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Beta-Elliptic Model for Writer Identification from Online Arabic Handwriting

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***Abstract*: The growth of artificial intelligence and pattern recognition fields owes greatly the online writer identification challenge. In this work, a new method is proposed to the widely neglected problem of text-independent online writer identification from Arabic handwriting. This method is based on Beta-elliptic model in order to explore the utility of this model to discriminate multiples writing styles. In fact, Beta-elliptic model provides a rich output in terms of graphical, kinematical and biometrical data. The information provided by the feature extraction with Beta-elliptic model has been evaluated using Feed Forward Neural Network classifier. Experiments are conducted on ADAB Database involving respectively 19 and 60 writers show that the proposed online Arabic writer identification based on Beta-elliptic model is worth to receive further exploration in capturing the writer's individual.**

Keywords: Biometric, writer identification, Beta-elliptic model, online Arabic handwriting, velocity profile, geometric profile.

I. Introduction

Biometric refers to automatic identifying of an individual based on his action or his physical characteristic. Thereby, biometric modalities are categorized into two general groups: Physiological biometrics, which are based on the direct measurement of parts of human body such as iris, fingerprint, retinal, and face [1]-[5]. The second group of modalities is behavioral biometrics, which are based on the manner or the behavior exhibited by individual to perform tasks such as gait, voice, keystroke, signature, handwriting [6]-[10]. Accordingly, writer identification pertains to the group of behavioral biometrics. Thus, the task of writer identification is to identify the author of a document, from group of writers known by the system [11].

The considerable emergence and the development of new technologies in these last years has led to a large appearance of devices such as Personnel Digital Assistant (PDA), digital pen (d-pen), paper technology, Tablet Personal Computer (Tablet PC) and smartphones, which are able to produce online handwriting documents [12]. Thus, the growth of these documents raises the question for identifying the author of a given document. Besides, online writer identification relatively can be considered as a new area of handwriting research compared to the signature verification or handwriting recognition [13].

In the last decade, many researches focused on the studies of writer identification task, that can be useful in a variety of applications such as digital rights management in the financial sphere, control access and document analysis. Moreover, writer identification has also a long tradition in forensics science where it has been accepted by the court as evidence for more than a century [14]. Nevertheless, several difficulties and challenges remains an important study field such as the handwriting can unconsciously modify during the lifetime of writers [15]. We can also added to the challenges the four factors causing variability in handwriting, which are the affine transforms, the neuro-biomechanical variability, the sequencing variability and the allographic variation [16].

Writer identification can be generally classified into two methods as offline and online [17]-[19]. In offline case, only a scanned image of the handwritten text is available, In contrast with online techniques, the spatial and the temporal information about the handwritten text is available. Several approaches of writer identification can be categorized into two types namely text independent and text dependent methods [20]-[22]. In text independent methods, the writer has the freedom to write any text in the test phase. Otherwise, in text dependent methods, the writer should write the same text in the test phase as in the training process. Consequently, text dependent methods are not applicable for many practical situations, for example in criminal justice in which the content of the different documents should be compared [23]. In general, text independent writer identification considered more difficult than text dependent writer identification [24].

Online Arabic Writer identification remains a challenge because of several factors. First, the Arabic text are inherently cursive which the letters are joined together along a writing line [25]. Second, the shape of the letter is context sensitive, appears in four different forms according to its position in the word [26]. These positions are: form in the beginning, form in the Middle, form in the end and isolated form. Third, Some Arabic character have the same letter body and only differ in these dots which identify them [27], for example the letters “ث“ ”ت“ ”ب”. Moreover, Arabic script varies vertically and horizontally, and this for the existence of ligatures between characters of the same word.

Handwriting is a movement that is produced as a result of neuromuscular exerted on the hand, arm and fingers. Thus, the handwriting style of person is heavily influenced by his

Table 1. Summaries of some works on online Western writer identification field.

