality and extract features. Next, in the enrollment phase, a single-template strategy including the mean template creation and local/global weighting estimation is implemented on the basis of the reference set. In the verification phase, the dissimilarities between a test sample and the mean templates of a purported user are evaluated based on the LG-DTW distance. Finally, the proposed method outputs a genuine/forgery result for the test sample if the dissimilarity is below/above a designated threshold.

The details of the calculation steps are explained in the following subsections.

2.2 Preprocessing

To address with natural fluctuations in signature samples, in this study, we adopt a common normalization approach for horizontal and vertical pen coordinates $\{x(i), y(i)\}$ that are set forth in [17], [18] as follows:

$$\hat{x}(i) = \frac{x(i) - x_g}{x_{max} - x_{min}}, \quad \hat{y}(i) = \frac{y(i) - y_g}{y_{max} - y_{min}}$$
(1)

where (x_g, y_g) is the centroid of a signature, and $\{x_{min}, y_{min}\}$ and $\{x_{max}, y_{max}\}$ are the minimum and maximum values of $\{x(i), y(i)\}$, respectively, for i = 1, 2, ..., I with an *I*-point length signature.

2.3 Feature Extraction

In the present study, we adopt the following widely used seven function-based features [12], [14]–[18], [20]:

• Three original features: horizontal and vertical pen coordinates {*x*(*i*), *y*(*i*)}, and pen pressure *p*(*i*).

Enrollment phase	Single-template strategy
Reference set → Preprocessing → Feature extraction	(1) Mean {LS-DTW ₁ } templates LS-DTW _D
	(2) Local weighting weighting
Verification phase	
Test sample → Preprocessing → Feature extraction	{LS-DTW _i } → LG-DTW → Genuine or Forgery

Fig. 1 Outline of the proposed online signature verification method.



Fig. 2 Examples of a signature and corresponding features (pen coordinates " \hat{X} " and " \hat{Y} ," pen pressure "P," path-tangent angle "Ang," path velocity magnitude "Vel," log curvature radius "Logcr," and total acceleration magnitude "Tam"). To protect privacy, only a forged signature image is depicted.

• Four additional features: path-tangent angle $\theta(i)$, path velocity magnitude v(i), log curvature radius $\rho(i)$, and total acceleration magnitude $\alpha(i)$, derived from the original features as follows:

$$\theta(i) = \arctan(\dot{y}(i)/\dot{x}(i)), \tag{2}$$

$$v(i) = \sqrt{\dot{x}(i)^2 + \dot{y}(i)^2},$$
(3)

$$\rho(i) = \log \left(\nu(i) / \dot{\theta}(i) \right), \tag{4}$$

$$\alpha(i) = \sqrt{\dot{\nu}(i)^2 + (\nu(i) \cdot \dot{\theta}(i))^2}.$$
(5)

Here, the derivatives of discrete-time signals (i.e., $\dot{x}(i)$, $\dot{y}(i)$, $\dot{\theta}(i)$, $\dot{v}(i)$) are calculated using the second-order regression while removing small noisy variations according to the following formula:

$$\dot{f}(i) = \frac{\sum_{\epsilon=1}^{2} \epsilon (f(i+\epsilon) - f(i-\epsilon))}{2\sum_{\epsilon=1}^{2} \epsilon^{2}}.$$
(6)

Finally, we normalize each time series into a mean of zero and unit standard deviation to rearrange values into different ranges between the seven function-based features (Fig. 2).

2.4 Single-Template Strategy

To improve the discriminative power of single-template matching, we develop a novel single-template strategy using a set of mean templates and local/global weighting estimates to obtain an LG-DTW distance. Specifically, in the enrollment phase, the following steps are included: (1) a set of mean templates for each feature is first calculated using a time series averaging method called EB-DBA; (2) local weighting estimate corresponding to the mean templates are acquired based on MMPs to obtain multiple LS-DTW distances; (3) finally, global weighting estimate corresponding to LS-DTW distances are calculated through the GB model. Consequently, we can obtain the LG-DTW distance using the local and global weighting estimates derived in the verification phase. Figure 3 represents the schematic process of the proposed single-template strategy.



Fig.3 Process of the proposed single-template strategy: (1) mean template creation per feature through EB-DBA (solid black lines) using an example of five reference time series (dashed lines in different colors); (2) local weighting of the mean templates for each DTW warping; (3) global weighting for LS-DTW distances through the GB model.

The details of the implemented steps are explained below.

