IEEE Access Multidisciplinary | Rapid Review | Open Access Journal

Received May 13, 2019, accepted June 10, 2019, date of publication June 14, 2019, date of current version July 3, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2923093

Template Matching Using Time-Series Averaging and DTW With Dependent Warping for Online Signature Verification

MANABU OKAWA, (Member, IEEE)
Forensic Science Laboratory, Metropolitan Police Department, Tokyo 100-8929, Japan
e-mail: m_okawa.lab1@m.ieice.org

This work was supported by JSPS KAKENHI Grant Number JP19H00498.

ABSTRACT Online signature verification has been widely applied in biometrics and forensics. Due to the recent demand on high-speed systems in this era of big data, to simultaneously improve its performance and calculation complexity, this study focuses on a single-template strategy that uses dynamic time warping (DTW) with dependent warping for online signature verification, and attempts to construct a novel time-series averaging method called Euclidean barycenter-based DTW barycenter averaging (EB-DBA). Specifically, this study proposes a single-template strategy using a mean template created by the EB-DBA to achieve higher performance at lower calculation complexity for online signature verification. The method's discriminative power is enhanced upon the exploration of two DTW warping types, where it is found that the DTW with dependent warping exhibits better performance. The popular MCYT-100 dataset is utilized in the experiments, which confirms the effectiveness of the proposed method in simultaneously achieving lower error rate and lower calculation complexity, for online signature verification.

INDEX TERMS Biometrics, forensics, online signature verification, template matching, time-series averaging, dynamic time warping (DTW), DTW barycenter averaging (DBA), Euclidean barycenter-based DTW barycenter averaging (EB-DBA).

I. INTRODUCTION

Signatures are among the most important means of securing a person's endorsement of the contents of a document. To date, there has been significant progress on the use of automated signature verification systems, particularly in the fields of biometrics and forensics. On one hand, signature verification in biometrics enables the authentication of writers with respect to their behavioral characteristics in security situations (e.g., border control, financial fraud, and cyber security) [1]–[7]. On the other hand, automated signature verification methods in forensics support forensic document examiners (FDEs) in performing their work efficiently [8]–[14].

Data acquisition by automated signature verification systems can be done offline or online. Offline methods verify a person's identity by comparing a present query signature with previously written reference signatures [1], [2], [7], [11], [15]–[25]. Online methods analyze the dynamic information of the writing (e.g., pen location, pen pressure, and pen inclination angle) through recent digital devices (e.g., digitizing tablets, tablet PCs, and smart phones). Therefore, online methods tend to provide higher accuracy and be more robust than offline methods [1]–[5].

The systems of online signature verification include enrollment and verification phases. In the former, users are encoded into the system with their provided reference signatures, through the application of preprocessing and feature extraction techniques. In the latter, a query signature is compared with the reference set of the claimed user by the employment of the extracted features, and then the system accepts/rejects it when the dissimilarity is below/above a certain threshold.

Feature extraction in online signature verification can be either feature- or function-based, using global information (e.g., signature duration and number of pen ups) [26]–[30] or signature time sequences (e.g., pen position trajectory and pressure) [31]–[35], respectively. Generally, function-based approaches have achieved better recognition performance than feature-based systems [26], [27], [33], [36]. Nevertheless, they share the common method of template matching,

The associate editor coordinating the review of this manuscript and approving it for publication was Irene Amerini.

which applies distance measurement, such as dynamic time warping (DTW) [37].

More specifically, template matching consists of both multiple- and single-template strategies [33]. The multiple-template strategy employs different measures (e.g., min, max, mean, or median) after calculating the distances between a test sample and all the reference samples, whereas the single-template strategy uses a representative sample directly selected from the reference set or a mean template generated from one. Typically, single-template strategy has lower recognition performance in this method than the multiple-template strategy [33], but the single-template strategy conducts a more rapid matching with its ability to execute a single matching in the verification phase, even if provided with many reference samples [34], [35]. Based on the recent demand for high-speed systems in this big data era, online signature verification systems that meet lower calculation complexity while achieving sufficient performance are needed.

To tackle these challenges, this study focuses and investigates the single-template strategy for online signature verification, followed by the construction of a novel time-series averaging method to simultaneously improving its performance and calculation complexity. The main contributions of this study include:

- Introduction of a novel time-series averaging method called Euclidean barycenter-based DTW barycenter averaging (hereinafter referred to as "EB-DBA"), which is inspired by the DTW barycenter averaging (DBA) [38], for simultaneously achieving lower error rates and lower calculation complexity in online signature verification. The method is applied to create the mean template for the single-template strategy.
- Exploration of two DTW approaches, namely, dependent and independent warping, for enhancing the method's discriminative power. Most online signature verification methods have used DTW with no regard for the effects of one approach over the other [34], [35], [39].
- Comparison of the major template-matching strategies using the famous MCYT-100 signature dataset, for confirming the effectiveness of the proposed single-template strategy.

This study can be regarded as the first in the exploitation of a mean template-based method for a function-based approach of online signature verification, with its proposed effective time-series averaging method. As such, its findings are expected to lead to new research directions and application opportunities.

The remainder of this study is organized into the following structure: recent and relevant work for this study is summarized in Section II; the proposed method is described in Section III; the experimental methods and results are presented in Section IV; and conclusions are discussed and summarized in Section V.

II. RELATED WORK

A. ONLINE SIGNATURE VERIFICATION WITH TEMPLATE MATCHING

For decades, online signature verification has extracted the characteristic features of a person's signature acquired through various digitizing devices [1]–[7]. Finding effective negative examples (forgeries) for a verification system is a challenging and costly task; therefore, a user-specific template is usually created from a reference set of genuine signatures without the need for skillfully forged signatures. Thus, the template-matching approach is commonly adopted in online signature verification systems [32], [33].

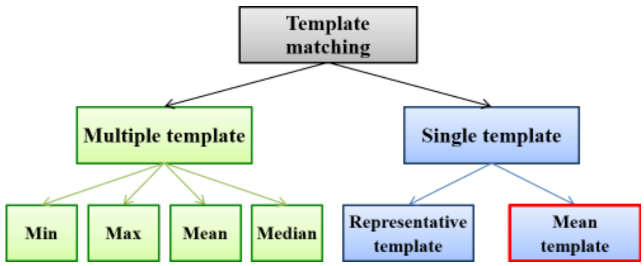

FIGURE 1. Taxonomy of the template-matching strategy.

