Off-line Features Integration for On-line Handwriting Graphemes Modeling Improvement

Houcine Boubaker , Aymen Chaabouni,
Najiba Tagougui, Monji Kherallah, Adel M. Alimi
REGIM: REsearch Group on Intelligent Machines
University of Sfax
National School of Engineers (ENIS)
BP 1173, Sfax, 3038, Tunisia
e-mail: {houcine-boubaker , ayman.chaabouni ,
najiba.tagougui , monji.kherallah , adel.alim}@ieee.org

Haikal El Abed
Institute for Communications Technology (IfN)
Technische Universität
D-38106 Braunschweig, Germany
elabed@tu-bs.de

***Abstract*—This paper deals with the improvement of an on-line Arabic handwriting modeling system based on graphemes segmentation. The presented strategy consists in the integration of off-line features to assimilate and take up the handwriting style variation in a multi-writer context. The main contribution of the presented work consists in making off-line fuzzy template for each on-line segmented graphemes trajectory and the extraction of geometric moments invariants by using a method adapted to the irregular spatial sampling of their on-line trajectory. The experimental results prove the added value of the introduced features on the discriminative power of the developed handwriting modeling system.**

Keywords- on-line handwriting modeling; Grapheme segmentation; Off-line features; fuzzy template; geometric moments invariants

I. INTRODUCTION

The feature extraction is the most important step in a pattern modeling and recognition process. Indeed the relevance of the features vector, extracted in this step to represent the characteristics of the modeled shapes, affects directly the level of discrimination between different classes and therefore on the classification result.

The objective of the presented work is to improve the discriminative power of an on-line Arabic handwriting modeling system based on graphemes segmentation by the integration of off-line parameters in the graphemes features vectors to assimilate the writing style variation and the chronologic order change of handwriting grapheme strokes from one writer to another. For this we extract for each segmented grapheme an off-line template and we compute its geometric moments invariant by a tailored formula to a continuous drawn line to compensate the irregular spatial sampling of the online handwriting trajectory points. Then, in the evaluation phase, we apply the system on the ADAB database [12], [13] of online Tunisian town names using a classifier module based on Hidden Markov Models implemented through the 'HTK' Toolkit.

In the next sections, after reviewing the principals approaches of on-line handwriting modelling, first we present an overview of the developed Arabic handwriting grapheme segmentation system. Then we introduce successively in the two following sections the extraction of two groups of off-line features : grapheme template and adapted geometric moments invariants before ending up presenting the experimental results.

II. THE STATE OF THE ART

In the field of on-line handwriting recognition, the input data form a sequence of points representing the evolution of the trajectory sampled in time. Among the modeling approaches used in the literature, some called dynamic approaches describe the handwriting trajectory by the chronological evolution of its dynamic and / or geometric characteristics to extract global information, visual code [9] or to compare it to a probabilistic states graph model. In this context we cite first the delta – lognormal model developed by Plamondon et al [3] and the Beta model of Alimi et al [1],[2] that model the trajectory curvilinear velocity as the result of a series of overlapped neuromuscular impulses. Other approaches combine geometric and dynamic characteristics such as the Beta – elliptical model of Bezine et al [5] allowing to model the handwriting trajectory in its both profiles speed and trace, respectively by superposition of beta impulses and concatenation of elliptical arcs.

In contrast, the graphical approaches do not use the velocity profile modeling which is sensitive to changes in conditions and styles of writing. Indeed, these approaches treat the path as a string of graphic symbols called graphemes. For this, they undertake a first detection of particular points on the cursive handwriting trajectory prior to the segmentation of its draw. For examples Hollerbach and Higgins [6] use the inflection, cusp and spatial extremum points for Latin handwriting trajectory segmentation.

978-0-7695-4774-9/12 $26.00 © 2012 IEEE
DOI 10.1109/ICFHR.2012.244

The advantage of the analytical approaches is the division of the recognition problem of a word into several complementary sub - problems of graphemes or characters recognition. This makes analytical approaches adapted to the problems of word recognition in very large or even opened vocabulary context. As examples of a system adopting an analytical approach with external segmentation we mention that proposed by Menier [7] for online Arabic handwriting which consists of two modules: the first is a classifier of segmented graphic shapes. The second is a module for generating lexical composition that uses a genetic algorithm for optimization.

