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Research paper

A New Learning-based Spatiotemporal Descriptor for Online Symbol Recognition

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Abstract

The success of handwriting recognition methods based on digitizer-pen signal processing is mostly dependent on the defined features. The strong and discriminating feature descriptors can play a main role in improving the accuracy of pattern recognition. Moreover, most recognition studies utilize the local features or a sequence of them, whereas it has been shown that a combination of the global and local features can increase the recognition accuracy. This paper addresses two topics. First, a new high discriminative local feature, called Rotation Invariant Histogram of Degrees (*RIHoD*), is proposed for online digitizer-pen handwriting signals. Secondly, a feature representation layer is proposed, which maps the local features into the global ones in a new space using some learning kernels. Different aspects of the proposed local feature and learned global feature are analyzed, and its efficiency is evaluated in several online handwriting recognition scenarios.

1. Introduction

Feature extraction from raw or processed data is one of the most important pattern recognition's steps. Accuracy of the classification algorithms in pattern recognition is highly dependent on the power of the extracted features. The existence of high-level discriminative features, which provide useful information about raw data, can lead to a higher precision rate of the classifier. In contrast, the indiscriminating data, question the ability of the classification algorithms [1].

When raw data is time series signals, the aforementioned issues are highlighted. With the success of deep learning [2,3], the convolutional neural network (CNN) and recurrent neural network (RNN) have been successfully performed for pattern recognition [4-8]. Since time series is a sequence of signs, an algorithm like RNN can be useful for processing these sequences. However, such machine learning efficiency has been merely exploited to achieve an acceptable level of accuracy in pattern recognition. An essential defect of these methods is the high computational complexity of processing deep neural network layers, which imposes a huge overhead on the whole system [9]. It should be noted that the computation time and recognition process speed-up are considerably important for the online recognition of pen signals [10-12].

In addition to the deep learning-based approaches, the other methods such as Hand-Craft Feature Generation have emerged. In these approaches, the feature extraction and final character recognition processes take place in two discrete phases. The fast Fourier transforms (FFTs), discrete cosine transform (DCT), wavelet transforms, and symbolic representation are regarded as some of the most popular hand-craft feature extraction algorithms. The geometric features extracted from the shape of the characters are included in these methods. At the same time, as stated in [10], proper feature extractions from a sequence of character samples are considered as a specialized procedure and an engineering-based technique that necessitates prior knowledge concerning the structure of characters in a language. The hand-craft feature generation approaches abolish the generalization feature, which is one of the disadvantages of these approaches. They do not contribute to the building of a robust character recognition system as well. Despite these weaknesses, the primary benefit of hand-craft feature generation approaches appears to be their lower computational complexity and minimum resource consumption, which are advantageous in the operational and online environments. In order to tackle the challenges and make use of the hand-craft feature generation algorithms, applying automated methods for learning features in conjunction with the hand-craft feature generation approaches may be a preferable alternative. The techniques such as evolutionary algorithms and evolutionary programming are often used in these approaches in order to enhance the quality of handcrafted features by raising the resolution between distinct class samples as well as the correlation between the samples of a given class.

In this work, we propose a high-level local discriminative feature, called Rotation Invariant Histogram of Degrees (*RIHoD*), for online symbol classification. As we require an intuition of how the classifiers work [13], we need to know about the features as well. For this reason, we develop the feature step by step with a concise explanation. Accordingly, the pen position angles are calculated, transformed into a histogram-like structure, and normalized according to the number of used points. Subsequently, the space of this local feature is mapped to several global features. This mapping is performed by global kernel (e.g. the Genetic Programming (GP) algorithm). Therefore, a combination of the local and global features is achieved, which has high recognition capabilities.

The presented article is innovative in the following cases:

1. It proposes a new high discriminative feature for symbol recognition that has not been done so far;
2. It presents a kernel-learning framework for mapping the proposed local features into the global features, and improving the recognition rate.

The rest of this paper is organized as what follows. Section 2 briefly reviews the achievements in the related works. Section 3 presents the proposed feature and the details of its calculation. Section 4 analyzes and evaluates the proposed features. The application of the proposed features is shown by case studies. The proposed feature is tested for Persian handwritten, English handwritten, and signature verification. Section 5 presents the discussion and draws a conclusion.

2. Related Works

In online recognition of pen signals, the existing features mostly focus on applying pre-defined functions on the X and Y position signals (pen movements in a 2D coordination system). For instance, by applying the sinus and cosines functions on the X and Y signals in [14-16], the recognition accuracy of Persian sub-words with the obtained features has been reported 93% on average. Although the position data can be first converted into an image to utilize image-processing-based approaches [17], they are not suitable due to their high cost and their low accuracy. Converting a position coordination into an image means adding many points between the sampled points and applying morphology operators, which multiply the number of initial points. Furthermore, applying the image-based features, e.g. Local Binary Pattern (LBP) [18,19], Histograms of Oriented Gradients (HOG) [20], and Spatial Pyramid Learning (SPLE) [21], performs more computations on the image.