System	Database	Feature extraction	Classification	Accuracy
[30]	600 handwriting phrases	Point distribution model feature	k-nearest neighbor algorithm	97.30% for 12 writers.
[31]	IAM-OnDB Database	Stroke-based feature and point-based feature from text line	Gaussian Mixture Model	94.75% for 200 writers.
[32]	Plucoll database	Lead-in features, loop features, loop and lead-in features	k-nearest neighbor algorithm	98% for 41 writers.
[33]	NLPR handwriting database	Static features, hierarchical structure in shape primitives and fusion dynamic	Nearest-neighbor classification	93% for 55 writers.
[34]	IAM-OnDB Database	Stroke-based feature set, point-based feature set, extended point-based feature set, off-line point-based feature set and all point-based feature set	Gaussian Mixture Models	98.56% on the paragraph for 200 writers.
[35]	IRONOFF database	x-y coordinates, direction, curvature of x coordinates and the status of pen up or pen down.	Euclidean distance	95% for 82 writers.
[36]	NLPR handwriting database	shape codes and temporal sequence	Nearest-neighbor classification	90% for 242 writers.
[37]	IBM_UB_1	Probability distribution feature	Support Vector Machines	89.47% for 43 writers
[38]	CASIA-OLHWDB 1.0 dataset	Path-signature feature	Deep convolutional neural network	99.52% for 420 writers.
[39]	IAM-OnDB Database	Coordinates x, y and the Speed feature	Nearest prototype schemes, modified tf-idf scheme	96.30% for 100 writers.

psychological characteristics such as education, apprehension, stress level, fright and neurophysiological characteristics such as finger, wrist joint, hand, muscles, nervous system, and arm. Hence, an important challenge consists of developing and enhancing techniques capturing the writer's individual [28]. Consequently, we are interested to use the Beta-elliptic model in our writer identification method from online Arabic handwriting. The motivation for the use of Beta-elliptic model is the rich output in terms of biometrical, kinematical and graphical data. Indeed, Beta-elliptic model is characterized by a description combining two aspects of the handwriting trajectory: geometric and velocity profiles modeling [29].

This paper is organized as follows: In Section II, we give a summarization of text independent from online writer identification system on Western and Arabic scripts. After that, the motivation and the definition of the newly proposed method to text independent writer identification from online Arabic handwriting based on Beta-elliptic model presented in Section III. Section IV is for experimental results and discussions. Finally, our conclusions provided in Section V.

II. Related work

In this section, we present a brief survey on writer identification from online handwriting, in which documents are described by a successive coordinates of the trajectory of pen points in the handwriting. Many researchers have been attracted towards the field of text-independent Western online writer identification and many approaches have been made during the last decade. Table 1 summarizes some systems on online Western writer identification field.

Despite the great progress made in the field of online writer identification and its applications, this area in the Arabic language remains yet an under-exploited compared to Latin or Chinese [40]. In the literature, a small number of researches has been addressed in the field of text independent writer Identification from online Arabic Handwriting. A possible explanation for this is the citation of bulacu that the automatic writer identification on Arabic script seems to be more difficult than on Western script [41]. We present in the last of this section a brief description of three systems [42], [43] and [44] concerning online Arabic Writer identification.

Namboodiri et al. [42] proposed a text independent writer identification from online handwriting. Thus, they used sub character level features and the velocity profile of the pen movement to extract the shape primitive. After that, they calculate the similarity measure by Euclidean distance, and they used unsupervised k-means clustering algorithm to identify repetitive shape primitives. In addition, they used Neural Network based classifier for classifying each curve primitive. Experiments were performed on their own data from 15 writers. They have 85% of writer identification rate.

Chaabouni et al. [43] defined online writer identification system from Arabic handwriting. For realized their system, segmentation of graphemes is elaborated and decomposed into five groups: graphemes in the beginning, graphemes in the middle, graphemes in the end, diacritics and isolated graphemes. Moreover, they used multi-fractal technique to characterize online handwriting styles. In their experiment, they have 87.80% of writer identification rate for 100 writers with 10 words in the test and each writer has wrote 120 words.

Gargouri et al. [44] proposed an online Arabic writer identification system based on sets of dynamic and statistic features used in different levels in the word. In their experiments, they used ADAB database, presented in Section IV, and they have 45.67% of writer identification rate for 19 writers. We resume this sub section in Table 2.

Table 2. Summaries of works on online Arabic writer identification field.

System	Database	Feature extraction	Classification	Accuracy
[42]	Own database	The velocity profile and sub character level features	Neural Network	85% for 15 writers.
[43]	ADAB Database	Multi-fractal technique used in feature extraction	Own algorithm scoring	87.80% for 100 writers.
[44]	ADAB Database	Stroke speed, point-based features, distance between strokes, word-based features and horizontal histogram	Support Vector Machine and Dynamic Time Warping	45.67% for 19 writers.

III. Proposed online Arabic writer identification method

The Beta-elliptical model is very used in several areas of research for online handwriting, such as in regeneration of handwriting [45], [46] and in Optical Character Recognition [47]. In the work of [48], Beta-elliptic model has used in writer identification from offline handwriting with the Elliptic model, which represent the offline projection of the Beta model.