2.4.1 Distance Measurement

To effectively evaluate the dissimilarity between two online signatures, which generally have different sequence lengths even when written by the same user, in this study, we adopt a distance measurement method based on DTW [19]. DTW is used to identify an optimal match between two time series by comparing their nonlinear mapping results and finally, outputs the minimized distance between them.

Concerning *D*-dimensional multivariate time series, we can calculate DTW using two types of warping: dependent and independent ones [17], [24]. DTW with independent warping denoted as DTW_I is individually calculated for each feature, assuming that each DTW is a one-dimensional trajectory in the one-dimensional Euclidean space. DTW with dependent warping referred to as DTW_D is directly derived as a single DTW corresponding to the set of features, assuming that the considered *D*-dimensional time series as a one-dimensional trajectory in the *D*-dimensional Euclidean space. According to the results of the recent research dedicated to online signature verification [17], [18], we utilize both types of DTW distances corresponding to multiple features. The details of the DTW calculation are presented below.

Let us assume that A and B are two univariate time series of different lengths I and J, respectively, defined as follows:

$$A = \{a(1), a(2), \dots, a(i), \dots, a(I)\},\$$

$$B = \{b(1), b(2), \dots, b(j), \dots, b(J)\}.$$

Considering the *D*-dimensional multivariate time series $a(i) \in \mathbb{R}^D$ and $b(j) \in \mathbb{R}^D$, *d*-th dimensions of the time series elements are denoted as $a_d(i)$ and $b_d(j)$.

Then, $I \times J$ cost matrix is constructed using the cost function $d(\cdot, \cdot)$ between two points of the time series according to the following formula:

$$d(a(i), b(j)) = \begin{cases} (a(i) - b(j))^2 & (\text{DTW}_{\text{I}}), \\ \sum_{d=1}^{D} (a_d(i) - b_d(j))^2 & (\text{DTW}_{\text{D}}). \end{cases}$$
(7)

Thereafter, a warping path $W = \{w_p\}_{p=1}^{P}$ with $\max(I, J) \le P \le (I + J - 1)$ is derived based on the cost matrix, satisfying the boundary, continuity, and monotonicity conditions set forth in [19].

Finally, DTW can be defined as follows:

$$DTW(A,B) = \min_{W} \left\{ \sum_{p=1}^{P} d(w_p) \right\},\tag{8}$$

where $d(w_p) = d(a(i), b(j))$ corresponds to *i* and *j* at position *p* in the warping path. This distance can be obtained by recursively calculating the cumulative distance as follows:

$$D(i, j) = d(a(i), b(j)) + \min \begin{cases} D(i, j-1), \\ D(i-1, j-1), \\ D(i-1, j). \end{cases}$$
(9)

2.4.2 Mean Template Creation

The single-template strategy using mean templates is applied to improve the performance. To obtain mean templates from the reference set, we apply EB-DBA, which provides effective mean templates while considering intra-user variability among all reference samples [17].

Specifically, EB-DBA is an iterative algorithm that is used to refine an average sequence calculated from N reference samples so that each iteration follows an expectation-maximization scheme. First, we obtain a Euclidean barycenter (EB) sequence based on the reference set in which the elements are resampled to reach their average length equally. Then, DBA [25] based on the original reference set is computed utilizing the EB sequence for the initial sequence, according to the following two steps:

- Step 1 that computes DTW between each individual and temporary averaged sequences to identify the best alignment between the averaged sequence and all reference ones.
- Step 2 that updates each alignment of the averaged sequence as a barycenter of an alignment associated with it.

Applying EB-DBA to all seven function-based features, a mean template set composed of seven univariate time sequences can be finally obtained (Fig. 3 (1)).

2.4.3 Local Weighting Calculation

To calculate local weighting estimate relying on withinfeature variation, we adopt MMPs [20] to evaluate the local stability of the mean template set.

Specifically, MMPs are used to detect multiple matching points of DTW warping trajectories in which there is a



Fig.4 Example of estimation process for the local stability using toy samples: the warping relation between the mean template "MT" and five references "R1" to "R5," the MMPs, and the local stability sequence.

significant distortion between the mean template set and the reference signatures; consequently, the MMP sequence indicates the local instability of the mean template sequence, and the inverse sequence can be considered as the local stability. Finally, we utilize each local stability sequence as the weights for the DTW cost function, which is applied to obtain LS-DTW distances.

It should be noted that the previous study [20] suggested applying local weighting only to DTW with dependent warping, whereas the method proposed in this study applies it to DTW with both dependent and independent warping to enhance the discriminative power according to the following global weighting (Sect. 2.4.4). Therefore, we update conventional LS-DTW so as to apply dependent and independent warping as described further.