Template matching consists of multiple- and single-template strategies (Fig. 1). The former applies different measures (e.g., min, max, mean, or median) after distances between a test sample and all the reference samples are calculated. In contrast, the latter employs a representative sample directly selected from the reference set or a mean template generated from one; moreover, it consists of two template types, namely a representative template selected with the minimum average distance from all other reference samples, and a mean template generated from all the reference samples. Here, the representative template has been widely used in function-based approaches, whereas the mean template has generally been employed only in feature-based approaches [26], [33], [40].

Typically, the single-template strategy can conduct much lower calculation complexity than the multiple-template strategy thanks to the single matching in the verification phase [34], [35]; however, it has lower recognition performance for template matching [33] because the conventional single-template method in function-based approaches adopts a representative template that loses intra-user variability.

As such, this study attempts to develop an effective mean template, while preserving intra-user variability, in the form of an effective time-series averaging method.

B. TIME-SERIES AVERAGING METHODS

Time-series averaging methods have mainly been studied in data mining fields, and are categorized into either local or global averaging strategies [38].

1) A LOCAL AVERAGING STRATEGY

A local averaging strategy uses pairwise averaging to compute the average of two sequences and to incorporate one sequence into the average sequence in iteration.

There have been some pairwise averaging methods proposed for time-series in the data mining fields. For example, the nonlinear alignment and averaging filters (NLAAF) uses a tournament scheme and a coordinate by an associative averaging method that recursively aligns pairs of time-series with DTW until the whole set is aligned [41]. Prioritized shape averaging (PSA) is NLAAF's extended version and uses an ascendant hierarchical scheme, putting the time-series in order of shape similarity prior to averaging [42].

Nevertheless, these iterative pairwise averaging methods with DTW create much longer resulting average sequences compared to the original sequences, beside their insensitive quality to the average order of sequences [38]; thus, they tend to demonstrate an average that is so unstable it induces low performance. Recently proposed global averaging seems to mitigate this problem.

2) A GLOBAL AVERAGING STRATEGY

A global averaging strategy computes the average of a set of time sequences in order to minimize its distance simultaneously.

DBA provides a reasonable length for the average sequence and outperforms the conventional NLAAF and PSA [38]. By principle, DBA is an iterative algorithm that refines an average sequence calculated from a target set where the iteration would follow an expectation–maximization scheme. Two aspects of initialization are determined to effectively produce the DBA: (a) the length of the initial average sequence and (b) the values of its coordinates. In the conventional DBA, the around average length of references is used for (a), while the randomly selected sequence from the target set is applied for (b). Nevertheless, note that the length of the initial average sequence for (a) depends on the initial average sequence of (b).

However, the optimal values of the initial coordinates in (b) are described as theoretically impossible to determine [38]. In actuality, the local DBA waveform is sensitive to the aperiodic amplitude fluctuation contained in the target set, whereas its global waveform is sensitive to the selected initial sequence. These phenomenons cause the aberrant shapes in the DBA and lose the intra-user variation contained between the target sequences.

These challenges are tackled in the time-series averaging method, EB-DBA, which this study uses to generate the mean template for a single-template strategy in an online signature verification system.

III. THE PROPOSED ONLINE SIGNATURE VERIFICATION METHOD

A. OUTLINE

Figure 2 shows an outline of the proposed method. Initially, online signature samples are obtained. Preprocessing is applied to improve image quality, and function-based features are extracted. Next, in the enrollment phase, a mean template is created with the proposed EB-DBA from a reference set and is applied for the single-template strategy. Afterward, in the verification phase, similarities between the test sample and the template of the claimed user are calculated via the DTW with dependent warping. Finally, the test sample is classified as genuine/forgery when the dissimilarity is below/above a certain threshold.

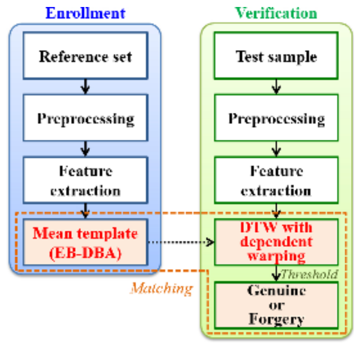

FIGURE 2. Outline of the proposed signature verification method.

Details of the subprocesses are explained in the subsequent sections.

B. PREPROCESSING

Signatures generally exhibit some fluctuations even when they come from the same user. These natural fluctuations can be dealt with using common normalization [31] for horizontal and vertical pen coordinates $\{x(i), y(i)\}$ described as:

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

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

In the proposed single-template strategy, preprocessing also plays an important role in creating a high-quality mean template. The effectiveness of preprocessing is demonstrated in the experiments (Section IV-B) that follow.

C. FEATURE EXTRACTION

With digital devices, original online signatures data generally comprise horizontal and vertical pen coordinates $\{x(i), y(i)\}$, pen pressure $p(i)$, pen azimuth $\gamma(i)$, and altitude $\phi(i)$ angles. Some recent devices provide us signature data, except for pen inclinations information.

Many studies have proposed the various attributes measurable by function- and feature-based systems. For example, an effective seven function-based feature set combined with the first-order derivative per signature, which demonstrates high performance in verifying online signatures, was described in [33], [36]. Therefore, the seven function-based features are adopted in this study.

Concretely, in addition to the three original features $\{\hat{x}(i), \hat{y}(i), p(i)\}$, four additional, dynamic features are derived from the original features $\{\hat{x}(i), \hat{y}(i)\}$ as follows:

$$\text{Path-tangent angle: } \theta(i) = \arctan(\dot{y}(i)/\dot{x}(i)),$$
$$\text{Path velocity magnitude: } \nu(i) = \sqrt{\dot{x}(i)^2 + \dot{y}(i)^2},$$
$$\text{Log curvature radius: } \rho(i) = \log(\nu(i)/\dot{\theta}(i)),$$
$$\text{Total acceleration magnitude: } \alpha(i) = \sqrt{\dot{\nu}(i)^2 + (\nu(i)\cdot\dot{\theta}(i))^2},$$

where the derivatives of discrete-time signals ($\dot{x}(i)$, $\dot{y}(i)$, $\dot{\theta}(i)$, $\dot{\nu}(i)$) are calculated using a second-order regression [43], while the small, noisy variations are removed by:

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

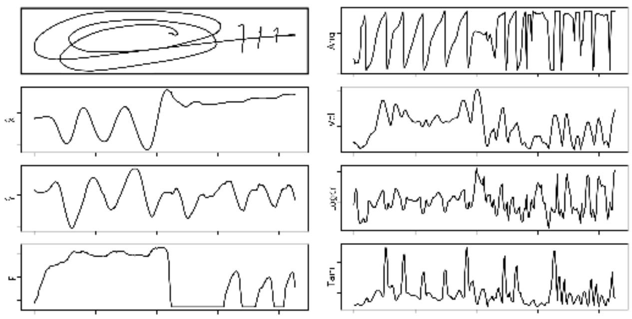

FIGURE 3. **Examples of a signature and its corresponding features (pen coordinates "$\hat{X}$" and "$\hat{Y}$," pen pressure "P," path-tangent angle "Ang," path velocity magnitude "Vel," log curvature radius "Logcr," and total acceleration magnitude "Tam"). For privacy reasons, only the forged signature is displayed.**

Finally, each time series is normalized to a zero mean and a unit standard deviation to alleviate the different ranges of values taken by the seven function-based features. Figure 3 shows an example of a signature.