For the online Arabic handwriting systems, Baseline detection is a step principally used for delay strokes detection or removal [8] [14] or character segmentation and features extraction [10] [11]. Moreover, many segmentation techniques are involved in such systems and they were discussed by Abuzaraida et al. [15].

Izadi et al. [16] decompose the signal into convex/concave segments representing elementary shapes. In order to avoid finding segments of very short lengths, a threshold is applied on the segment curve length representing the sum of the lengths of the piecewise linear segments which construct the curve. Daifallah et al. [17] present an algorithm that works on strokes and segments them into letters by four stages: arbitrary segmentation, segmentation enhancement, connecting consecutive joints and finally locating segmentation points. Eraqi and Abdelazeem [8] segment the pseudo - words in graphemes based on the detection of significant points and inspecting the local writing direction. Sternby et al. [18] invoke segmentation technique based on the principle of Frame Deformation Energy, where each stroke is subdivided into segments based on the orthogonal direction of the writing direction using a set of heuristic rules.

In order to have better recognition accuracy, Liwicki et al [19] propose to not only use one recognition classifier but to combine several individual recognition systems based on hidden Markov models (HMMs) and bidirectional long short-term memory networks (BLSTM). Schenk et al [20] use the Viterbi algorithm to identify script lines and then to normalize the skew and size of the text lines reducing the confusions between characters differing in size rather than in shape. Ahmed and AbdelAzeem [4] presents on-line Arabic handwriting modeling and recognition system using also a state graph models such as HMMs.

Although graphical approaches do not use dynamic characteristics (speed, acceleration), the fact remains that they exploit parameters that directly depend on the chronological ordering of the trajectory points. But the chronological scheduling of handwriting trajectory strokes can completely change from a writing style to another [21], affecting then significantly the relevance of the extracted on-line parameters. Yet the shapes of graphemes obtained at the end of the word tracing appear similar. Hence the need and advantage that may result in a multi – writers context from the integration of Off-line features to enhance the generalization power of the parametric model.

III. Graphemes Segmentation and Basic Online Features Extraction

A. Baseline detection algorithm

The developed baseline detection process consists of two stages: The first one permits the detection of sets of trajectory points of nearly aligned neighbourhood. For this, we detect first a starting set of trajectory points verifying a low tangent inclination angle α_{tgM}. The starting set $\{M\}_{Str}$ is then decomposed in *q* groups of points, $\{M\}_{1,\ldots,q}$, by affecting a point candidate $M_k \in \{M\}_{Str}$ to the already constituted group $\{M\}_m$ which minimizes the average sum of the absolute deviation angles $\Delta\alpha_{k,i}$ and $\Delta\alpha_{i,k}$ between the direction of the interpolation segment (M_k, M_i) and the trajectory tangent directions at the respective points M_k et M_i, for all points members $M_i \in \{M\}_m$:

$$\begin{aligned} &\Delta\theta_{M_k}(m) = \underset{n=1,\ldots,q}{\mathrm{Min}}\left\{\Delta\theta_{M_k}(n)\right\} \\ &\textit{with}: \quad \Delta\theta_{M_k}(n) = \frac{1}{N_n}\cdot\sum_{M_i\in\{M\}_n}\left\{\Delta\alpha_{k,i} + \Delta\alpha_{i,k}\right\} \end{aligned} \tag{1}$$

The baseline detection, at this stage of the treatment, consists in looking for the most numerous group among the constituted sets of points.

The second stage of the algorithm involves an assessment function S for the first three most extended set of points (of which the probability that one of them carries the baseline is ≈ 100%) in order to optimize the baseline detection result (see Figure 1). This cost function excels the size of the set of points (*npt*) and penalize:

- The average angle $\theta_{\cap\_bl}$ of intersection between the upward trajectory and the assumed baseline.
- The average angle $\theta_{m\_|Curv|}$ of absolute curvature of the graphemes segmented respect to the assumed baseline.
- The bending on the left (*bbl*) of the centroide of the set of contact between continuous handwriting stroke *COHS* (handwriting trajectory limited between pen – down and pen – up moments) and the assumed baseline respect to the horizontal limits of their bounding box [10][11].

$$S = (\alpha_1 \cdot npt) - (\alpha_2 \cdot \theta_{\cap\_bl}) - (\alpha_3 \cdot \theta_{m\_|Curv|}) - (\alpha_4 \cdot bbl) \tag{2}$$

The coefficients α_1, α_2, α_3, and α_4 of the assessment function are estimate by ADALINE network simple layer trained according to the 'least mean square error' on a training set of manually classified baselines [10],[11] as follows :

S = 1 if the set of points handles the true baseline

S = -1 if not.