We assume that there is an *I*-length multivariate time sequence corresponding to mean template *A*, and that the original set of *N* references $\mathcal{B} = \{B^n\}_{n=1}^N$ with a J_n -length multivariate time sequence. Then, the estimation process of the local stability can be outlined as follows (Fig. 4):

1. First, we compute standard DTW for each warping between A and \mathcal{B} and then, obtain a set of N optimal warping paths according to the formula below:

$$W(A,\mathcal{B}) = \{W^n(A,B^n)\}_{n=1}^N$$

2. Next, for each DTW warping, we calculate *N* MMP sequences from $W(A, \mathcal{B})$ and then, obtain the averaged MMP sequence as follows:

$$\{mmp_i\}_{i=1}^{I} = \left\{\frac{1}{N}\sum_{n=1}^{N}c_i^n\right\}_{i=1}^{I}$$
(10)

where c_i^n is the cardinality of a set belonging to the *i*th point of the mean template sequence defined as follows:

$$c_i^n = card\{(i_k^n, j_k^n) \in W^n(\boldsymbol{A}, \boldsymbol{B}^n) \mid i_k^n = i\}.$$

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3. Finally, we obtain *I*-length local weight sequences $\mathcal{LS}_{I} = \{LS_{I}^{d}\}_{d=1}^{D}$ for independent warping and LS_{D} for dependent warping defined as follows:

$$LS_{\rm I}^{d} = \{ ls_{\rm I}^{d}(1), ls_{\rm I}^{d}(2), \dots, ls_{\rm I}^{d}(i), \dots, ls_{\rm I}^{d}(I) \}$$
$$LS_{\rm D} = \{ ls_{\rm D}(1), ls_{\rm D}(2), \dots, ls_{\rm D}(i), \dots, ls_{\rm D}(I) \}$$

where $ls(i) = 1/mmp_i$ is $0 < ls(i) \le 1$, which is equal to one when a pair of matching points corresponds to direct/single matching and approaches zero with an increase in the number of MMPs.

Then, to obtain a locally weighted DTW distance denoted as LS-DTW, cost function $d(\cdot, \cdot)$ between two points of the considered time series, as defined in Eq. (7), can be rewritten by weighting it by the corresponding local weight sequences as follows:

$$d(a(i), b(j)) = \begin{cases} ls_{I}(i) \times (a(i) - b(j))^{2} & (LS-DTW_{I}), \\ ls_{D}(i) \times \sum_{d=1}^{D} (a_{d}(i) - b_{d}(j))^{2} & (LS-DTW_{D}). \end{cases}$$
(11)

Examples of local weight sequences, \mathcal{LS}_{I} and LS_{D} , are represented in Fig. 3 (2).

2.4.4 Global Weighting Calculation

To improve the discriminative power of the system inspired by between-feature variations, we construct a fusion method by summing up a set of $\{LS-DTW_I^d\}_{d=1}^D$ and $LS-DTW_D$ with a global weighting, in which the variable importance is calculated using the gradient boosting (GB) model.

GB is a machine learning technique for performing supervised learning tasks, which produces a prediction model in the form of an ensemble of weak learners, typically decision trees [26]. It is a step-wise, additive-type model that sequentially fits new tree-based models, while minimizing the loss function. The GB algorithm attempts to construct the new base-learners to be maximally correlated with the negative gradient of the loss function, based on the previously assembled trees. Then, the GB model can provide the information about the importance of variables, which can be used to select and rank the features determined by the variable average relative influence across all trees generated by the algorithm.

While constructing a GB model in this study, we use positive instances (the intra-user variability between the target signer mean template and the reference set) and negative instances (the inter-user variability between the target signer mean template and the other signer one) for each user. For example, when using five genuine signatures as the reference set in the SVC2004 Task2 dataset, we obtain 5 positive instances and 39 negative ones (Sect. 3). A grid search is then applied to tune the parameters of the GB model.

After implementing the GB model, we finally obtain the global weighting factors $\{\alpha_d\}_{d=1}^{D}$ for the seven LS-DTW distances with independent warping denoted as LS-DTW_I while satisfying $\sum_{d=1}^{D} \alpha_d = 1$ for each user.

Figure 3 (3) illustrates an example of the variable importance of a user using the GB model.

2.4.5 LG-DTW Calculation

After obtaining the local and global weighting estimates in the enrollment phase, we evaluate dissimilarities between a test sample and the mean template set based on LG-DTW in the verification phase as described below.