If we consider a line between each two consecutive sample point in handwriting, the angles between these lines are one of the most important features that many previous studies have utilized to improve the accuracy of recognition. This feature reflects the direction and warp of handwriting. In [12,22], the angle between the position signals (X, Y), and in [23], the angle between velocity and between acceleration vectors of the corresponding position signals has been extracted as a feature. Also the angle between the points of pen position has been utilized for identifying the baseline in [24] and has been mentioned for segmentation of signature in [25]. In [26,27], a character has been divided into some sections, and then some features have been extracted for these segments. For the segmenting characters, the angle between the points of position signals has been used. In [23], after grouping Persian alphabets to 9 groups, the angle between pre-defined lines has been extracted for decision tree classifier. The angle between the horizon and the connection line of each pair of consecutive points in the handwriting image in the X and Y signals has been used as a feature in [9], where the sequence of angles has been fed into HMM for pattern recognition.

Extracting many purposeless features is not only futile, but it may lead to outliers and noisy data, which reduces the accuracy of the classifier. This can be somewhat improved by the feature selection methods. The proposed statistical, mathematical, and evolutionary feature selection approaches like the genetic algorithm [28] have shown a promising performance. However, despite eliminating the indiscriminating and outlier features, feature selection does not make any changes in the provided knowledge.

Genetic Algorithm (GA) is one of the approaches that have been used to select the best features in order to increase the accuracy of recognition [29,30]. In [31], Genetic Programming (GP) has been used to explore different combinations of the segmentation points. A learning system that uses GP for inferring the set of classification rules during a pre-classification step for handwritten digit recognition system has been mentioned in [32,33].

3. Proposed Learning-based Geometric Feature Descriptor framework

What man processes by seeing handwriting and distinguishes letters are the rotations that pen tip creates. These rotations can be explained as the angles that the consecutive handwriting points delineate when making lines. Moreover, the occurrence order of these angles is important and deterministic. If a feature can describe this property, it could be a high-level discriminative feature. The proposed feature in the present article is the rotation invariant histogram of degrees. The angle between each pair of consecutive points in the movement signals X and Y has been used in many previous symbol recognition studies. The *RIHoD* feature has been modified for the mentioned feature with the following differences:

- *RIHoD* is not sensitive to the number of created angles. In other words, these angles are not used in the raw form but they are considered as a kind histogram of angles. Thus the problem of different signal lengths has been solved.
- Direction of handwriting is important in *RIHoD*. In other words, if a symbol is written with two different directions (from start to end and from end to start), the values of *RIHoD* will be different for this symbol. The image-based methods (for example, filters like EOH or HOG) will not be able to detect such a difference.
- The order of creating angles between each pair of consecutive points with horizon line is important. In other words, if the total angles of two symbols are the same, the order of these angles is not the same; *RIHoD* is different for these two symbols.

The proposed system overview is given in Figure 1. First, the input signals are divided into k parts. For each part of signals, *RIHoDs* are extracted.

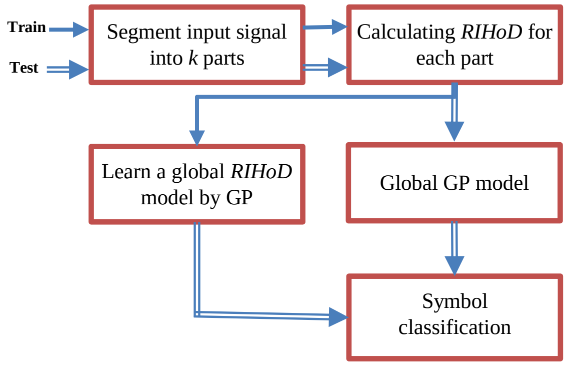

Figure 1. Steps of proposed system.

In the training phase, by applying a kernel function (e.g. GP-based learning technique), a model for mapping the local *RIHoDs* to the global features is created. In the test phase, by applying the obtained model on the local *RIHoDs*, the global *RIHoD* vector is calculated, and then by employing the KNN classifier to the global *RIHoD* vector, the input symbol is recognized.

3.1. *RIHoD*: Proposed Segmental Feature Descriptor

The handwriting processing devices record the P position signal across time. P is a set of tuples, which are, respectively, the pen movement on the horizontal and vertical axes. Sampling is usually performed by a recorder device in specific intervals. The digitizer pens like Wacom directly provide the position information along with the pen pressure, whereas the IMU-based pens provide acceleration, gyroscope, and magnetometer signals along nine axes (i.e. 9 Degrees of freedom; DOF). Therefore, extracting the position signals from this information requires separate processing in order to convert the inertia signals into the position ones [34,35].

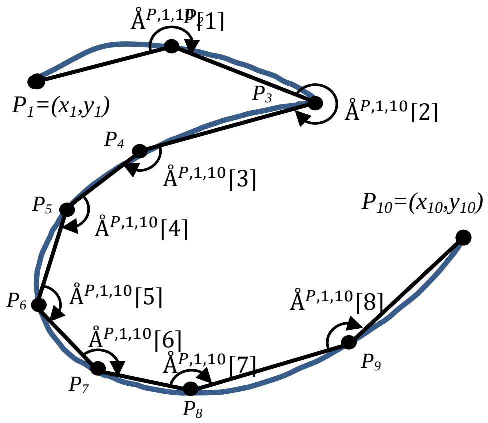

Figure 2. Calculating degree between consecutive points. Some points are sampled from a typical handwritten character. Then angle between these points construct Å array.