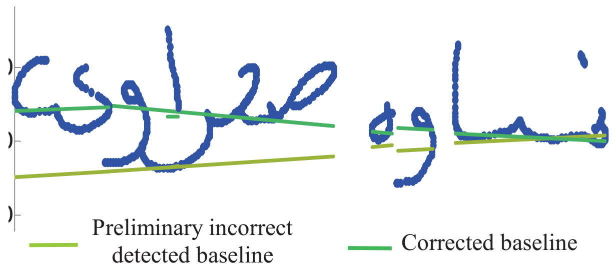

Figure 1. Example of baseline correction result

B. Handwriting graphemes segmentation

The segmentation of the Arabic pseudo – words in graphemes is based on the detection of two types of topologically particular points M_{PP} [10] , [11] (see Figure 2):

- Bottom of the ligature valleys: the trajectory point verifying a local baseline most near point with a trajectory tangent parallel to the baseline direction.
- Angular points: the point representing the extremum of a vertical shaft trajectory turning back.

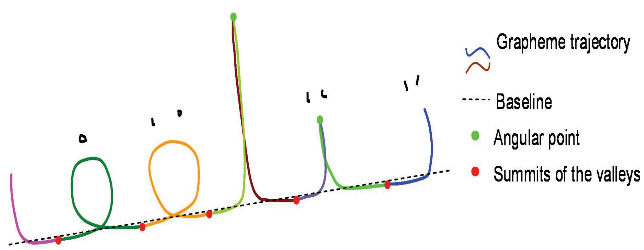

Figure 2. The detected topologic particular points M_{tm}

Each handwriting segment limited between two successive particular points M_{PP} or trajectory end points: points of trajectory starting (pen – down) or ending and (pen – up), represents a basic handwriting shape called grapheme.

C. Basic on-line features extraction for handwriting graphemes modeling

The basic features vector extracted to model the segmented graphemes trajectories is an association of Fourier descriptors and geometric parameters for extremum trajectory location.

To extract the Fourier descriptors modeling the grapheme trajectory, we defined first the signature $\theta_i = f(\ell_i)$ marking the variation of the inclination angle θ_i of the grapheme trajectory tangent at a point Mi according to its curvilinear abscissa ℓ_i:

$$\ell_i = \sum_{j=1}^{i} dL_j \quad , \quad L_{Total} = \ell_{graphme\ end} \tag{3}$$

where dLi is the elementary curvilinear distance between the current point Mi and its previous : $dL_i = \|M_i\, M_{i-1}\|$ for $i > 1$ and $\ell_1 = dL_1 = 0$

We calculate then the coefficients a0, aj and bj for j=1,…,k of the Fourier series that approximates the function $\theta_i = f(\ell_i)$, at the kth harmonic. The optimal number of harmonics k is estimated experimentally to k=8 .

The other geometric parameters permit to locate The positions of 3 reference points M_1, M_n and M_i in their grapheme bounding box and to determine the slant angles θ1, θi, and θn, of their trajectory tangents.

The considered points reference marks are :

- The starting point of the grapheme trajectory M_1 .
- The point of arrival M_n .
- The point corresponding to the absolute minimum of curvature radius $M_i \in \left]M_1 , M_n\right[$.

IV. INTEGRATION OF OFF-LINE FEATURES IN THE GRAPHEME MODEL

In its basic form, the features vector is composed of parameters that depend directly on the chronological ordering of the trajectory segment drawing which depends also on the writer handwriting style. To overcome this weakness effect especially in in a multi – writers context we propose to integrate Off-line features aiming to enhance the generalization power of the parametric model.