- 1. First, we calculate a set of $\{LS-DTW_{I}^{d}\}_{d=1}^{D}$ and $LS-DTW_{D}$ distances using the local weighting estimate as follows: $\mathcal{LS}_{I} = \{LS_{I}^{d}\}_{d=1}^{D}$ and LS_{D} . Then, we apply min-max scaling to each distance, which parameters are estimated using the reference set.
- 2. Then, we calculate the LG-DTW distance using the global weighting factors $\{\alpha_d\}_{d=1}^{D}$ for LS-DTW_I and the constant weighting β for LS-DTW_D as follows:

$$LG-DTW = \left(\sum_{d=1}^{D} \alpha_d \times LS-DTW_{I}^{d}\right) + (\beta \times LS-DTW_{D}).$$
(12)

It should be noted that the previous studies [15], [16] estimated the global weighting factors using the GB model while satisfying $\sum_{d=1}^{D} \alpha_d + \beta = 1$; however, the recent studies [17], [18] have outlined that DTW_D allows achieving significantly better performance compared with DTW_I. Therefore, this study estimates the weighting β for LS-DTW_D independently while satisfying $\sum_{d=1}^{D} \alpha_d = 1$ in the preliminary experiments, and we finally obtain the optimal $\beta = 1$, which leads to further improvement its verification performance and calculation complexity (Sect. 3.2).

2.5 Evaluation

After evaluating the dissimilarities between the mean template of the purported user and the test sample based on LG-DTW in the verification phase, the system outputs an accept/reject result based on whether the extent of dissimilarities is below/above the designated threshold.

Finally, we evaluate the signature verification performance by analyzing the equal error rate (EER) with a writerdependent threshold, which is calculated at the point where the false rejection rate (namely, a fraction of genuine signatures rejected as forgeries) and the false acceptance rate (namely, a fraction of skilled forgeries accepted as genuine) are equal.

3. Experiments

3.1 Methods

At present, skilled forgery detection is considered as a challenging task, specifically, concerning FDEs [3]–[5].

To facilitate the implementation of this task and to distinguish skilled forgeries from genuine signatures, in this



Fig. 5 Overall performance of the proposed method for the SVC2004 Task2 dataset.

study, we considered the common SVC2004 Task2 [27] and MCYT-100 [28] online signature datasets. In both datasets, skillfully forged signatures were collected from other contributors who had the sufficient training time and powerful tools to produce valid forged signatures that were as close as possible to the targeted genuine signatures; therefore, in this study, we adopted both datasets to conduct experiments.

The SVC2004 Task2 dataset [27] comprised 1,600 signatures, including Western and Asian signatures, from 40 writers. For each of them, 20 genuine and 20 skillfully forged signatures were registered. The signature data included the horizontal and vertical coordinates, pen pressure, azimuth, inclination with a time stamp, and pen up/down status. All these characteristics were captured using a digitizing tablet at the sampling rate of 100 Hz. To avoid privacy issues, the writers were requested to provide the invented signatures as genuine after performing sufficient practice. Following the experiments described in the previous studies (Table 1), in each experiment on this dataset, we randomly selected N = 5 or N = 10 genuine signatures as the reference set.

The MCYT-100 dataset [28] comprised 5,000 Western signatures obtained from 100 writers. Here 25 samples of both genuine and skillfully forged signatures were registered for each writer. The signature data included the horizontal and vertical coordinates, pen pressure, azimuth, and inclination with a time stamp. All these characteristics were captured using a digitizing tablet at the sampling rate of 100 Hz. According to the experiments conducted in the previous studies (Table 2), in each experiment on this dataset, we randomly selected N = 5 genuine signatures as the reference set.

To prevent selection bias, we repeated all experiments five times and finally, reported the averaged EERs.

3.2 Results

3.2.1 Overall Performance

To confirm the effectiveness of the proposed method, we compared the three DTW weighting methods using the common SVC2004 Task2 and MCYT-100 datasets under the same mean template set and experimental conditions (Sect. 3.1), as described below:

• S-DTW: calculating a simply summed DTW distance



Fig.6 Overall performance of the proposed method with N = 5 as the reference set for the MCYT-100 dataset.

for dependent and independent warping, without applying any weightings.

- G-DTW: estimating a DTW distance applying global weighting to the S-DTW distance.
- L-DTW: computing a DTW distance applying local weighting to the S-DTW distance (i.e., a sum of $\{LS-DTW_1^d\}_{d=1}^D$ and LS-DTW_D distances).
- LG-DTW: obtaining the proposed LG-DTW distance applying both local and global weighting to the S-DTW distance.

Figures 5 and 6 represent the comparison between the performance estimates of the proposed method and the single-template strategy based on the conventional DTW distance in terms of EER.