Therefore, in each case, the data is provided in the following sequences:

$$P = \{ p_i \mid p_i = (x_i, y_i) \text{ and } 1 \le i \le n \} \quad (1)$$

where $|P| = n$ is the number of input samples, and $P_i = (x_i . y_i)$ is the coordination of the ith point sampled from pen movements in the Cartesian system. The proposed *RIHoD* feature is calculated utilizing these points.

The RIHoD feature is the normalized histogram of the angles that the user creates when moving the pen on the media, defined in Equation 2.

$$RIHoD : P \rightarrow R^{\mathrm{B}} \quad (2)$$

$\mathbb{B}$ is the size of the feature vector. Following, shows the formulation of this feature descriptor. First, as shown in Equation 3, the sequence of points is converted into a sequence of degrees and stored in an array named Å. Figure 2 visualizes this process with a typical handwritten character and its sampled points P. The *RIHoD* feature can be calculated for a sub-segment of written symbol. The parameters *l* and *h* ($1 \le l \le h \le |P|$) are the lower and upper indices of such an interval in the point sequences of pen samples, respectively, which *RIHoD* was calculated for. Thus there are *L=h-l-1* angles between these points in array Å (i.e. $|\text{Å}| = L$).

The *angle* function calculates the degree formed by three consecutive points, as shown in Fig 2.

Then the 2D polar coordinate system is divided into the number of $\mathbb{B}$ distinct bins, where $\mathbb{B}$ is a system parameter. Each bin cover *D* degree is calculated as division of 360 by $\mathbb{B}$. For each element of Å array, its corresponding bin is calculated as in Equation 4.

For each bin, their values were converted into a bitmap index using Equation 5. Thus *I* is a 2D matrix, and has the number of $\mathbb{B}$ rows and *L* columns (i.e the size of Å array).

The *I* matrix is utilized in a recursive equation (i.e. Equation 6) in order to calculate the *RIHoD* feature for bin number $1 \le b \le \mathbb{B}$.

$$H_b^I(n) = \begin{cases} I[b,1] & n = 1 \\ \dfrac{H_b^I(n-1) + I[b,n]}{n} & n > 1 \end{cases} \quad (6)$$

Equation 7 shows the local *RIHoD* feature vector.

$$RIHOD_{\mathrm{B}}^{P,l,h} = (d_1, \mathrm{K}, d_{\mathrm{B}}) \, where$$
$$d_i = H_i^{I_{\mathrm{B}}^{\mathring{\mathrm{A}}^{P,l,h}}} \quad and \;\; 1 \le i \le \mathrm{B} \quad (7)$$

RIHoD is the normalized histogram vector of the angles between the consecutive lines formed from the consecutive input points with horizontal axis. It is important to see that it is not only a statistical histogram, as its formal definition shows. However, the order of point occurrences is important. Since in some research areas such as signature recognition problem, the complexity of shapes is high and pen movement direction changes too much, *RIHoD* may not reflect these situations in all handwritings as well. To this end, the input signals are partitioned into *k* segments for a better covering of the changes. Applying the *RIHoD* operator to each segment of the input signal results in a Local Feature Vector (*LFV*) of that segment. Concatenation of these vectors results in *LFV* of the input signal (i.e. character, signature, sign, etc.). Suppose that the input signals are partitioned into *k* segments. The local feature vector of these portions is calculated by applying *RIHoD* on these segments and concatenated by each other. Thus *LFV* of a part of input signals when partitioned into *k* segments is defined in Equation 8.

$$LFV^{n,k} : R^n \times R^n \rightarrow R^{k \times \mathrm{B}}, 2 \le k \le n/2 \quad (8)$$

The local *RIHoD* feature vector is calculated for each segment *i*, and LVF^k is, respectively, concatenated of these *RIHoDs,* as shown in Equation 9.

$$LFV^{n,k} = LVF_1^{n,k}, LVF_2^{n,k}, \ldots, LVF_k^{n,k} \quad (9)$$

$$\mathring{\mathrm{A}}_{1 \times L}^{P,l,h} = \left\{ \alpha_i \mid \alpha_i \leftarrow angle\left(P_j, P_{j+1}, P_{j+2}\right) \; for \;\; 1 \le i \le L \; and \; j = l + i - 1 \right\} \quad (3)$$

$$\mathrm{B}_{1 \times L}^{\mathring{\mathrm{A}}} = \left\{ b_i \mid b_i \leftarrow \left\lceil \frac{\mathring{\mathrm{A}}[i]}{D} \right\rceil \; for \;\; 1 \le i \le L \right\} \quad (4)$$

$$I_{\mathrm{B} \times L}^{\mathrm{B}} = \left\{ I[i,j] \mid \forall 1 \le i \le \mathrm{B} \, and \; 1 \le j \le L, I[i,j] \leftarrow \left(\mathrm{B}[j] == i\right) \right\} \quad (5)$$