D. SINGLE-TEMPLATE STRATEGY USING MEAN TEMPLATE

The single-template strategy is adopted by this study using a mean template for online signature verification, to simultaneously improve the performance and calculation complexity of the proposed method. A time-series averaging method is required to create the mean template from the reference set; thus, an effective time-series averaging method for the mean template, which can preserve intra-user variability, is investigated herein.

1) TIME-SERIES AVERAGING WITH THE DBA

DBA has recently been proposed for time-series averaging in the data mining field [38], due to its ability to provide a reasonable length of the average sequence and achieve higher performance than the conventional NLAAF and PSA. Accordingly, DBA is an iterative algorithm that refines an average sequence calculated from K reference samples, where every iteration follows an expectation–maximization scheme, involving two phases:

- Phase 1 includes the computation of the DTW between each individual sequence and temporary averaged sequence, so as to find the best alignment between the averaged sequence and the K reference sequences.
- Phase 2 involves the updating of each alignment of the averaged sequence as the barycenter of the alignment associated to it.

Here, the DBA is produced by obtaining two aspects of the initialization: (a) the length of the initial average sequence and (b) the values of its coordinates. The approximate length of the averaged references for (a) and a sequence randomly selected from the reference set for (b) were used in the conventional DBA [38].

Nevertheless, it has been described that the optimal values of the initial coordinates in (b) are theoretically impossible to determine [38]. Actually, the local waveform of DBA is sensitive to the aperiodical amplitude fluctuation contained in the target set, whereas its global waveform is sensitive to the selected initial sequence, causing the aberrant shapes in the DBA and the loss of intra-user variation contained between the target sequences (Section IV-B).

As mentioned earlier, these challenges are tackled with the proposed DBA-inspired time-series averaging method, EB-DBA, which creates a mean template for a single-template strategy, as follows.

2) TIME-SERIES AVERAGING WITH THE EB-DBA

Below is a detailed procedure of the EB-DBA:

- Firstly, a Euclidean barycenter (EB) sequence is created from the reference set.
  - Step 1 involves the calculation of the average length of the reference set.
  - Step 2 includes creating the resampled sequences of the reference set, for them to equally reach the average length.
  - Step 3 involves the generation of an EB sequence that averages all the reference set per points from the resampled sequence.
- Finally, Step 4 proceeds with the computation of the DBA from the original reference set using the EB for the initial sequence and the average length for the length of the initial sequence.

Note that EB is a simple averaging method, which means that EB-DBA requires simple calculation, apart from the conventional DBA. Details of the above procedure are described in Algorithm 1.

The method is applied to all seven function-based features, with a mean template comprising seven univariate sequences being initially constructed. The details of effectiveness are demonstrated in the experiments (Section IV-B) that follow.

E. DISTANCE MEASUREMENT

The time-series length generally varies from signature to signature, even when the same person writes the signatures.

Algorithm 1 EB-DBA

Input: A set of K time series $\mathcal{S} = \{S_k\}_{k=1}^{K}$ with N_k length $S_k = \{S_k^n\}_{n=1}^{N_k}$, iteration $T \in \mathbb{Z}$
Output: Average sequence $\bar{A}_{\text{EB-DBA}}$
/* [Step 1] Calculate the average length L of $\mathcal{S}$. */
$L \leftarrow \sum_{k=1}^{K} N_k / K$
/* [Step 2] Compute the resampled $\mathcal{S}' = \{S_k'\}_{k=1}^{K}$ with L length $S_k' = \{S_k'^l\}_{l=1}^{L}$ from $\mathcal{S}$. */
for $k = 1$ **to** K **do**
  $S_k' \leftarrow resample(S_k, L)$ // resample using linear interpolation
/* [Step 3] Create the average sequence of EB, $\bar{A}_{\text{EB}} = \{\bar{A}_{\text{EB}}^l\}_{l=1}^{L}$, from $\mathcal{S}'$. */
for $l = 1$ **to** L **do**
  $\bar{A}_{\text{EB}}^l \leftarrow \sum_{k=1}^{K} S_k'^l / K$
/* [Step 4] Compute $\bar{A}_{\text{EB-DBA}} = \{\bar{A}_{\text{EB-DBA}}^l\}_{l=1}^{L}$ using $\bar{A}_{\text{EB}}$ as the initial sequence. */
$\bar{A}_{\text{EB-DBA}} \leftarrow \bar{A}_{\text{EB}}$ // initialize $\bar{A}_{\text{EB-DBA}}$
for $t = 1$ **to** T **do**
  $assoc[l] = \emptyset$ // array of L empty set
  for $k = 1$ **to** K **do**
    /* Calculate DTW with warping path $W = \{w_p\}_{p=1}^{P}$ (Section III-E). */
    $W \leftarrow DTW\left(\bar{A}_{\text{EB-DBA}}, S_k\right)$
    $P \leftarrow length(W)$
    for $p = 1$ **to** P **do**
      $(l, n) \leftarrow w_p$
      $assoc[l] \leftarrow assoc[l] \cup \{S_k^n\}$
  for $l = 1$ **to** L **do**
    $\bar{A}_{\text{EB-DBA}}^l \leftarrow mean(assoc[l])$
return $\bar{A}_{EB\text{-}DBA}$

DTW [37] is applied to overcome such difficulty with discerning the length, while the time distortion is alleviated by finding a time-flexible alignment between two time series for the measurement of the similarity in two online signatures.

Moreover, DTW can be calculated with dependent and independent warping [39] to handle the multi-dimensional time series. Although studies on online signature verification have rarely mentioned which approach of the two have they used, many have applied DTW with no regard for the effects of choosing one approach over the other. Furthermore, a recent study [39] in data mining showed that the two DTW methods produce different classification results. The detailed procedure of the DTW calculation is shown below.