The goal of our method is to fully exploit the Beta-elliptic model that models efficiently on real time writing movements, in online writer identification, by involving together its both profile entities: the elliptic arcs and the Beta impulses. Thus, the correspondence between these two profiles allowed a better characterization of the online handwriting compared to other existing approaches such as oscillatory approach and geometric approach.

A. Training process

Firstly, we extracted features with Beta-elliptic model. Secondly, we affected the features of segment in groups, then in subgroups according to its geometric characteristics. Finally, we trained networks with Feed Forward Neural Network for each sub-group of segment.

An overview on the architecture of the training module presented in Figure 1.

B. Features extraction

In the field of online handwriting modeling, the Beta-elliptic model is characterizing by a description combining two aspects of profiles: dynamic and static. In the dynamic profile, overlapped Beta signals model the velocity, whereas in the static profile named also geometric profile, elliptic arcs model segmented trajectory. Thus, the combination of the two types of features characterizing the extracted Beta impulse and its corresponding arc of ellipse allows decompose a complicated trajectory in elementary parts named strokes [49].

Figure 2 shows the application of Beta-elliptic model on online handwriting.

Each trajectory stroke corresponds in the velocity domain to the generation of one Beta signal as defined in the following expression:

$$pulse\ \beta(K,t,q,p,t_0,t_1) = \begin{cases} K.\left(\dfrac{t-t_0}{t_c-t_0}\right)^p.\left(\dfrac{t_1-t}{t_1-t_c}\right)^q & if\ t\in[t_0,t_1] \\ 0, & elsewhere \end{cases} \quad (1)$$

With:

- t_0 is the starting time of Beta function.
- t_1 is the ending times of Beta function.
- t_c is the instant when the Beta function reaches its maximum value K.
- K is the Beta impulse amplitude.
- p, q are intermediate parameters;

$p, q \in$ IR.

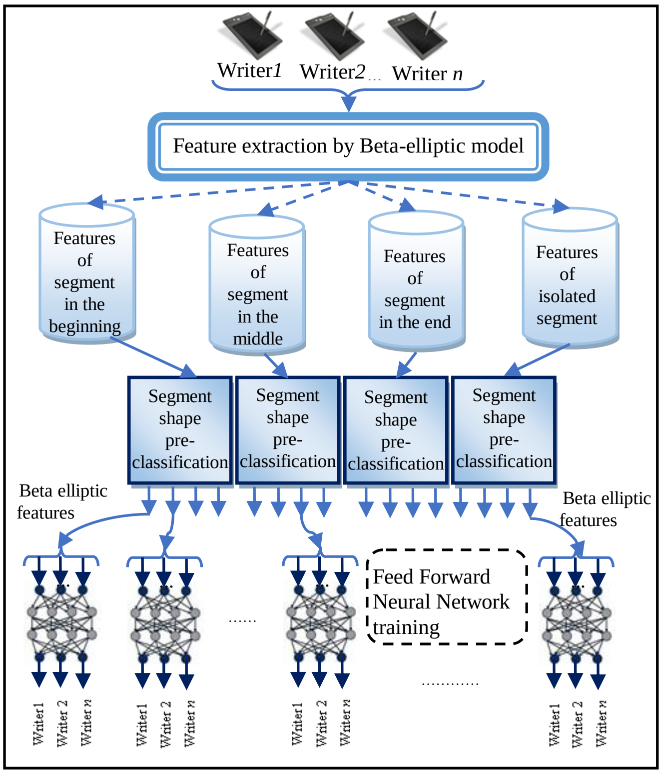


Figure 1. Architecture of the training module.

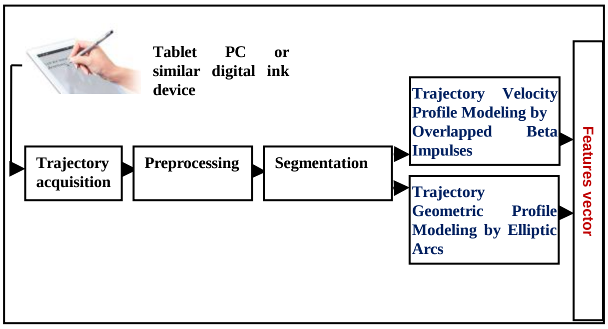


Figure 2. Application of Beta-elliptic model on online handwriting.

Table 3. Features extraction from beta-elliptic model.