A. Off-line fuzzy templates of graphemes

The fuzzy template of a segmented grapheme constitutes a matrix of trajectory density rates R_{ds} measured in (n x m) cells of the grapheme bounding box (see Figure 3 and 4). Each cell admits a specific rectangular area and a neighborhood rectangular area shared with its 8 nearby cells. First, we measure for each cell, the length l_S of the trajectory segment included in the specific area that we added the trajectory length l_N included in the neighborhood area weighted proportionally to the inverse of the minimum distance d_{min} between trajectory and cell center. Then we compute the rate R_{ds} of trajectory density correspondent to each cell :

$$R_{ds} = \frac{l_S + \left(\frac{1}{d_{min}} \cdot \frac{L_V}{m} \cdot l_N \right)}{\sqrt{\left(\frac{L_H}{n}\right)^2 + \left(\frac{L_V}{m}\right)^2}} \tag{4}$$

where L_H and L_V represent respectively the horizontal and vertical dimensions of the grapheme bounding box (see Figure 3 and Figure 4).

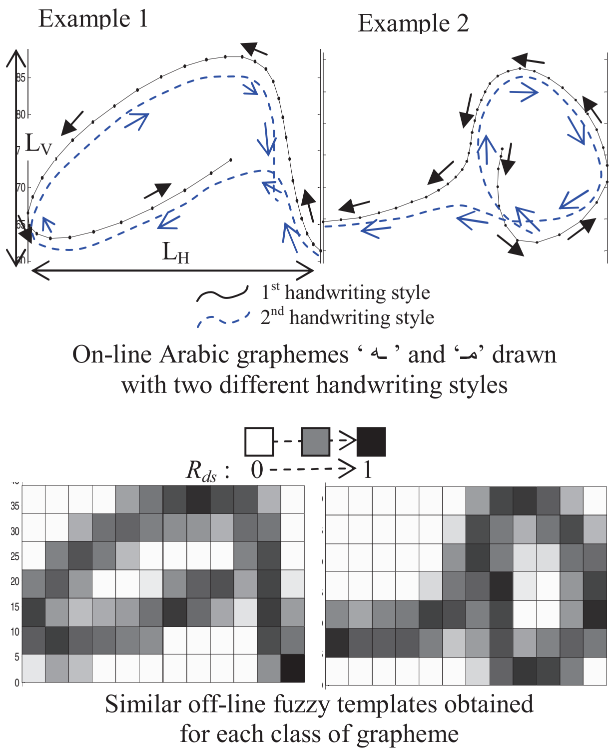

Figure 3. Fuzzy template of the Arabic segmented graphemes ' ـهـ ' and 'ـمـ' estimated for different handwriting styles

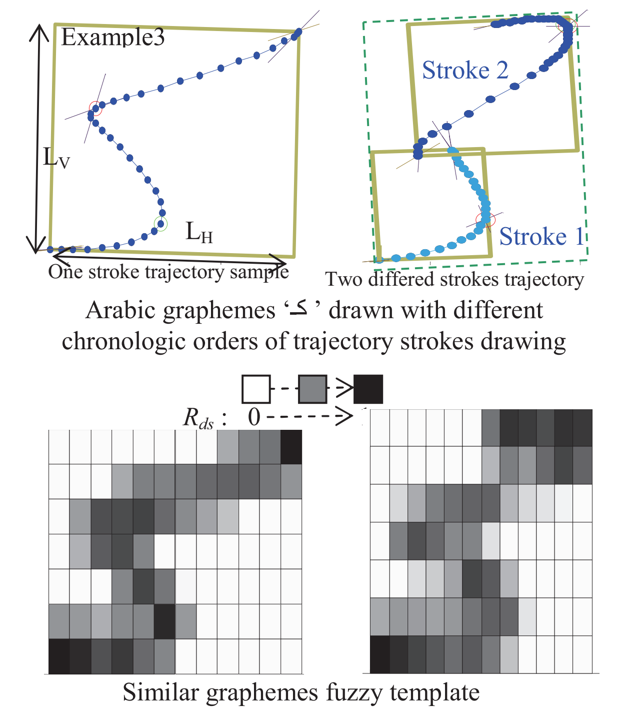

Figure 4. Fuzzy template of the Arabic segmented graphemes 'ک' estimated for different chronologic order of trajectory strokes drawing