1) DTW CALCULATION FROM THE UNIVARIATE TIME SERIES

Assume A and B to be two univariate time series of different lengths I and J, respectively, then

$$A = \{a(1), a(2), \ldots, a(i), \ldots, a(I)\},$$
$$B = \{b(1), b(2), \ldots, b(j), \ldots, b(J)\}.$$

An $I \times J$ warping matrix is constructed using a cost function $d(\cdot,\cdot)$ between two points of the time series defined as

$$d(a(i), b(j)) = (a(i) - b(j))^2. \tag{3}$$

Consequently, a warping path $W = \{w_p\}_{p=1}^{P}$ is constructed from the warping matrix. Given $w_p = (i, j)$ and $w_{p+1} = (i', j')$, the warping path W must satisfy following conditions:

1) *boundary condition*: $w_1 = (1, 1)$ and $w_P = (I, J)$;
2) *continuity condition*: $i' \le i + 1$ and $j' \le j + 1$;
3) *monotonicity condition*: $i' \ge i$ and $j' \ge j$.

Upon satisfying boundary, continuity, and monotonicity conditions set forth in [37], DTW can be defined as

$$DTW(A, B) = \min_{W} \left\{ \sum_{p=1}^{P} d(w_p) \right\}, \tag{4}$$

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 found by recursively calculating the cumulative distance as

$$D(i, j) = d(a(i), b(j)) + \min \begin{cases} D(i, j-1) \\ D(i-1, j-1) \\ D(i-1, j). \end{cases} \tag{5}$$

2) DTW CALCULATION FROM THE MULTIVARIATE TIME SERIES

Consequently, we expand the DTW calculation from the univariate time series to the multivariate ones. Consider the two D-dimensional multivariate time series $\boldsymbol{A}$ and $\boldsymbol{B}$ of different lengths I and J, respectively, then

$$\boldsymbol{A} = \{A_1, A_2, \ldots, A_d, \ldots, A_D\},$$
$$\boldsymbol{B} = \{B_1, B_2, \ldots, B_d, \ldots, B_D\},$$

where

$$A_d = \{a_d(1), a_d(2), \ldots, a_d(i), \ldots, a_d(I)\},$$
$$B_d = \{b_d(1), b_d(2), \ldots, b_d(j), \ldots, b_d(J)\}.$$

The time-series elements of $\boldsymbol{A}$ and $\boldsymbol{B}$ are referred to as $\boldsymbol{a}(i) = \{a_d(i)\}_{d=1}^{D}$ and $\boldsymbol{b}(j) = \{b_d(j)\}_{d=1}^{D}$, respectively.

Then, two DTW warping types can be calculated as below (Fig. 4):

- *DTW with independent warping* (“DTW_I”): The DTW of each feature is calculated with independent warping as

$$\text{DTW}_\text{I} = \sum_{d=1}^{D} DTW(A_d, B_d). \tag{6}$$

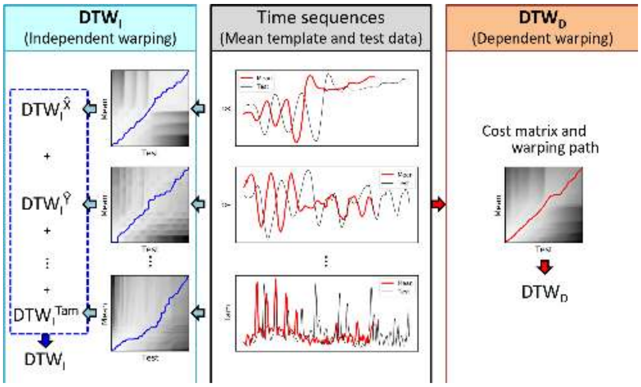

FIGURE 4. Flow of $\mathrm{DTW_I}$ and $\mathrm{DTW_D}$ calculations from a multi-dimensional time series.

- *DTW with dependent warping* ("$\mathrm{DTW_D}$"):
  The DTW from all features is calculated with dependent warping to obtain a single distance from the set of features, in a similar way to DTW for univariate time series as

$$\mathrm{DTW_D} = DTW(\boldsymbol{A}, \boldsymbol{B}), \tag{7}$$

where $d(a(i), b(j))$ in Eq. (3) is replaced with

$$d(\boldsymbol{a}(i), \boldsymbol{b}(j)) = \sum_{d=1}^{D} (a_d(i) - b_d(j))^2.$$

Thus, from multivariate time series, either $\mathrm{DTW_I}$ or $\mathrm{DTW_D}$ is obtained following the methods described above. Nevertheless, $\mathrm{DTW_D}$ is adopted in this study due to its more discriminative power for online signature verification, as demonstrated in the experiments (Section IV-B) that follow.

F. MATCHING

After its generation in the enrollment phase, the mean template is compared with the test sample in the verification phase using DTW. A query signature is verified upon the determination of an optimal threshold.

In forensics, a signature has been generally examined by FDEs via consideration of its different characteristics in different writers with different writing conditions [13], [14]. In biometrics, better performance has been demonstrated through the use of writer-dependent features and threshold, as compared to the use of a common threshold [44], [45]. Thus, with its capacity to set an optimal threshold for each writer, the writer-dependent threshold is applied in this study.

Signature verification is either accepted/rejected by the system when the computed DTW distance is either below/above the threshold; moreover, its performance is finally evaluated by the equal error rate (EER), where the false rejection rate equals the false acceptance rate.

IV. EXPERIMENTS

A. METHODS

Skilled forgeries detection is a challenging task even for FDEs [8]–[14]. Thus, signature verification from skilled forgeries was one of the feats attempted by this study.

MCYT-100 [46], a famous online database consisting of 5,000 western signatures from 100 writers and containing highly skilled forgeries was analyzed in this study. The data included horizontal and vertical coordinates, pressure, azimuth, and inclination as time, were captured through a digitizing tablet at a sampling rate of 100 Hz. Each user was represented by 25 samples each of both genuine and skill-forged signatures, the latter having been produced by five users after observing and imitating static signature images, trying to copy them, and produce valid acquired forgeries, as is evident in forensic cases.

The existing methods in Table 2 were employed for each experiment to randomly select $K = 5$ genuine signatures as references for the enrollment phase; the remaining $25 - K = 20$ genuine signatures and 25 skilled forgeries were otherwise used for the verification phase. Repeating all experiments five times prevented selection bias. The averaged EERs were reported following the methods used by previous studies.