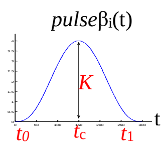
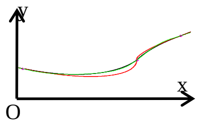
Feature section	**Parameter and formula**	**Signification**
Dynamic profile model	$\Delta t = (t_1 - t_0)$	Beta impulse duration
	$RapT_c = \frac{t_c - t_0}{\Delta t}$	Rapport of Beta impulse asymmetry or culminating time
	p	Beta shape parameters
	k	Beta impulse amplitude
	$\frac{k_i}{k_{i+1}}$	Rapport of successive Beta impulse amplitude
Static profile model	a	Ellipse major axis half length
	b	Ellipse small axis half length
	θ	Ellipse major axis inclination angle
	θ_p	Angle of inclination of the tangents at the stroke endpoint M2.
	P0SITION_ STROKE	Position of stroke

Figure 3 shows the various forms that can take the Beta function with the same amplitude K according to the values of p and q.

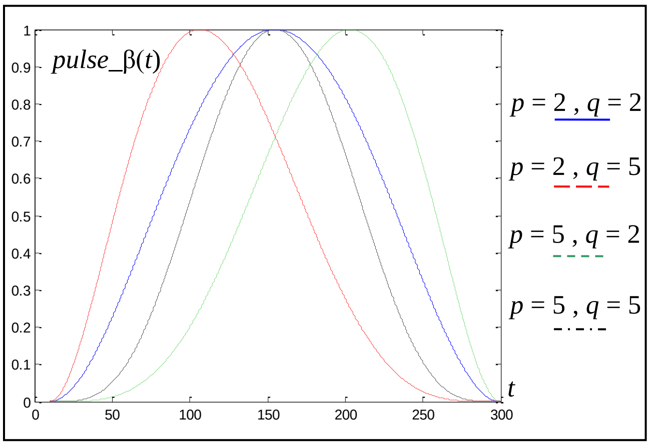


Figure 3. Various forms of Beta function according to the values of p and q [49].

The generation of a velocity model for a handwriting trajectory (shown in Figure 4.(a)) is the result of an algebraic addition of the velocity profiles of its successive segmented strokes:

$$V_\sigma(t) = \sum_{i=1}^{n} V_i(t - t_{0i}) \approx \sum_{i=1}^{n} pulse\,\beta_i(K_i, t, q_i, p_i, t_{0i}, t_{1i}) = V_r(t) \quad (2)$$

In this sub-section, we focus on the description of the static model. Indeed, each elementary trajectory Beta stroke executed in the space domain from an arbitrary starting position checks a monotony curvature variation that can be assimilated to an elliptic arc (shown in Figure 4.(b)) characterized by four parameters (a, b, θ, and θ_p) as represented in Figure 5. The parameters a and b are respectively the half dimensions of the large and the small axis of the elliptic shape. θ is the angle of the ellipse major axis inclination and θ_p is angle of inclination of the tangents at the stroke endpoint M_2.

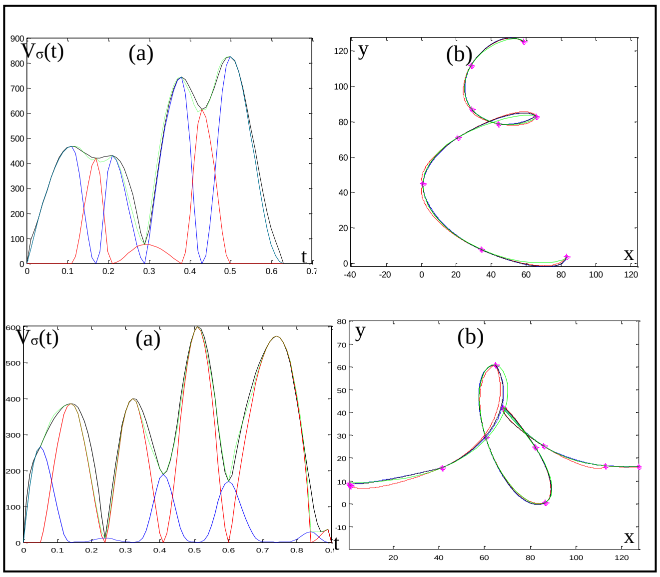


Figure 4. Application of Beta elliptic model on handwriting trajectory of 'ع' and 'ه' Arabic characters: (a) Velocity profile modeling and (b) Geometric profile modeling.

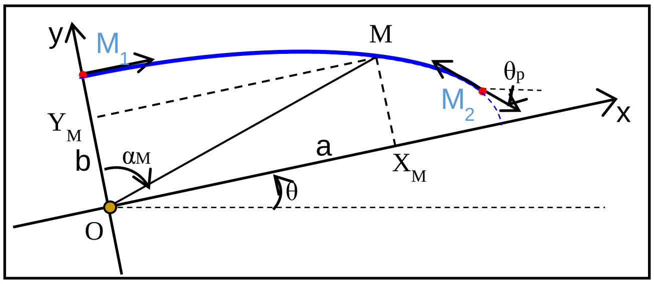


Figure 5. Explanation of geometric feature.