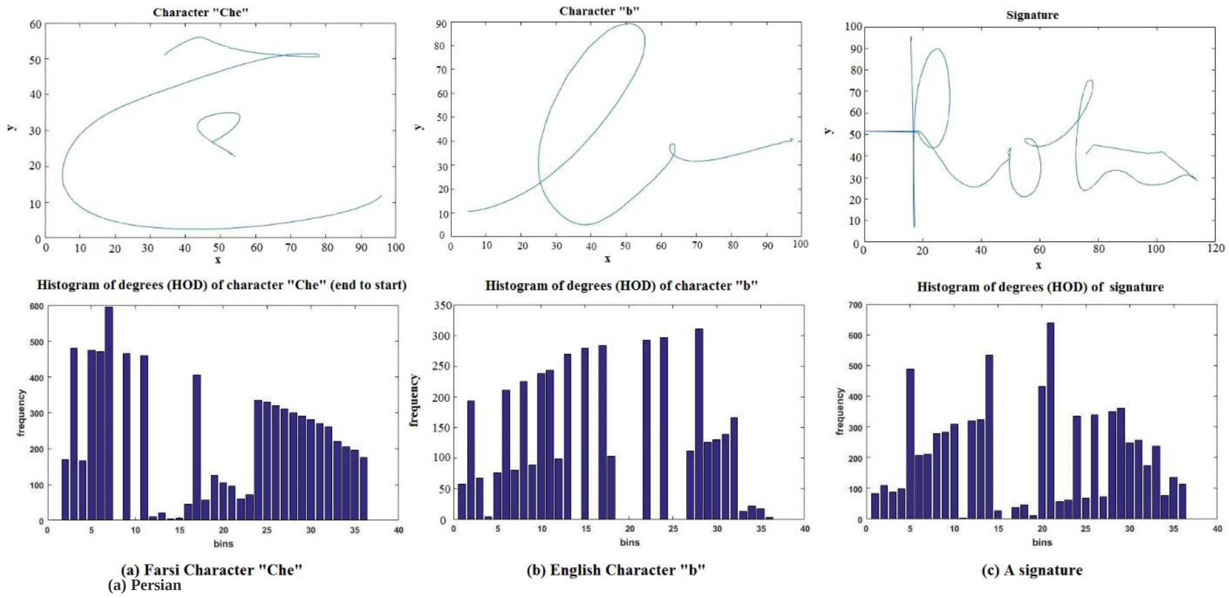

Figure 3. ***RIHoD*** **feature for some online symbols. All input points of symbols are utilized in calculating** ***RIHoD*****. a) A Persian character pronounce" Che". b) English lower-case" b" character. c) An example of a person signature in SUSIG dataset [36].**

where $\mathrm{n} = |P|$,

$$LVF_i^{n,k} = RIHOD_{\mathrm{B}}^{1+(i-1)\times\left(\left\lfloor \frac{n}{k} \right\rfloor\right) \ldots\ i\times\left\lfloor \frac{n}{k} \right\rfloor} \quad (10)$$
$$,1 \le i \le k$$

and i is the number of segments ($i=1, 2\ldots, k$).

Fig. 3 presents the result of applying algorithm 1 on a Persian handwritten character "چ" (pronounced "Che" in Persian language), an English handwritten character (i.e. 'b'), and a signature that considered as a one segment ($k = 1$). In order to show all columns of the histogram, the Figure presents the absolute value of the logarithm of $10\times\mathbb{B}$ frequency values.

The *RIHoD* feature descriptor has interesting properties. It is not sensitive to the size of the character but it is sensitive to the direction of the pen movements. Even if the appearance of two characters is similar, if the direction of the pen movement is different to write them, different *RIHoD* patterns are generated. Image processing-based methods are not capable of understanding this difference. For instance, the filters like HOG and EOH cannot recognize this difference. Different direction in writing a character results in different *RIHoD*, although the drawn character is the same. This property enhances the writer-dependent signature and handwriting recognition. Also it can be used for segmentation.

3.2. Global Learner Kernels

Experience has shown that a combination of the local and global features has a synergic effect [1], and results in a high classification rate. A kernel function can be utilized to map the local feature vector into the global space and enhance the classification accuracy. The kernel function can be generated by metric learning techniques, feature representation techniques or simply a user defined function. This kernel function receives LFV^kas the input and returns the Global Feature Vector (*GFV*) as the output. The kernel function causes a higher classification accuracy on *GFV* than *LFV*. The general prototype of such a function can be defined as:

$$GlobalKernel : R^{k\times\mathrm{B}} \to R^{\mathrm{T}} \quad (11)$$

$$GlobalKernel\left(LFV^{n,k}\right) = \begin{pmatrix} Kernel_1(LFV^{n,k}) \\ . \\ . \\ . \\ Kernel_{\mathrm{T}}(LFV^{n,k}) \end{pmatrix} \quad (12)$$

The global kernel is composed of the number of $\mathbb{T}$ functions (a system parameter) and maps the vectors of $k\times\mathbb{B}$ dimension into an array of $\mathbb{T}$ dimension. Each function $kernel_i$ of the global kernel is defined as bellow, and generates one dimension of *GFV*:

$$Kernel_i : R^{k\times\mathrm{B}} \to R \quad (13)$$

$$GFV_i = Kernel_i\left(LFV^{n,k}\right) \quad (14)$$

The resulting *GFV* is a $\mathbb{T}$ dimensional vector, as follows:

$$GFV = \left(GFV_1, GFV_2, \ldots, GFV_{\mathrm{T}}\right) \tag{15}$$

Algorithm 1. GLOBAL-RIHOD.