The choice of the fuzzy template resolution (*n* x *m*) is a compromise between precision and generalization. Indeed, when this resolution is properly adjusted, the template allows the distinction of the different classes of graphemes. However, when the template resolution increases further the obtained function $R_{ds}(i, j)$ become more specific to its antecedent grapheme sample. Thus, we conduct experimental tests to estimate the optimal fuzzy template resolution respectively ***n*** in the horizontal direction and ***m*** in the vertical direction. First we initialize ***m*** = 10 , and calculate the average difference ΔR_{ds_Av} between the fuzzy template of a grapheme test sample and those of a base of 100 other grapheme samples from the same class.

$$\Delta R_{ds\_Av} = \text{Average}\left\{\sum_{i}^{n}\sum_{j}^{m}\left|R_{ds\_G1}(i,j) - R_{ds\_G2}(i,j)\right|\right\} \tag{5}$$

$$\text{for } R_{ds\_G1}(i,j) \neq 0 \text{ and } R_{ds\_G2}(i,j) \neq 0$$

The experiment was repeated by varying the horizontal resolution ***n*** from 1 to 20 for 49 different classes of graphemes in different positions on the word (isolated , beginning , middle and end). The curve representing the variation of the ΔR_{ds_Av} average result respect as a function of ***n*** shows that the optimal template horizontal resolution giving more information and minimizing ΔR_{ds_Av} is ***n*** = 12 (see Figure 5).

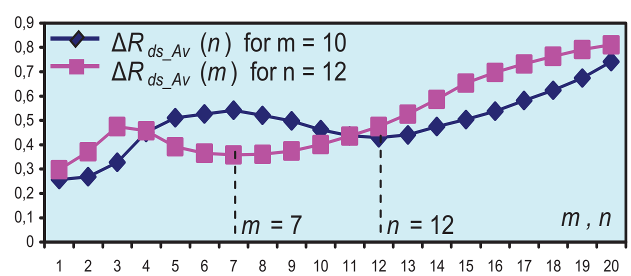

Figure 5. Estimation of the optimal horizontal and vertical resolution *n* and *m* of the grapheme Fuzzy template which minimise ΔR_{ds_Av}

Similarly, the optimal vertical resolution **m** of the grapheme fuzzy template is estimated by calculating ΔR_{ds_Av} for values of **m** ranging from 1 to 20 and while fixing **n** = 12. The selected value of **m** = 7 corresponds to a local minimum of ΔR_{ds_Av} that guarantees significant information about the grapheme drawing (see Figure 5).

B. Adapted geometric moments invariants

The geometric moments $m_{p,q}$ are one of the most accurate techniques to model the geometric properties of continuous two-dimensional functions $f(\mathrm{x}, \mathrm{y})$.

$$m_{p,q} = \iint \mathrm{x}^p \cdot \mathrm{y}^q \cdot f(\mathrm{x}, \mathrm{y}) \cdot \mathrm{dx} \cdot \mathrm{dy} \qquad (6)$$

In their discrete form, they are used to describe the properties of the spatial distribution of pixels characteristics (intensity and color) in an image $\mathrm{I}(\mathrm{x}, \mathrm{y})$. The general formula of discrete geometric moments is given by the following:

$$m_{p,q} = \sum_{\mathrm{y}=1}^{\mathrm{n}} \sum_{\mathrm{x}=1}^{\mathrm{m}} \mathrm{x}^p \cdot \mathrm{y}^q \cdot \mathrm{I}(\mathrm{x}, \mathrm{y}) \qquad (7)$$

When a handwriting word is completed, a complete image of the off-line drawing incorporate on the bounding box of each one of its graphemes is constituted. However all points of this image is not sampled at fixed intervals dx and dy respectively in the horizontal and vertical direction as this set of points is the result of a temporal sampling (see Figure 6).