As can be seen from these figures, the single-template strategy based on the DTW weighting method performs much better compared with the conventional S-DTW for both SVC2004 Task2 and MCYT-100 datasets. We indicate that the proposed method, LG-DTW, using both the local and global weighting estimates for DTW, achieves the lowest EERs in the experiments.

These results confirm that the proposed LG-DTW provides an effective single-template strategy for online signature verification.

3.2.2 Comparative Analysis

To further confirm the effectiveness of the proposed method, its EERs were compared with those of other systems applied to the SVC2004 Task2 and MCYT-100 datasets.

Tables 1 and 2 summarize EERs obtained for the proposed method and the alternative ones proposed in the previous studies that were considered relevant if they have used only genuine signatures in the enrollment phase and both genuine and skillfully forged signatures in the verification phase.

As can be seen from these tables, concerning both SVC2004 Task2 and MCYT-100 datasets, the proposed method achieves the best verification performance compared with the other conventional methods, as it is based on the proposed single-template strategy, which is advantageous in terms of speed, security, and tolerance.

Thus, we conclude that the proposed single-template strategy is effective for online signature verification.

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 Table 1
 Comparison between the proposed method and alternative systems for the SVC2004 Task2 dataset.

Method	#References	EER (%)
Dynamic time functions and hidden Markov models [12]	5	6.90
Support vector machine with the longest common subsequences kernel function [29]	5	6.84
Score fusion issuing from hidden Markov models [30]	5	4.83
Feature selection and DTW [22]	5	3.38
Template matching using mean templates and a weighted sum of DTW distances using GB [18]	5	2.98
Enhanced contextual DTW based system using vector quantization [31]	5	2.73
Convolutional neural network using synthesized signatures [32]	5	2.63
Discriminative feature selection and DTW with signature curve constraint [23]	5	2.60
DTW and warping path-based features [33]	5	2.53
Two-stage method using shape contexts and function features [34]	5	2.39
Proposed	5	2.11
Semi-parametric method based on discrete cosine transform and sparse representation [11]	10	3.98
Template selection and DTW [35]	10	2.84
DTW and warping path-based features [33]	10	2.79
Template matching using mean templates and a weighted sum of DTW distances using GB [16], [18]	10	1.80
Proposed	10	1.36

Table 2 Comparison between the proposed method and alternative systems for the MCYT-100 dataset.

Method	#References	EER (%)
Signature partitioning and the weights of importance for selected partitions [36]		4.88
Histogram-based features and Manhattan distance [10]	5	4.02
Combination of global and regional features [37]	5	3.69
Score fusion issuing from hidden Markov models [30]	5	3.37
Information divergence-based matching strategy [14]	5	3.16
Interval valued symbolic representation with writer-dependent parameters [38]	5	2.2
Modified DTW with signature curve constraint [23]	5	2.17
Enhanced contextual DTW based system using vector quantization [31]	5	1.55
Template matching using mean templates and DTW distances [17]	5	1.34
Template matching using mean templates and a weighted sum of DTW distances using GB [18]	5	1.28
DTW and warping path-based features [33]	5	1.15
Convolutional neural network using synthesized signatures [32]	5	0.93
Proposed	5	0.91

4. Conclusion

In the present study, we aimed to develop an effective online signature verification method inspired by within-feature and between-feature variations for each user. To achieve this, we proposed a novel single-template strategy based on a mean template set and LG-DTW to improve the performance.

Specifically, in the enrollment phase, we adopted EB-DBA to obtain a mean template set, considering intra-user variability among reference samples. Then, we calculated the local weighting based on the local stability sequence estimated from MMPs and the global weighting on the basis of the variable importance estimated through applying a GB model. Finally, in the verification phase, we considered the local and global weighting estimates to obtain the LG-DTW distance between the mean template set and a query sample. The results of the experiment conducted on the public SVC2004 Task2 and MCYT-100 signature datasets confirmed the effectiveness of the proposed method for online signature verification.

We conclude that the proposed method is relevant to time series classification, and therefore, can be expanded to other time series analysis tasks with a need for systems with high speed, security, and tolerance. Furthermore, unlike recent black-box modeling strategies, including deep learning algorithms, the proposed method relies on explainable stepwise methods; therefore, it is particularly useful for specific applications, such as forensics and security, in which fairness, accountability, and transparency are critically important [39].

The limitations of this study include the need for multiple reference samples to obtain a set of mean templates and local/global weighting estimates. In this context, it would be interesting to extend the proposed method to the writerindependent system.

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