As the system proceeds to segment the velocity profile and the handwriting trajectory in overlapped Beta strokes, a vector of 10 features composed in table 3 models each Beta stroke in the trajectory of a handwritten word.

C. Segment distribution

With Beta-elliptic model, we extract features on a window of N=4 consecutive beta strokes sliding on the handwriting trajectories of all the training set. The obtained handwriting successive 4 strokes called segments are distributed in four groups, which are: segment in the beginning, segment in the middle, segment in the end and isolated segment. Some example of segment shown in Figure 6.

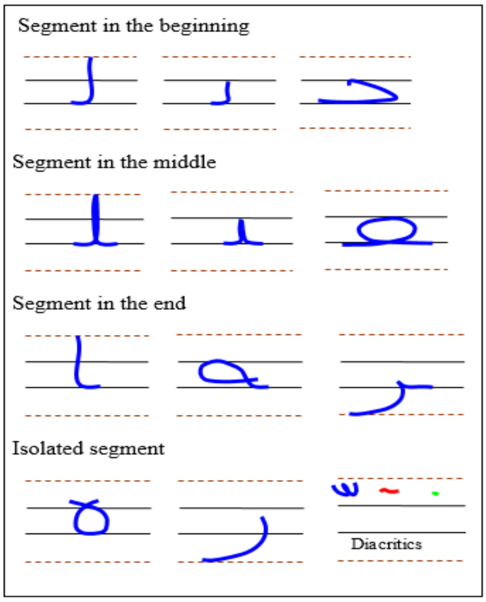


Figure 6. Example of segment groups

The Arabic handwriting are guided by four fictive lines, which are upper limit line, median line, baseline and lower limit line [50] as shown in Figure 7.

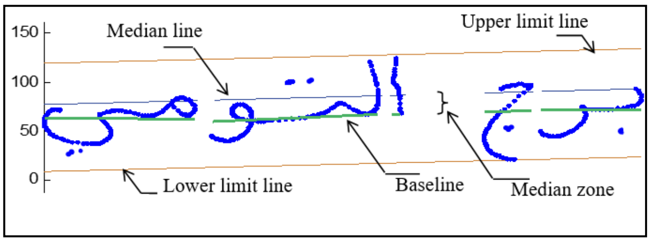


Figure 7. Arabic handwriting fictive guidelines and median zone.

Moreover, we can distinct different vertical position of trajectory segment in respect to the indicated guideline. In fact, we can represent the cursive Arabic handwriting trajectory as a concatenation of segment reaching the upper line as shaft; and other limited between the median and the baselines as the occlusion; and other descending below the baselines as the legs.

Thus, each one of the four groups is divided into subgroups of trajectory segments sharing a same visual shape. These automatic segments shapes pre-classification proceeds by examining the evolution of the geometric characteristics of the trajectory and in particular its tangent direction along the segment path. We used also in segments shapes pre-classification the starting point, the arrival point and the points extremas in the four positions (left, right, top, low).

Consequently, we have constitute:

- 11 subgroups from the group segment in the beginning such as ‘open curve on the right’ and ‘حـ in the beginning’ as represented in Figure 8.
- 12 subgroups from the group segment in the middle such as ‘middle shaft’ and ‘middle Nabra’ as represented in Figure 9.
- 8 subgroups from the group segment in the end such as ‘end shaft’ and ‘end leg’ as represented in Figure 10.
- 10 subgroups from the group isolated segment such as ‘diacritics’ and ‘isolated shaft’ as represented in Figure 11.

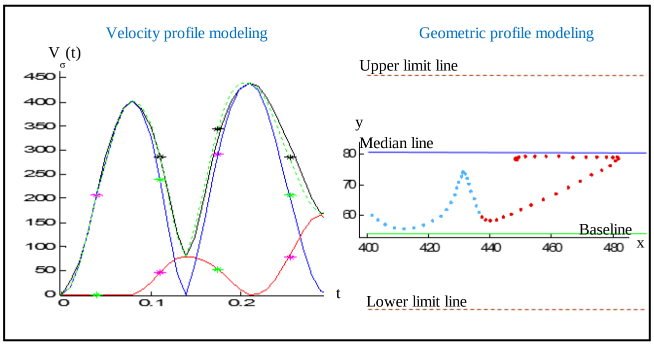


Figure 8. Example of sub group ‘حـ in the beginning’.