B. RESULTS

1) OVERALL PERFORMANCE OF THE PROPOSED METHOD

The effectiveness of the proposed single-template strategy for online signature verification was measured through comparative examination against conventional template strategies as follows:

- *Multiple-template strategy* ("Multiple"):
  a multiple-template strategy with different measures (e.g., min, max, mean, or median) after the distances between a test sample and all the reference samples were calculated;
- *Single-template strategy* ("Single"):
  a single-template strategy with representative template directly selected from reference set under the minimum average DTW distance from all other reference samples ("Rep"), and a mean template created with the proposed EB-DBA ("Proposed").

Accordingly, all the experiments were applied with $\mathrm{DTW_I}$ ("DTW_I") and $\mathrm{DTW_D}$ ("DTW_D") to confirm which warping provided the better results for each template method.

Figure 5 shows the compared performances between the proposed method and the conventional template-matching methods for each type of DTW, in terms of the EER. Note that the proposed method had the lowest EERs, although it was under a single-template matching strategy of lower performance than the multiple-template [33]. When the proposed EB-DBA was combined with $\mathrm{DTW_D}$, its EERs decreased further.

Note that the proposed method provided some verification errors. Then, we found that the sever verification

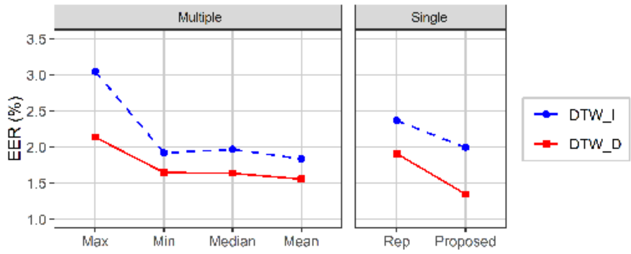

FIGURE 5. Overall performance of the proposed method and other template methods (multiple template with "Max," "Min," "Median," and "Mean"; single template with the representative template as "Rep" and the proposed mean template with EB-DBA as "Proposed.").

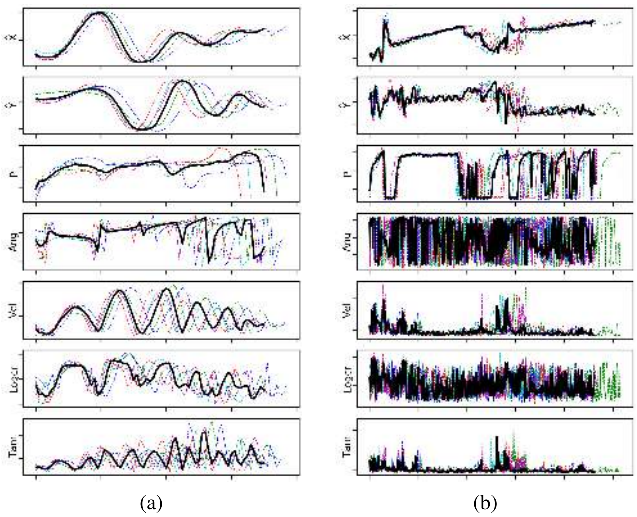

FIGURE 6. Examples of two types of the mean templates from (a) a low-complexity signature and (b) a high-complexity signature. Each example shows seven features with five original reference samples (dashed lines in different colors) and the mean templates with the proposed EB-DBA (solid black lines).

errors tended to be occurred in users who wrote low/high-complexity signatures (i.e., low/high total number of turning points, intersections and retraces). For examples, some users who provided low-complexity signatures or high-complexity signatures with high intra-user variations resulted in low performance (i.e., over 10% EERs in the worst cases). These findings indicate that (a) the simple signatures cause the mean templates to be so simple that the forged signatures can be easily accepted (Fig. 6a), and (b) the high-complexity signatures with high intra-user variations cause the mean templates to be so complicated that the genuine signatures can be easily rejected (Fig. 6b).

Nevertheless, these results confirm that the proposed method's combination, namely, EB-DBA and DTW_D, provides an effective template-matching strategy for function-based online signature verification.

2) EFFECT OF PREPROCESSING

The effectiveness of preprocessing for the proposed single-template strategy using EB-DBA and DTW_D was confirmed following a comparison of its results.

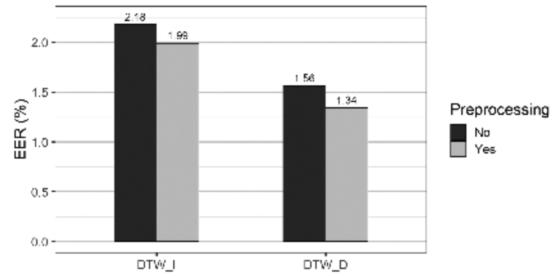

FIGURE 7. Effect of preprocessing in the proposed single-template strategy with EB-DBA for each DTW warping.

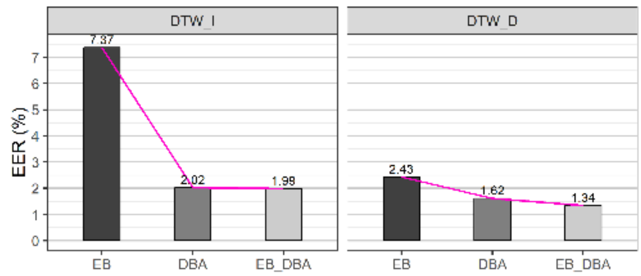

FIGURE 8. Effect of time-series averaging method in the single-template strategy for each DTW warping.

TABLE 1. Comparison of the number of DTW calculations in the verification phase.

Strategy	Type of DTW	#DTW (in this study)
Multiple	DTW_I	#References × #Features (35)
	DTW_D	#References (5)
Single	DTW_I	#Features (7)
	$\mathbf{DTW_D}$	**1 (1) [proposed]**

Figure 7 provides the compared EERs of the proposed single-template strategy with/without applying preprocessing for each DTW warping. As shown in the figure, by applying preprocessing, the proposed method reduced the EERs in both DTW_I and DTW_D.

These results confirm that preprocessing facilitates appropriate verification of the proposed single-template strategy; therefore, this study adopted preprocessing in Section III-B.

3) EFFECT OF THE EB-DBA

The effectiveness of the proposed EB-DBA to create the mean template in the single-template strategy was verified upon comparison of its results with those of the simple EB and the conventional DBA.