1. $LFV \leftarrow \bigcup_{i=1\cdots|dataset|} RIHOD_b^{P_i,1,|P_i|}$
2. **for each** $fold \in Folds$ **do**
3. $(X_{train}, Y_{train}, X_{test}, Y_{test}) \leftarrow makeFold(fold, LFV)$
4. $GFV_{train} \leftarrow GlobalLearner(X_{train}, Y_{train})$
5. $GFV_{test} \leftarrow GlobalLearner(X_{test})$
6. $accuracy_{fold} \leftarrow KNNclassify(GFV_{train}, Y_{train}, GFV_{test}, Y_{test})$
7. **end for**

Algorithm 1 shows how to combine the *RIHoD* local features and global kernels. The local features are first generated (line 1). In each fold, the local dataset is then divided into the test and training datasets (line 3). The training dataset is used to learn the global feature (line 4). The learned model is used in order to create the mapped data (line 5), and then its accuracy is evaluated (line 6).

3.2.1. Captions Global *RIHoD* Kernel Case Studies

If we divide an input signal into k segments, we have a local *RIHoD* for every segment (Equation 5). By applying a kernel function on each local *RIHoD*, $GlobalKernel_{1,2,\ldots,t}$ is created as follows:

$$GlobalKernel^{j}\left(LFV^{n,k}\right) = \begin{pmatrix} Kernel_{1,j}\left(RIHOD_{\mathrm{B}}^{P,1,\lceil k/n \rceil}\right) \\ . \\ . \\ . \\ Kernel_{1,j}\left(RIHOD_{\mathrm{B}}^{P,n-\lfloor k/n \rfloor,n}\right) \end{pmatrix} \tag{16}$$

$where\ j = 1,2,\ldots,k$

The global *RIHoD* vector (*GRIHoDV*) is composed of $GRIHoDV_i$ (*i = 1, 2…,* $\mathbb{T}$). Each $GRIHoDV_i$ is calculated as follows:

$$GRIHODV_i = \frac{1}{k}\sum_{j=1}^{k} kernel_{1.i}\ (RIHOD^{j}) \tag{17}$$

$$GRIHODV = (GHODV_1, GHODV_2, \ldots, GHODV_t) \tag{18}$$

3.2.2. Evolutionary Global Learner Kernel

In this section, we calculate the global features from the *RIHoD* local features by applying a novel GP-based feature learning method. Algorithm 2 presents the pseudo-code of the GP-based learning algorithm. In algorithm 3, $\mathbb{T}$ is a parameter that states that the learning algorithm maps the local features space from the $\mathbb{B}$ dimension to the $\mathbb{T}$ dimension. In other words,

$$GlobalGPLeaner : R^{\mathrm{B}} \rightarrow R^{\mathrm{T}} \tag{19}$$

where $\mathbb{T} < \mathbb{B}$.

In this algorithm, an initial multi-gene population of chromosomes is first generated, in which each population consists of the number of $\mathbb{T}$ genes. Each gene is a computational tree that creates one of the learned destination features. The root of the tree is a destination features. The leaves of this tree represent a constant value or a local feature, and the inner nodes are the operators. Subsequently, a KNN classifier evaluates the learned genes and computes their fitness. A new population is generated using the mutation and cross-over operators. These stages are then repeated again. The number of iterations is the parameter of the learning algorithm. In the cross-over operation (Algorithm 2, line 10), two fit chromosomes are selected randomly. Two operations can be selected for the cross-over operation: In the first case, a gene of a chromosome is replaced by a gene of another. In the second case, a sub-tree of a gene of a chromosome is replaced by a sub-tree of the second chromosome.

Algorithm 3 presents the mutation operation in which a node is randomly selected, and different operations are applied to it. If the node is an inner node (i.e. operator), in the first case, it is replaced by another operator (line 5).

Algorithm 2. GLOBAGPLEARNER.

1. **Input:** $LFV, Classes$
2. **Param:** $t, generationNo$
3. $population \leftarrow new(GP).Initialize(LFV, t)$
4. **for** $j = 1$ to GenerationNo **do**
5. **for** $pop \in population$ **do**
6. $global_{s_{1\cdots t}} \leftarrow pop.map(LFV)$
7. $pop.fitness \leftarrow KNNclassify(globals, classes)$
8. **end for**
9. $population \leftarrow LearnerMutation(population)$
10. $population \leftarrow LearnerCrossover(population)$
11. **end for**
12. $globalLearner \leftarrow bestGene(population)$

Algorithm 3. LEARNERMUTATION.

1. **Input:** $gene$
2. $node \leftarrow randomselect(gene)$
3. **if** $node$ is $operator$ **then**
4. **if** $rand \leq 0.5$ **then**
5. $node.operator \leftarrow operator(rand)$
6. **else**
7. $node \leftarrow newTree()$
8. **end if**
9. **else if** $node$ is $const$ **then**
10. $node \leftarrow rand()$
11. **else**
12. $node \leftarrow HOD(rand(36))$
13. **end if**

In the second case, its sub-tree is replaced with a new tree that is generated randomly (line 7). If the selected node is a leaf node and contains a constant value, its value is replaced by another constant number (line 10). If the leaf node is an operand (i.e. a local feature), it is replaced by another local feature (line 12).