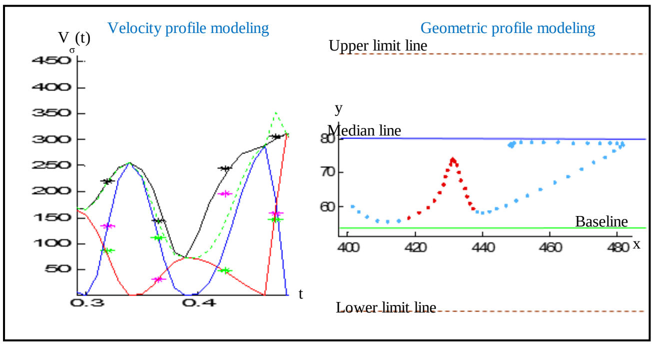


Figure 9. Example of sub group ‘middle Nabra’.

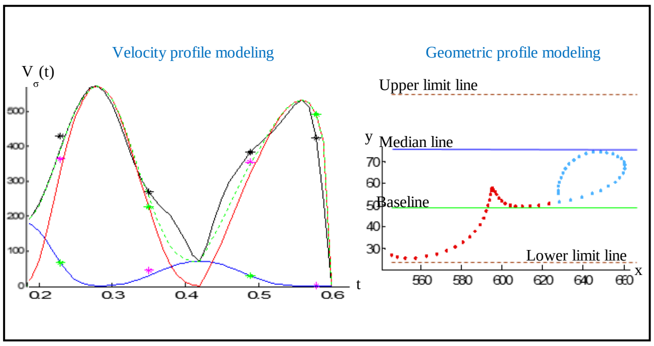


Figure 10. Example of sub group ‘end leg’.

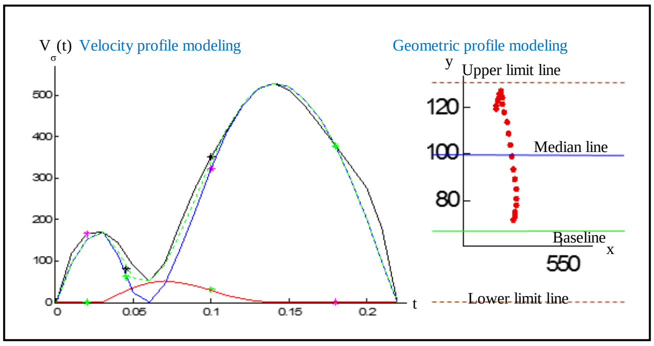


Figure 11. Example of sub group ‘isolated shaft’.

D. *Feed Forward Neural Network training*

Since the discriminating power of a neural network is related to the nature of the information data used for its training [51], we chose to compare similar handwriting segments in term of shape and position in order to discern the handwriting style of each writer and to identify its specific calligraphic forms. Thus, we devote Feed Forward Neural Network for each sub-group of segment shape pre-classification [52].

A Feed Forward Neural Network is a biologically inspired classification algorithm, known also as multi-layer perceptron. It consist of a series of layers, and each layer contains nodes or neurons. Firstly, the first layer has a connection from the network input. Secondly, each subsequent layer has a connection from the previous layer. Finally, the final layer produces the network's output [53] as shown in Figure 12.

Thereby, calculations and data flow in a single direction, from the input data to the outputs. Output of the i^{th} neuron can be represented by the following expression:

$$y_i = f_i\left(\sum_{j=1}^{n} W_{ij} x_j + \theta_i\right) \tag{3}$$

With:
y_i: the output of the node.
f_i : the node transfer function.
W_{ij}: the weight of the connection between input x_j and the node.
x_j: the j^{th} input to the node.
θ_i : the threshold of the node.

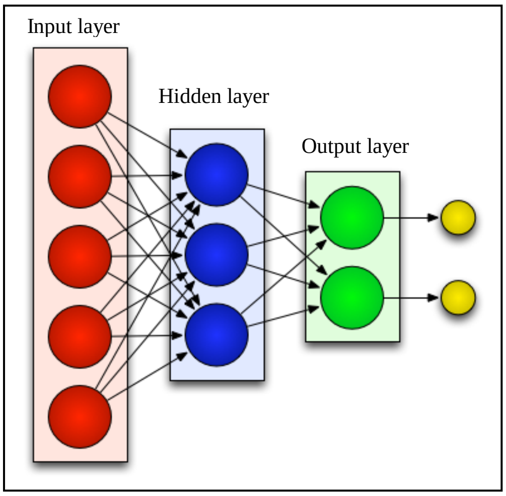


Figure 12. Example of Feed Forward Neural Network.