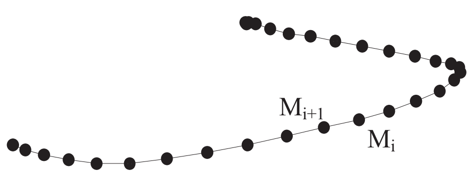

Figure 6. Variation of the horizontal and vertical intervals between the successive points of an on-line handwriting trajectory

This variable intervals between image points is in contradiction with the conditions of approximation allowing the passage from the continuous form (6) of geometric moments to the discrete one (7) for the computing of the grapheme geometric moments. We considered two options to avoid this problem. The first is to resample the grapheme trajectory on a grid of points with regular intervals of coordinates dx and dy. This procedure generates a rough picture of grapheme trajectory whose accuracy is proportional to its resolution and therefore its cost in computation time. The second solution is to consider the continuous aspect of the trajectory by performing a linear interpolation of its points. Applying the continuous formula (6) of geometric moments computing on the line segment between two successive points $\mathrm{M}_{\mathrm{i}}(\mathrm{x}_{\mathrm{i}}, \mathrm{y}_{\mathrm{i}})$ and $\mathrm{M}_{\mathrm{i+1}}(\mathrm{x}_{\mathrm{i+1}}, \mathrm{y}_{\mathrm{i+1}})$ of the grapheme trajectory we get:

$$m_{p,q}\left[\mathrm{M}_{\mathrm{i}}\mathrm{M}_{\mathrm{i+1}}\right] = \int_{\mathrm{y}_{\mathrm{i}}}^{\mathrm{y}_{\mathrm{i+1}}} \int_{\mathrm{x}_{\mathrm{i}}}^{\mathrm{x}_{\mathrm{i+1}}} \mathrm{x}^p \cdot [a \cdot \mathrm{x} + b]^q \cdot \mathrm{dx} \cdot \mathrm{dy} \qquad (9)$$

where $a = \dfrac{\mathrm{y}_{\mathrm{i+1}} - \mathrm{y}_{\mathrm{i}}}{\mathrm{x}_{\mathrm{i+1}} - \mathrm{x}_{\mathrm{i}}}$ and $b = \mathrm{y}_{\mathrm{i+1}} - (a \cdot \mathrm{x}_{\mathrm{i+1}})$

The calculation of geometric moments of the entire grapheme drawing is obtained by the sum of the moments of the N_S line segments $\left[\mathrm{M}_{\mathrm{i}}\mathrm{M}_{\mathrm{i+1}}\right]_{\mathrm{i}=1,\dots,Ns}$ that compose, whether performed in a single pen down tracing or separated by pen up. The commutativity of this sum proves that the result is independent of the chronological order of stroke drawing.

$$\begin{aligned} m_{p,q} &= \sum_{\mathrm{i}=1}^{Ns} m_{p,q}\left[\mathrm{M}_{\mathrm{i}}\mathrm{M}_{\mathrm{i+1}}\right] \qquad (10) \\ &= \sum_{\mathrm{i}=1}^{Ns} \int_{\mathrm{y}_{\mathrm{i}}}^{\mathrm{y}_{\mathrm{i+1}}} \int_{\mathrm{x}_{\mathrm{i}}}^{\mathrm{x}_{\mathrm{i+1}}} \mathrm{x}^p \cdot [a \cdot \mathrm{x} + b]^q \cdot \mathrm{dx} \cdot \mathrm{dy} \\ &= \sum_{\mathrm{i}=1}^{Ns} (\mathrm{y}_{\mathrm{i+1}} - \mathrm{y}_{\mathrm{i}}) \cdot \Bigg[\sum_{k=0}^{q} (\text{-}1)^k \cdot \frac{\mathrm{a} \cdot p! \cdot k!}{(p+k)! \cdot q!} \cdot \\ &\quad \cdot \left[\left(\mathrm{x}_{\mathrm{i+1}}^{p+k} \cdot (\mathrm{a} \cdot \mathrm{x}_{\mathrm{i+1}} + \mathrm{b})^{q-k}\right) - \left(\mathrm{x}_{\mathrm{i}}^{p+k} \cdot (\mathrm{a} \cdot \mathrm{x}_{\mathrm{i}} + \mathrm{b})^{q-k}\right)\right] \Bigg] \end{aligned}$$

For each segmented grapheme, the modeling system extracts the first sixteen geometric moments invariants that represent the drawing incorporation on its delimited bonding box and integrate them in its correspondent features vector.