Figure 8 provides the compared EERs of the three mean template generation methods for single-template strategy, namely, "EB," "DBA," and "EB-DBA," under two types of DTW warping. Note that in any DTW warping, the global averaging (i.e., DBA and EB-DBA) provided much lower EERs than the simple EB. Additionally, the proposed EB-DBA achieved the lowest EERs of all the methods.

Furthermore, the detailed effects, in terms of time sequences, were confirmed upon comparison of the mean template of the conventional DBA and the proposed

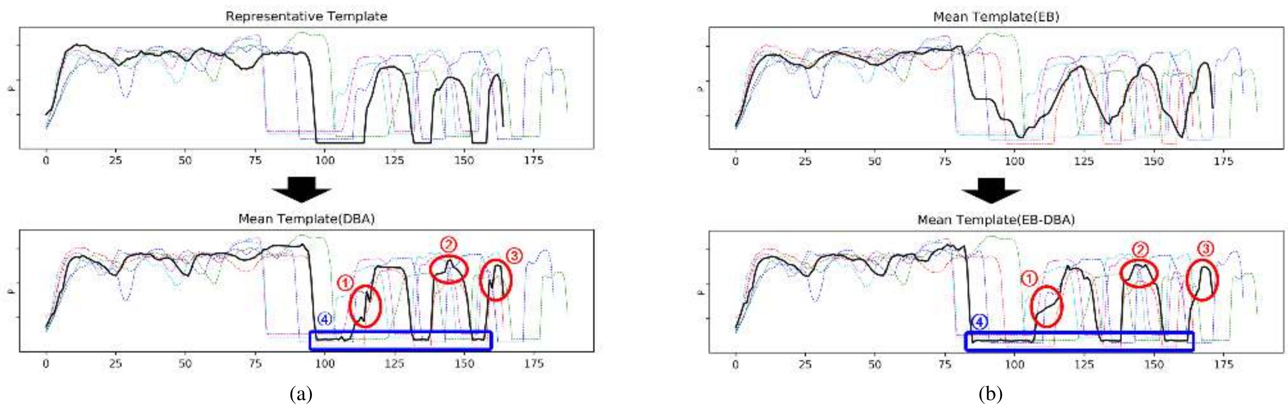

FIGURE 9. Example of five original reference samples (dashed lines in different colors) of a user's pen pressure, and the representative/mean templates (solid black lines). (a) The mean template with DBA (bottom) by using the representative template (top) as the initial sequence. (b) The mean template with the proposed EB-DBA (bottom) by using the mean template with EB (top) as the initial sequence.

TABLE 2. Comparison between the proposed method and recent systems for MCYT-100 dataset with five genuine signatures as reference set. "UD threshold" refers to the systems with user-dependent matching threshold.

Method	UD threshold	EER (%)
Interval valued symbolic features [44]	✓	5.84
Signature partitioning and the weights of importance for selected partitions [47]		4.88
Histogram-based features and Manhattan distance [26]		4.02
Combination of global and regional features [48]		3.69
Information divergence-based matching strategy [33]		3.16
Interval valued symbolic representation with writer dependent parameters [45]	✓	2.2
Modified DTW with signature curve constraint [32]		2.17
Recurrent neural networks for representation learning in the DTW framework [49]		1.81
Enhanced contextual DTW based system using vector quantization [50]	✓	1.55
Proposed method (a single-template strategy using EB-DBA and $\mathbf{DTW_D}$)	✓	**1.34**

EB-DBA. Figure 9 shows examples of the mean templates created by each method, as calculated from the five original reference sets of a user. Compared to the conventional DBA, note that the EB-DBA effectively averaged the original sequences as it preserved the intra-user variability. Concretely, the local waveforms of DBA became sensitive to the aperiodical amplitude fluctuation contained in the target set, whereas the EB-DBA seemed to provide smoothly changed alignments (①–③ in Fig. 9). Likewise, the global waveform of DBA became sensitive to the selected initial sequence, whereas the EB-DBA seemed to catch the phase shift between the original sequences based on the initial sequence of EB (④ in Fig. 9).

These results confirm the effectiveness of the EB-DBA; therefore, this study adopted EB-DBA in creating the mean template for the single-template strategy in online signature verification.

4) COMPARATIVE ANALYSIS

The effectiveness of the proposed method for online signature verification was confirmed following a comparison between the calculation complexity and EERs of the proposed method and other systems.

As the DTW between two time-series of different lengths I and J was calculated, the computational complexity yielded $\mathcal{O}(IJ)$ due to the recursive operation; thus, the smaller number of DTW calculations contributed to the rapid verification. Table 1 illustrates the comparison between the number of DTW calculations of the proposed method and those of the conventional multiple-template strategy in the verification phase; the former was able to calculate only a single DTW, by totally reducing at most 34 DTW calculations from 35 (multiple-template with $\mathrm{DTW_I}$) to 1 (single-template with $\mathrm{DTW_D}$) in this study. Moreover, note that the larger the number of features and references use in the system, the higher reduction rate of DTW calculations can provide in the verification phase.

Table 2 displays the EERs of the proposed method and those from other relevant previous studies that use the MCYT-100 dataset. The previous studies were considered a relevant situation if they used only five genuine signatures for the enrollment phase and the remaining genuine and skillfully forged signatures for the verification phase. From the table, the proposed method demonstrated lower EER than the other conventional methods, although it needed much lower calculation complexity from the rest in the verification phase.

Therefore, the proposed method can simultaneously achieve lower EER and lower calculation complexity, which makes it effective for online signature verification.

V. CONCLUSION

Due to the recent demand on high-speed systems in the present big data era, this study focused on the single-template strategy of online signature verification and attempted to simultaneously improve its performance and calculation complexity through the construction of a novel time-series averaging method called EB-DBA, an extension of the conventional DBA. This method was applied for the creation of a mean template for the single-template strategy. Afterward, the method's discriminative power was enhanced through an exploration of two DTW types, wherein the DTW with dependent warping was found to outperform that with independent warping. The method's effectiveness for online signature verification was confirmed upon a comprehensive analysis of template-matching strategies using the famous MCYT-100 signature dataset, where it achieved simultaneous lower error rate and calculation complexity. This result demonstrates that the method is suitable for a real-time system.

This work is a preliminary study on the broader goal of finding an effective template strategy for the function-based approach of online signature verification, and targets on the development of an effective time-series averaging method with lower calculation complexity while achieving lower error rates through a standard DTW method. Given that the time-series averaging methods have been widely used in several application domains (e.g., biology, finance, and multimedia), this work is expected to lead to new research directions and provide more application opportunities.