For training networks, firstly, we used the generated features with Beta-elliptic model as inputs. Secondly, the later are fed simultaneously into the units making up the input layer, which consists of just the inputs to the network. Thirdly, the responses of the units in the input layer are weighted and fed simultaneously to a hidden layer. Thus, the weighted outputs of the last hidden layer are input to units making up the output layer that emits the network's prediction. Knowing that neural network is trained by minimizing an error function, we used in our work the Mean Squared Error (MSE) as the performance function, which can be represented by the following expression:

$$MSE(W_{ij}) = \frac{1}{pm} \sum_{i=1}^{p} \sum_{j=1}^{m} (T_{ij} - F_{ij})^2 \tag{4}$$

With:
W_{ij}: the weight of the connection between input x_j and the node.
pm: the number of training patterns.
m: the number of Feed Forward Neural Network outputs.
T_{ij}: the target.
F_{ij}: the actual value for the input i and the output j.

Moreover, the function of our training updates the weights and bias values in accordance with Levenberg–Marquardt optimization. Finally, we obtained our networks in order to use its in identification process.

E. Identification process

Figure 13 shows the architecture of the identification module of our online Arabic writer identification.

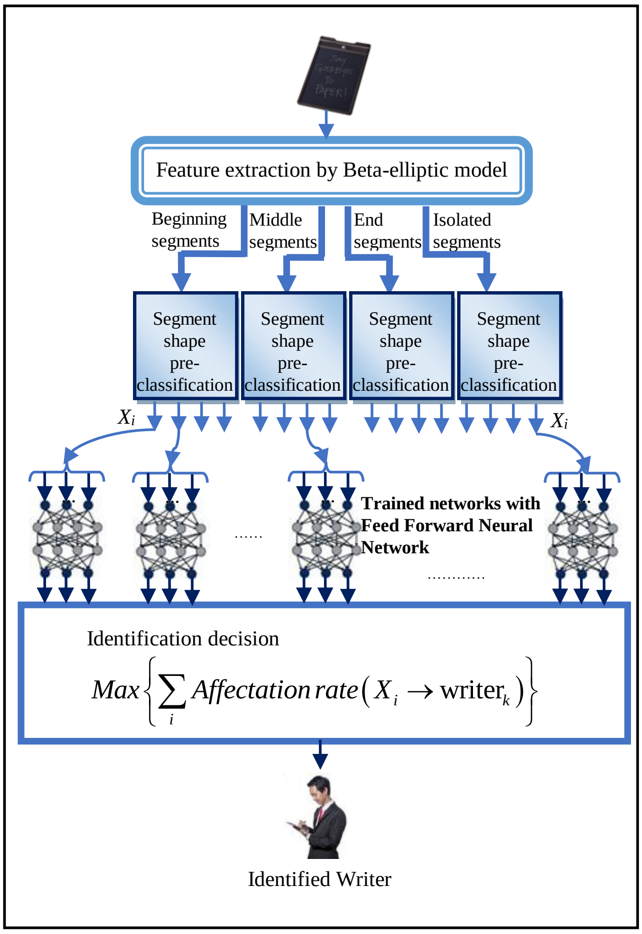


Figure 13. Architecture of the identification module.

In the purpose to evaluate the performance of the proposed features for writer identification, we extract feature vectors from the testing data in the same way as in the training process. Then, we calculate the sum of the simulation output of the correspondent trained networks activated for each pre-classified segment extracted from the testing script data. Finally, writers are ranked according to their obtained sum of output affectation rate simulation T_{affect}, and consequently the identified writer is retained as the writer who has the maximum of output sum, as represented by the following expression:

$$Iw = \underset{k\in\{1,\dots,Nw\}}{ArgMax}\left\{\sum_{i=1}^{S} T_{affect}\left(X_i\ ,k\right)\right\} \tag{5}$$

With:
Iw: the index number of the identified writer.
k: Index number of the k^{th} suspect writer.
Nw: the number of suspect writers.
S: Number of segments of N Beta strokes recuperated from the

tested handwriting.

T_{affect}: Rate of affectation of the i^{th} tested segment to the k^{th} writer, as detailed in the following expression:

$$T_{affect}\left(X_i\ ,k\right)\ =\left[net_j\left(X_i\right)\right]_k \tag{6}$$

X_i: Feature vector of the i^{th} tested segment affected to the j^{th} subgroup.

net_j: Output of the j^{th} trained network to which is assigned the feature vector X_i.