4. Evaluation of Proposed Descriptor

The evaluations of the proposed system were performed using the MATLAB 2020b software on a PC with Microsoft Windows 10 OS, Intel i7-9750H processor, 64GB of RAM, and Nvidia RTX 2060 GDDR6 SLI GPU with 8GB memory. A tablet equipped with a digitizer pen (Samsung ATIV Smart PC Pro 700T) was used to collect the data required for the experiments in Section 4.1 and 3.2 from 17 individuals, recording 42 Persian and 36 English characters. The reason for selecting the Persian characters is the complexity of their recognition (i.e. letters with the same main body but with different delayed strokes) in comparison to the English characters. The English characters were used to represent a high accuracy of the proposed algorithm. In addition, we tested the proposed method on TMU-OFS [37], the only online dataset available for the Persian handwritten. The datasets used for the experiment of signature was the standard dataset, SUSIG [36]. TMU-OFS is similar to all tablets; the digitizer pen is able to record the *x* and *y* coordination, as well as any other information including the pressure and the point recording time in nanoseconds. Here, only the *x* and *y* signals were considered to make the *P* set (Eq. 1). The experiment in Section 4.3 uses a pen equipped with the IMU MPU-9250 sensor to collect the Persian and English character data.

4.1. Parameter Investigation

First, the effects of different values on the pattern recognition accuracy were investigated for the dimension of the *RIHoD* local feature space (i.e. parameter $\mathbb{B}$), global feature space (i.e. parameter $\mathbb{T}$), number of segmentation in a sign (i.e. Parameter k), type of fitness functions in global learner, and type of used classifier in classification of local *RIHoD*. Furthermore, in all experiments, with a GP's iterations number of 100 generations, the problem is always converged. The mutation rate is 0.9 and the cross-over rate is 0.1 empirically. According to the experiments, the best values for the parameters are $\mathbb{B}$ = 36, $\mathbb{T}$ = 20, and k = 4, and the classifier is KNN. The following shows the evidences. For the GP kernel, the parameters are: population size = 100, iteration number = 1000, mutation probability = 0.1, cross-over probability = 0.9, function sets = {+,_,*,/, sin, cos, linear, quadratic, cubic, square, exponential, log} [38].

Table 1 presents the result of recognizing the Persian and English handwritten characters and the signature dataset for different $\mathbb{B}$ values. The experiment was executed for different values (24, 36, and 48). According to the results obtained, the appropriate value of $\mathbb{B}$ parameter for the Persian handwriting processing and signature processing is 36 but for the English handwriting processing, the appropriate value is 24.

Parameter $\mathbb{B}$ states that the rotation space is partitioned into several separate sub-sets. The larger number of these sub-sets, the less information is provided to the local classifier, which increases the effect of the learning algorithm. By a higher value of $\mathbb{B}$, the global algorithm plays a more important role as a feature learner. The evaluation of the proposed method was carried out using the accuracy evaluation criteria, detailed in Equation 20.

$$Accuracy = (TP + TN)/Total \tag{20}$$

where TP represents the "true positive" and TN represents the "true negative".

As the result of Table 2 shows, the global feature vector dimension (i.e. $\mathbb{T}$) of 20 shows better values, and these dimensions are used for the experiments in this work. The result of recognition is presented in Table 2.

Table 1. Investigation of $\mathbb{B}$ parameter with Accuracy (Algorithm 1).

	Local *RIHoD*			**Global *RIHoD***			**GP-based global learning**		
$\mathbb{B}$	24	36	48	24	36	48	24	36	48
Persian characters	95.91	96.09	95.88	96.88	97.48	97.34	97.2	97.48	96.92
TMU-OFS	95.23	95.89	95.77	96.35	96.49	96.30	96.3	96.42	95.94
English characters	96.15	93.86	92.57	96.75	96.15	93.27	92.98	92.85	91.52
Signature	95.50	97.50	96.00	96.00	98.00	98.00	90.00	99.5	98.24

Table 2. Investigation of $\mathbb{T}$ parameter with Accuracy (Algorithm 3).

	Global *RIHoD*			**GP-based global learning**		
$\mathbb{T}$	10	20	30	10	20	30
Persian characters	97.34	97.48	97.48	90.05	97.48	95.46
TMU-OFS	94.53	96.49	96.24	92.08	96.42	95.98
English characters	94.12	96.15	96.03	92.67	92.85	93.54
Signature	92.00	98.00	95.00	92.00	99.50	93.00

Table 3. Investigation of classifier method with Accuracy (Algorithms 1, 2, 3).

	Local *RIHoD*			Global *RIHoD*			GP-based global leaner		
Classifier	KNN	DT	SVM	KNN	DT	SVM	KNN	DT	SVM
Persian characters	95.55	96.09	89.86	97.48	97.2	93.99	97.48	96.05	97.21
TMU-OFS	94.81	95.89	78.21	96.49	95.29	95.89	96.42	96.42	96.37
English characters	94.82	93.86	96.15	96.15	96.15	92.12	92.85	93.85	91.25
Signature	99.50	97.50	92.00	98.00	95.00	97.80	99.50	92.50	99.00

Table 4. Investigation of *k* parameter with Accuracy (Algorithm 3).