C. On-line and Off-line features combination

The new extracted off-line parameters are introduced in the grapheme features vector to improve its discriminative power. Thus, the new feature set includes a combination of 138 parameters representing two groups: The first contains 17 Fourier descriptors and 21 geometric parameters of extremum point's location, describing the direction of chronological development of the trajectory. The second group consists of 87 parameters of the off-line fuzzy template and 16 geometric moments invariants that describe the density distribution of the drawing on the area limited by the horizontal grapheme bounds independently of its chronological order which depends on the writing style.

V. TESTS AND RESULTS

In the evaluation phase, we applied the system on the online database ADAB [12], [13] which includes 937 labels of online Tunisian names towns acquired in a total of 33146 samples. The modeling system uses a grapheme crisp segmentation approach and the classifier module is based on Hidden Markov Models implemented through the 'HTK' Toolkit. The used HMMs are of 'left to right' discrete type. The size of the codebook is 256. The three first sets of the ADAB database are used in the training phase, while the fourth is used as a test set. The following table (see Table 1) presents the recognition results obtained by the system before and after integrating the off-line features fuzzy template and geometric moments invariants in the grapheme features vector:

TABLE I. RECOGNITION RATE OBTAINED ON THE ADAB DATABASE BEFORE AND AFTER INTEGRATING OFF-LINE FEATURES

System version		Basic Version	Version integrating off-line features
Training set n°1	Top 1	88.40	91.15
	Top 5	97.93	99.26
Training set n°2	Top 1	85.17	89.54
	Top 5	97.05	89.84
Training set n°3	Top 1	83.76	89.27
	Top 5	95.28	98.61
Test set	Top 1	81.37	87.24
	Top 5	92.25	97.82

The comparison between the results of the two versions shows an improvement in the discriminating power of the system due to the consolidation of the features vector by the integration of the proposed off-line parameters.

VI. CONCLUSION

We have presented in this paper an experiment study proving the improvement result of the integration of off-line parameters in the features vector of an on-line handwriting modeling system based on grapheme segmentation. Indeed, in a multi-writers context, the introduction of off-line parameters graphemes permits to assimilate the writing style variation and the chronologic order change of grapheme strokes handwriting from one writer to another. Two groups of off-line parameters are extracted for each segmented grapheme : the first one constitutes the drawing density rates on the different cells of a grapheme fuzzy template. The second represents the geometric moments invariant of the drawing delimited by the grapheme bounding box which are computed by a tailored formula to a continuous drawing line to compensate the irregular spatial sampling of the online handwriting trajectory points. As continuity to this work, we project to adapt the off-line parameters extraction to the result of the fuzzy grapheme segmentation approach.

ACKNOWLEDGMENT

The authors acknowledge the financial support of this work by grants from the General Direction of Scientific Research and Technological Renovation (DGRST), Tunisia, under the ARUB program 01/UR/11/02.

REFERENCES

[1] A. M. Alimi, “Evolutionary neuro-fuzzy approach to recognize on-line Arabic handwriting,” Proceedings of the Int. Conf. on Document Analysis and Recognition, ICDAR, 1997, Volume 1, pp 382-386I.

[2] A. M. Alimi, “Evolutionary computation for the recognition of on-line cursive handwriting ,” IETE Journal of Research, Vol. 48, Issue 5 Spec., September 2002, pp. 385-396.

[3] R. Plamondon, A. M. Alimi, “Speed/accuracy trade-offs in target-directed movements,” Behavioral and Brain Sciences Volume 20, Issue 2, 1997, pp. 279–349.

[4] H. Ahmed, S. AbdelAzeem, “On-line Arabic Handwriting Recognition System based on HMM,” in Proc. of the 11th Inter. Conf. Document Analysis and Recognition ICDAR, 2011, Beijing, pp 1324-1328.

[5] H. Bezine, A.M. Alimi, and N. Derbel “An Explanation for the feature of a Handwriting Trajectory Movement ontrolled by a Beta Elliptic Model”, Proc. 7th Int. Conf. ICDAR’03, Edinburgh, UK, Aug., 2003, pp. 1228-1232.