In the future, the additional uses of the DTW variants in the single-template strategy and the proposed method's applicability in other fields will be interesting areas for investigation.

ACKNOWLEDGMENT

The author would like to thank the Biometric Recognition Group – ATVS, Universidad Autonoma de Madrid, for providing the MCYT-100 signature dataset.

REFERENCES

[1] R. Plamondon and S. N. Srihari, "On-line and Off-line handwriting recognition: A comprehensive survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 1, pp. 63–84, Jan. 2000.

[2] D. Impedovo and G. Pirlo, "Automatic signature verification: The state of the art," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 38, no. 5, pp. 609–635, Sep. 2008.

[3] J. A. Unar, W. C. Seng, and A. Abbasi, "A review of biometric technology along with trends and prospects," *Pattern Recognit.*, vol. 47, no. 8, pp. 2673–2688, 2014.

[4] M. I. Malik, S. Ahmed, A. Marcelli, U. Pal, M. Blumenstein, L. Alewijns, and M. Liwicki, "ICDAR2015 competition on signature verification and writer identification for on- and off-line skilled forgeries (SigWIcomp2015)," in *Proc. 13th Int. Conf. Document Anal. Recognit. (ICDAR)*, 2015, pp. 1186–1190.

[5] A. K. Jain, K. Nandakumar, and A. Ross, "50 years of biometric research: Accomplishments, challenges, and opportunities," *Pattern Recognit. Lett.*, vol. 79, pp. 80–105, Aug. 2016.

[6] R. Plamondon, G. Pirlo, E. Anquetil, C. Rémi, H.-L. Teulings, and M. Nakagawa, "Personal digital bodyguards for e-security, e-learning and e-health: A prospective survey," *Pattern Recognit.*, vol. 81, pp. 633–659, Sep. 2018.

[7] M. Diaz, M. A. Ferrer, D. Impedovo, M. I. Malik, G. Pirlo, and R. Plamondon, "A perspective analysis of handwritten signature technology," *ACM Comput. Surv.*, vol. 51, no. 6, pp. 117:1–117:39, 2019.

[8] S. N. Srihari, S.-H. Cha, H. Arora, and S. Lee, "Individuality of handwriting," *J. Forensic Sci.*, vol. 47, no. 4, pp. 856–872, 2002.

[9] S. N. Srihari and K. Singer, "Role of automation in the examination of handwritten items," *Pattern Recognit.*, vol. 47, pp. 1083–1095, Mar. 2014.

[10] Y. Akao, A. Yamamoto, and Y. Higashikawa, "Assisting forensic writer verification by visualizing diversity of digit handwritings: An approach by multidimensional scaling of earth mover's distance," in *Proc. 14th Int. Conf. Frontiers Handwriting Recognit. (ICFHR)*, 2014, pp. 110–115.

[11] M. Okawa and K. Yoshida, "Offline writer verification based on forensic expertise: Analyzing multiple characters by combining the shape and advanced pen pressure information," *Jpn. J. Forensic Sci. Technol.*, vol. 22, no. 2, pp. 61–75, 2017.

[12] M. Hosoe, T. Yamada, K. Kato, and K. Yamamoto, "Offline text-independent writer identification based on writer-independent model using conditional autoencoder," in *Proc. 16th Int. Conf. Frontiers Handwriting Recognit. (ICFHR)*, 2018, pp. 441–446.

[13] D. Ellen, S. Day, and C. Davies, *Scientific Examination of Documents: Methods and Techniques*, 4th ed. Boca Raton, FL, USA: CRC Press, 2018.

[14] J. Linden, R. Marquis, S. Bozza, and F. Taroni, "Dynamic signatures: A review of dynamic feature variation and forensic methodology," *Forensic Sci. Int.*, vol. 291, pp. 216–229, Oct. 2018.

[15] M. Okawa and K. Yoshida, "Off-line writer verification using shape and pen pressure information," in *Proc. 13th Int. Conf. Frontiers Handwriting Recognit. (ICFHR)*, 2012, pp. 625–630.

[16] M. Okawa and K. Yoshida, "A combined pseudo-dynamic approach for off-line writer verification," in *Proc. 16th Int. Graphonomics Soc. Conf. (IGS)*, 2013, pp. 14–17.

[17] M. Okawa and K. Yoshida, "User generic model for writer verification using multiband image scanner," in *Proc. 13th IEEE Int. Conf. Technol. Homeland Secur. (HST)*, Nov. 2013, pp. 375–380.

[18] M. Okawa and K. Yoshida, "Offline writer verification using pen pressure information from infrared image," *IET Biometrics*, vol. 2, no. 4, pp. 199–207, 2013.

[19] M. Okawa and K. Yoshida, "Text and user generic model for writer verification using combined pen pressure information from ink intensity and indented writing on paper," *IEEE Trans. Human-Mach. Syst.*, vol. 45, no. 3, pp. 339–349, Jun. 2015.

[20] M. Okawa, "Offline signature verification based on bag-of-visualwords model using KAZE features and weighting schemes," in *Proc. 29th IEEE Conf. Comput. Vis. Pattern Recognit. Workshops (CVPR)*, Jun./Jul. 2016, pp. 252–258.

[21] M. Okawa, "Vector of locally aggregated descriptors with KAZE features for offline signature verification," in *Proc. 5th IEEE Global Conf. Consum. Electron. (GCCE)*, Oct. 2016, pp. 1–5.

[22] M. Okawa, "KAZE features via Fisher vector encoding for offline signature verification," in *Proc. Int. Joint Conf. Biometrics (IJCB)*, 2017, pp. 10–15.

[23] M. Okawa, "Offline signature verification with VLAD using fused KAZE features from foreground and background signature images," in *Proc. 14th IAPR Int. Conf. Document Anal. Recognit. (ICDAR)*, 2017, pp. 1198–1203.

[24] M. Okawa, "From BoVW to VLAD with KAZE features: Offline signature verification considering cognitive processes of forensic experts," *Pattern Recognit. Lett.*, vol. 113, pp. 75–82, Oct. 2018.

[25] M. Okawa, "Synergy of foreground–background images for feature extraction: Offline signature verification using Fisher vector with fused KAZE features," *Pattern Recognit.*, vol. 79, pp. 480–489, Jul. 2018.

[26] N. Sae-Bae and N. Memon, "Online signature verification on mobile devices," *IEEE Trans. Inf. Forensics Security*, vol. 9, no. 6, pp. 933–947, Jun. 2014.