	Local *RIHoD*			Global *RIHoD*			GP-based global learning		
k	2	3	4	2	3	4	2	3	4
Persian characters	95.84	95.96	96.09	95.27	94.4	97.48	97.48	97.48	97.48
TMU-OFS	94.25	94.45	95.89	94.76	94.67	96.49	96.27	96.27	96.42
English characters	92.97	93.64	93.86	92.60	96.15	96.15	93.85	94.15	92.85
Signature	96.89	97.12	97.50	94.00	93.50	98.00	93.50	94.50	99.50

In order to obtain the best fitness function in the global leaner and classifier in classification of local *RIHoD*, different classifiers like K-Nearest Neighbor (KNN), Decision Tree (DT), and Support Vector Machines (SVMs) with RBF kernel were tested. The result obtained is shown in Table 3. For the Persian character DT, for English character SVM, and for the signature, KNN is the best classifier function for classification of the local *RIHoD*. For all datasets, KNN is the best fitness function in this work for classification of the global *RIHoD*.
One of the important parameters for best covering of *RIHoD* is the number of segments (i.e. *k*). The result of testing different value of *k* (2, 3, 4) is mentioned in Table 4. The best value of *k* is 4. Thus segmentation of the input signals into 4 parts can improve the accuracy of the proposed algorithm.

4.2. Classification Power of *RIHoD*

In this experiment, the *RIHoD* feature descriptor is compared with the features proposed by the other researchers for Persian and English handwriting and also signature recognition. Since *RIHoD* uses the genes of the GP algorithm (Algorithm 1) for feature learning, the number of features employed in the proposed method is equal to the number of genes of the GP algorithm for which the value of 10 has been chosen. Accordingly, a set of time and frequency domain features are separately extracted for each signal axis. The set of time domain features include mean, standard deviation, variance, square root mean [3], axes correlation, the mean in the first quartile, second, and third quartile of the signal [39,40]. Thus the number of statistical features is equal to 8. Moreover, by passing a mean filter, the ac and dc components of the signal [40] were also extracted and placed in this set. In order to form the feature vector of the frequency domain, first the fast Fourier transform (FFT) was applied to the signal. The feature-like energy, i.e. the sum of the frequency component squares, the entropy of frequency components [41], the range of the ten initial components (with more prominent frequencies), and the dc component [42] were then extracted and added to the set of frequency domain features. Thus the number of statistical features is equal to 4. Table 5 presents the results of this experiment. As one can see, this feature alone outperforms all the other features. The classification used in the aforementioned references was used for comparisons. A combination of the local and global features exhibited the highest accuracy.

4.3. Usage Case Study: Inertial and Digitizer Pen Character Recognition

First, by applying the fleet methods, the character paths were reconstructed to obtain the position information from acceleration, gyroscope, and magnetometer signals of inertial pen. Subsequently, the considered features, as well as *RIHoD*, were extracted from the reconstructed path data. No pre-processing was required for the digitizer pens. Table 6 compares the results with those of the best previous works on the TMU-OFS dataset. As one can see, the results obtained indicate significant improvements.

4.4. Usage Case Study: Online Signature Recognition

This experiment presents the effect of *RIHoD* on improving the online signature recognition. The dataset used in this experiment was the standard dataset, SUSIG [34].

Table 5. Application of *RIHoD* compared to time domain (TD) and frequency domain (FD) features in online pen character and signature recognition with accuracy.

Feature	TD	FD	TD + FD	Local *RIHoD*
Persian characters	95.89±0.3	87.10±0.2	95.51±0.2	96.09±0.40
TMU-OFS	95.42±0.4	86.25±0.4	95.53±0.5	95.89±0.55
English characters	93.57±0.1	82.90±0.4	92.83±0.2	93.86±0.10
Signature	63.15±2.8	72.12±3.4	75.01±2.2	97.50±0.20

Table 6. Comparison of *RIHoD* in online internal pen character recognition and TMU-OFS dataset with existing methods.

References	Method	Accuracy (%)
Proposed method	Global *RIHOD* + Global GP learner	96.42 ±0.55
Proposed method	Local *RIHOD* + Decision tree	95.89 ±0.60
Ghods and Kabir [23]	Geometric features + decision tree + minimum distance classifier	94.00 ±1.80
Valikhani *et al*. [43]	GP feature learner + decision tree	96.00 ±1.20
Abdelaziz *et al*. [44]	Hidden Markov Model	95.00 ±1.55
Mehralian and Fouladi [45]	Detection of position, number and shape of delayed strokes + support vector machine	88.00 ±0.45
Baghshah *et al*. [46]	Fuzzy technique	90.00 ±0.02
Razavi and Kabir [47]	Neural networks	93.00 ±0.25

Table 7. Comparison of *RIHoD* in online signature recognition on SUSIG dataset with existing methods.