[6] C. A. Higgins and R. Whitrow, "On-line cursive script recognition," in Proc. Interact'84, 1st IFIP Conf. Human Computer Interaction, Sept. 1984, pp. 140-144.

[7] G. Menier, G. Lorette, P. Gentric, IRISA, Rennes. “A new modeling method for on-line handwriting recognition,” Proc. of the Third International conf. on Document Analysis and Recognition, 1995, pp. 499-503.

[8] H. Eraqi and S. Abdelazeem, “An On-Line Arabic Handwriting Recognition System Based on a new On-line Graphemes Segmentation Technique,” in Proc. of the 11th International Conf. on Document Analysis and Recognition ICDAR, October 2011, Beijing, China, pp. 409-413.

[9] M. Kherallah, F. Bouri, And A. M. Alimi, “On-Line Arabic Handwriting Recognition System Based On Visual Encoding And Genetic Algorithm,” Engineering Applications of Artificial Intelligence,Vol.22, 2009, pp. 153–170.

[10] H. Boubaker, A. Elbaati, M. Kherallah, H. Elabed, and A.M. Alimi. “Online Arabic Handwriting Modeling System based on the Graphemes Segmentation,” the 20th International Conference on Pattern Recognition ICPR 2010, Istanbul, Turky , pp. 2061-2064.

[11] H. Boubaker, A. Chaabouni, M. Kherallah, H. El Abed, A. M. Alimi. “Online Fuzzy Segmentation and Graphemes Modeling for Online Arabic Handwriting Recognition,” The International Conf. on Frontiers of Handwriting Recognition ICFHR 2010, Kolkata, India.

[12] E. Grosicki, H. El Abed, ICDAR 2009 Handwriting Recognition Competition , ICDAR10th 2009 Barcelona pp 1398 – 1402.

[13] H. El Abed, M. Kherallah, V. Märgner, A. M. Alimi, “On-line Arabic handwriting recognition competition - ADAB database and participating systems,” IJDAR 14(1), 2011, pp 15-23

[14] R. I. Elanwar, M. A. Rashwan, and S. A. Mashali, "Simultaneous segmentation and recognition of Arabic characters in an unconstrained on-line cursive handwritten document", Proceedings of World Academy of Science, Engineering and Technology (WASET), vol. 23, International conference on Machine learning and Pattern Recognition MLPR2007, Germany, August 2007 , pp. 288-291.

[15] M. A. Abuzaraida and A. M. Zeki, "Segmentation Techniques for Online Arabic Handwriting Recognition: A Survey". Proceeding 3rd International Conference on ICT4M 2010.

[16] S. Izadi, M. Haji, Ching Y. Suen, “A New Segmentation Algorithm for Online Handwritten Word Recognition in Persian Script” , ICHFR 2008, pp 1140-1142.

[17] K. Daifallah, N. Zarka, H. Jamous, “Recognition-Based Segmentation Algorithm for On-Line Arabic Handwriting.” Proc. of the Int. Conf. on Document Analysis and Recognition, ICDAR 2009, Barcelona, Spain, July 2009, pp. 877–880.

[18] J. Sternby, J. Morwing, J. Andersson, C. Friberg “On-line Arabic handwriting recognition with templates”, Pattern Recognition Journal, Volume 42, Issue 12, New Frontiers in Handwriting Recognition December 2009, pp. 3278-3286

[19] M. Liwicki and H. Bunke, "Combining diverse on-line and off-line systems for handwritten text line recognition ", Pattern Recognition, Volume 42, Issue 12, New Frontiers in Handwriting Recognition, December 2009, pp. 3254-3263.

[20] J. Schenk, J. Lenz, and G. Rigoll. “Novel script line identification method for script normalization and feature extraction in on-line handwritten whiteboard note recognition.” Pattern Recognition Journal, Volume 42, Issue 12, New Frontiers in Handwriting Recognition, December 2009, pp.3383–3393

[21] A. Chaabouni, H. Boubaker, M. Kherallah, A. M. Alimi, H. El Abed, “Combining of Off-line and On-line Feature Extraction Approaches for Writer Identification,” in proceeding of ICDAR 2011, Beijing china, pp 1299-1303