IV. Experiments and results

A. ADAB Database

To test the robustness and to evaluate our proposed method, we used ADAB Database (The Arabic handwriting Data Base). It consists of more than 33000 Arabic words, includes Tunisian town and village names, handwritten by 166 different writers. Most of the writers selected from the narrower range of National School of Engineers of Sfax. ADAB Database is developed in cooperation between REsearch Groups in Intelligent Machines (REGIM-Lab.) and the Institut fuer Nachrichtentechnik (IfN) in order to advance the research and development of online Arabic handwritten text. It can be used to test writer identification and to perform Arabic online handwriting recognition systems [54]-[57].

Figure 14 shows some examples of words handwritten extracted from ADAB Database by different writers.

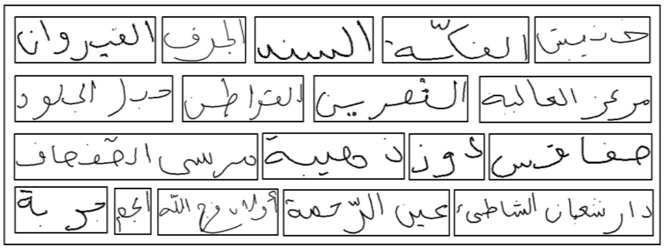


Figure 14. Examples of town and village names handwritten by different writers selected from ADAB Database.

The ADAB database divided into six sets. Some details about this database shown in Table 4.

Table 4. Statistics on the different sets composing the ADAB Database [54].

Set	Files	Words	Characters	Writers
1	5037	7670	40500	56
2	5090	7891	41515	37
3	5031	7730	40544	39
4	4417	6786	35832	25
5	1000	1551	8189	6
6	1000	1536	8110	3
Sum	21575	33164	174690	166

B. Test

In ADAB database, the numbers of words for the various writers are not equals, its varied from 1 to 829 words. For this reason and in order to give the same chance to all writers, we extracted 2 sub-datasets from ADAB database which contain the same words' number for each writer.

Tests are organized as follows: For each writer, we used 30 words divided into 3 sub-test contains each one 10 words. As presented in identification process, writers are ranked according to their obtained sum of output affectation rate. Thus, Top1 represent the average probability of correctly identifying a writer from the first ranked of writers. Moreover, Top5 and Top10 indicates if the correct writer is found in the first five and the first ten writers ranked results respectively.

Table 5 presents an overview on the 2 sub-datasets sizes and the correspondent identification results.

Table 5. Experiment results.

	Sub-dataset1	**Sub-dataset2**
Number of writers	19	60
Words training per writer	67	60
Words test per writer	30	30
Identification Rate Top1	91.22%	80.00%
Identification Rate Top5	100.00%	90.00%
Identification Rate Top10	100.00%	95.00%

For the test of sub-dataset1, the total number of tested propositions is: 3 x 19 = 57 samples of online handwritten words. We had 52 correct identification and 5 false identification, which corresponds to an identification rate of 91.22%.

For the test of sub-dataset2, the total number of tested propositions is: 3 x 60 = 180 samples of online handwritten words. We had 144 correct identification and 26 false identification, which corresponds to an identification rate of 80.00%.

C. Discussion

In the first experiment, and in order to compare our proposed work with the system of [44], we used the same number of words training per writer, extracted from ADAB Database, as their experimentation for 19 writers. Table 6 resume this comparison:

Table 6. Comparison of identification rate with other system.

System	**Top1**	**Top5**
Proposed system	91.22%	100.00%
System presented in [44]	45.67%	87.00%

Compared also to the results of [42], we obtained better identification rate than their results, how achieved 85% of writer identification, although the number of writers was 15.

In the second experiment used 60 writers, we obtained 80% Identification Rate, this result is encouraged and comparable to the work of [43] who have identification rate of 87.8% for 100 writers. However in their case, each writer has wrote 120 words, while in our case, each writer has only wrote 60 words.

V. Conclusion and future works

In this work, we proposed a text independent writer identification method from online Arabic handwriting based on Beta-elliptic model. To evaluate our method, we apply it to identify the writers who contributed on ADAB database, and we compared our obtained results of identification with that of recent works from literature.

Our empirical results indicate that the features extracted by Beta-elliptic model, describing simultaneously the dynamic and geometric profiles of handwriting trajectories using respectively Beta impulses and elliptic arcs, are useful to discriminate multiples writing styles.

The perspective of improvement of our method is located in the use of other features. We plan also to build and test our writer identification in a large-scale database and other scripts.

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