References	Method	Accuracy (%)
Proposed method	Global *RIHOD* + Global GP learner	99.50 ± 0.20
Theodorakopoulos [48]	DTW algorithm + KNN	98.01 ± 0.22
Sae-Bae and Memon [49]	Histogram of features	97.08 ± 0.32
Rashidi and Fallah [50]	Discrete cosine transforms	98.51 ± 0.20
Yanikoglu and Kholmatov [51]	Fourier transform	93.80 ± 0.50

5. Discussion and Conclusion

The efficiency of the *RIHoD* feature descriptor depends on the important parameter $\mathbb{B}$ in Algorithm 1. The horizontal and vertical lines in standard handwritings can be written by small changes in the direction of the writers' hand movements. This phenomenon moves the created angles to the next bin, and cause problems. Selecting an appropriate value for $\mathbb{B}$ is highly effective in this phenomenon. For instance, selecting the value 24 or 36 for $\mathbb{B}$ specifies 90 degree and 180 degree angles as the boundary of two bins. The letters with many horizontal or vertical movements create different patterns in different individuals for a character. Selecting value 18 for $\mathbb{B}$ solves this issue; however, a low number of $\mathbb{B}$ can reduce the descriptor's accuracy. The appropriate way is to select a large number of $\mathbb{B}$, and then combine the adjacent ones. This way, the intervals of each bin may not be symmetric.

The GP algorithm was selected for learning the global features due to its considerable and suitable characteristics. The genetic algorithm is inherently capable of feature selection. In other words, it removes the unusable or noisy features. Another inherent feature of this algorithm is feature extraction.

Table 8. Comparison of *RIHoD* training and testing phase run time with existing methods.

References	Training time	Training time
Proposed method	435 s	0.12 s
Ghods and Kabir [23]	835 s	0.91 s
Valikhani *et al*. [43]	743 s	0.79 s
Abdelaziz *et al*. [44]	994 s	0.36 s
Mehralian and Fouladi [45]	673 s	0.68 s
Baghshah *et al*. [46]	969 s	0.74 s
Razavi and Kabir [47]	991 s	0.79 s

Each gene in this algorithm learns a new feature, which is a discriminator, by applying some operations. On the other hand, KNN is a good compliment to evaluate and calculate the fitness. This algorithm requires no separate training and tests since it does not create a model and performs classification according to the current data. Moreover, it does not have a high computational cost in comparison to the complex classifications like SVM. Regarding the cost complexity, *RIHoD* is calculated by a linear equation based on the number of input signal points. Calculating the global feature using the genetic algorithm has a high time cost. Table 8 compares the time required to implement the proposed method with the model training and testing phases (Algorithm 1). Although the proposed method takes longer to implement in the training phase than the other methods, what matters in practice is the model's test time. According to Table 8, the time required to implement the proposed method in the test phase is equal to 0.12 s significantly less than it takes for other approaches.

6. Future Works

According to its low computational complexity, high speed in calculating the *RIHoD* descriptor, and powerful ability to describe and recognize related patterns, a hardware implementation can be proposed based on FPGA [52]. The obtained features can be written as the logical functions in a decision tree and implemented with logical modules. Therefore, a hardware keyboard can be generated based on this feature. Furthermore, combining this feature with the feature defined by others can enhance the recognition accuracy of different algorithms. For instance, the features used in the evaluation section for comparison with the propose descriptor can be combined with *RIHoD* in order to increase accuracy. Future works include the comparison of the proposed method using the online handwriting datasets of other languages and signature datasets.

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یک توصیفگر جدید فضا-زمانی مبتنی بر یادگیری برای تشخیص آنلاین نمادها

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چکیده:

موفقیت روش‌های تشخیص دستخط مبتنی بر پردازش سیگنال قلم دیجیتایزر بیش از همه وابسته به ویژگی‌های تعریف‌شده است. توصیفگرهای ویژگی قوی و متمایزساز می‌توانند نقش اصلی را در بهبود دقت تشخیص الگو ایفا کنند. علاوه بر این، در اکثر مطالعات صورت‌گرفته در زمینهٔ تشخیص الگو از ویژگی‌های محلی یا مجموعه‌ای از آنها استفاده شده است، درحالی‌که نشان داده شده ترکیب ویژگی‌های سراسری و محلی می‌تواند دقت تشخیص را افزایش دهد. در این مقاله به دو موضوع پرداخته می‌شود. اول، یک ویژگی محلی بسیار متمایزساز به نام هیستوگرام مستقل از چرخش درجات برای سیگنال‌های دستخط قلم دیجیتایزر آنلاین پیشنهاد شده است. دوم، یک لایهٔ نمایش ویژگی پیشنهاد شده که با استفاده از تعدادی کرنل یادگیری در فضایی جدید ویژگی‌های محلی را به ویژگی‌های سراسری نگاشت می‌کند. جنبه‌های مختلف ویژگی محلی پیشنهادی و ویژگی سراسری آموخته‌شده تحلیل شده و کارایی آن در چند سناریوی تشخیص آنلاین دستخط ارزیابی شده است.

کلمات کلیدی: برنامه نویسی ژنتیک، یادگیری ویژگی، هسیتوگرام درجات، ویژگی‌های محلی، ویژگی‌های سراسری.