[27] Y. Liu, Z. Yang, and L. Yang, "Online signature verification based on DCT and sparse representation," *IEEE Trans. Cybern.*, vol. 45, no. 11, pp. 2498–2511, Dec. 2014.

[28] T. Sowa, S. Sunada, Y. Yamazaki, and T. Miyazaki, "Biometric bit string generation from handwritten signatures on smart device," in *Proc. 4th Int. Symp. Comput. Netw. (CANDAR)*, 2016, pp. 662–665.

[29] T. Yoshida, Y. Tanaka, and S. Hangai, "A study on signature/sign authentication with touching information on smart phone," in *Proc. 9th Int. Conf. Bioinf. Biomed. Technol.(ICBBT)*, 2017, pp. 80–83.

[30] K. Matsuda, W. Ohyama, and T. Wakabayashi, "Multilingual-signature verification by verifier fusion using random forests," in *Proc. 4th IAPR Asian Conf. Pattern Recognit. (ACPR)*, 2017, pp. 941–946.
[31] D. Muramatsu and T. Matsumoto, "Effectiveness of pen pressure, azimuth, and altitude features for online signature verification," in *Proc. Adv. Biometrics (ICB)*. Berlin, Germany: Springer, 2007, pp. 503–512.
[32] X. Xia, X. Song, F. Luan, J. Zheng, Z. Chen, and X. Ma, "Discriminative feature selection for on-line signature verification," *Pattern Recognit.*, vol. 74, pp. 422–433, Feb. 2018.
[33] L. Tang, W. Kang, and Y. Fang, "Information divergence-based matching strategy for online signature verification," *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 4, pp. 861–873, Apr. 2018.
[34] M. Okawa, "A single-template strategy using multi-distance measures and weighting for signature verification," in *Proc. 18th IEEE Int. Symp. Signal Process. Inf. Technol.(ISSPIT)*, Dec. 2018, pp. 46–51.
[35] M. Okawa, "Online signature verification using multi-distance measures and weighting with gradient boosting," in *Proc. 1st IEEE Global Conf. Life Sci. Technol. (LifeTech)*, 2019, pp. 277–278.
[36] J. Fierrez, J. Ortega-Garcia, D. Ramos, and J. Gonzalez-Rodriguez, "HMM-based on-line signature verification: Feature extraction and signature modeling," *Pattern Recognit. Lett.*, vol. 28, no. 16, pp. 2325–2334, 2007.
[37] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 26, no. 1, pp. 43–49, Feb. 1978.
[38] F. Petitjean, A. Ketterlin, and P. Gançarski, "A global averaging method for dynamic time warping, with applications to clustering," *Pattern Recognit.*, vol. 44, no. 3, pp. 678–693, Mar. 2011.
[39] M. Shokoohi-Yekta, B. Hu, H. Jin, J. Wang, and E. Keogh, "Generalizing dtw to the multi-dimensional case requires an adaptive approach," *Data Mining Knowl. Discovery*, vol. 31, no. 1, pp. 1–31, 2017.
[40] A. Kholmatov and B. Yanikoglu, "Identity authentication using improved online signature verification method," *Pattern Recognit. Lett.*, vol. 26, no. 15, pp. 2400–2408, 2005.
[41] L. Gupta, D. L. Molfese, R. Tammana, and P. G. Simos, "Nonlinear alignment and averaging for estimating the evoked potential," *IEEE Trans. Biomed. Eng.*, vol. 43, no. 4, pp. 348–356, Apr. 1996.
[42] V. Niennattrakul and C. A. Ratanamahatana, "Shape averaging under time warping," in *Proc. 6th Int. Conf. Elect. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON)*, vol. 2, 2009, pp. 626–629.
[43] S. Young, G. Evermann, M. Gales, T. Hain, D. Kershaw, X. Liu, G. Moore, J. Odell, D. Ollason, D. Povey, A. Ragni, V. Valtchev, P. Woodland, and C. Zhang, "The HTK book (for HTK version 3.5, documentation alpha version)," Dept. Eng., Univ. Cambridge, U.K.: Cambridge, U.K., Tech. Rep., 2015. [Online]. Available: http://htk.eng.cam.ac.uk/
[44] D. S. Guru and H. N. Prakash, "Online signature verification and recognition: An approach based on symbolic representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 6, pp. 1059–1073, Jun. 2009.
[45] D. S. Guru, K. Manjunatha, S. Manjunath, and M. Somashekara, "Interval valued symbolic representation of writer dependent features for online signature verification," *Expert Syst. Appl.*, vol. 80, pp. 232–243, Sep. 2017.
[46] J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, J. Gonzalez, M. Faundez-Zanuy, V. Espinosa, A. Satue, I. Hernaez, J.-J. Igarza, C. Vivaracho, D. Escudero, and Q.-I. Moro, "MCYT baseline corpus: A bimodal biometric database," *IEE Proc.-Vis., Image Signal Process.*, vol. 150, no. 6, pp. 395–401, Dec. 2003.
[47] K. Cpałka, M. Zalasi ski, and L. Rutkowski, "A new algorithm for identity verification based on the analysis of a handwritten dynamic signature," *Appl. Soft Comput.*, vol. 43, pp. 47–56, Jun. 2016.
[48] Z. Xia, T. Shi, N. N. Xiong, X. Sun, and B. Jeon, "A privacy-preserving handwritten signature verification method using combinational features and secure kNN," *IEEE Access*, vol. 6, pp. 46695–46705, 2018.
[49] S. Lai and L. Jin, "Recurrent adaptation networks for online signature verification," *IEEE Trans. Inf. Forensics Security*, vol. 14, no. 6, pp. 1624–1637, Jun. 2019.
[50] A. Sharma and S. Sundaram, "An enhanced contextual DTW based system for online signature verification using vector quantization," *Pattern Recognit. Lett.*, vol. 84, pp. 22–28, Dec. 2016.

MANABU OKAWA received the B.S. degree in science from Tokyo Metropolitan University, Tokyo, Japan, in 2001, the M.S. degree in engineering from Shinshu University, Nagano, Japan, in 2008, and the Ph.D. degree in engineering from the University of Tsukuba, Tsukuba, Japan, in 2014. From 2016 to 2019, he was a part-time Lecturer with the University of Tsukuba. He is currently with the Forensic Document Section, Forensic Science Laboratory (formerly known as Criminal Investigation Laboratory), Metropolitan Police Department, Tokyo. His research interests include biometrics and forensics.