Fuzzy Segmentation and Graphemes Modeling for Online Arabic Handwriting Recognition

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Abstract—In this paper we present a new modeling approach for online Arabic handwriting which is based on fuzzy graphemes segmentation. In the literature, the result of the graphemes segmentation of a cursive writing not often reaches its optimum. This fact is due to the crisp aspect of the segmentation decision. In order to overcome this problem, we propose to introduce a fuzzy effect in this segmentation decision by overlapping the segmented graphemes in proportion to the confidence degrees associated with the detection of the particular points that separate them. The fuzzified boundary shapes of the extracted fuzzy graphemes are then modeled taking into account the coefficient of fuzzy membership of their points. The obtained results by using the ADAB database show an improvement of the recognition rate given by the fuzzy segmentation approach compared to the crisp one.

Keywords—Fuzzy segmentation; online handwriting; baseline detection; graphemes; Fourier descriptors;

I. INTRODUCTION

The cursive or semi-cursive handwriting such as Arabic and Latin represent concatenations of a limited number of basic graphic forms called graphemes [1, 2, 3, 12, 14]. The graphemes can represent whole characters or pseudo characters [5, 10, 13]. Their sequence verifies topologic rules that relate to their alignment and interconnection. In other words, these rules can be used to segment the cursive script in its basic components: the graphemes. However, these rules are subject to much variability from one writer to another and even for the same writer. Thus, the graphemes segmentation approaches have always suffered from the non-regularity of segmented trajectory due mainly to errors in estimating the baseline and / or to the variability in the observation of the concatenation rules.

Aimed to overcome this problem, we proposed a new approach of Arabic online handwriting modeling based on fuzzy graphemes segmentation. First we detect the baseline of the treated line handwriting script. Then the segmentation module extracted two types of particular points of fragmentation: the bottom of the valleys close to the baseline and the vertical angular points. A fuzzy effect is introduced in this segmentation decision by overlapping the segmented graphemes in proportion to the confidence degree DC associated to the particular points that separate them. The shapes with fuzzified boundary of the extracted fuzzy graphemes are then modeled by a Fourier descriptors features set. We apply the system on the ADAB database [7] of online Tunisian town names using the HTK, HMM Toolkit as classifier module.

We will present successively in the three following sections of this paper the different modules of the segmentation and modeling process before ending up presenting the experimental results.

II. BASELINE DETECTION MODULE

The baseline detection is an essential stage in a grapheme segmentation process of a cursive or semi-cursive handwriting [4, 8, 9, 10].

The developed baseline detection process consists of two stages: The first one is a basic stage permitting the detection of groups of points of aligned neighbourhood. For this, we inspect the alignment and the tangent direction accuracy of each current point \( M_k \) according to the elements of the points regrouping to which it is a candidate element, using two criteria:

- Validation criterion :

A point candidate \( M_k \) can be assigned to the points regrouping \( \{ M \} \) if it verifies:

\[
\forall M_{n,i} \in \{ M \}, \text{we have } \Delta \alpha_{i,k} + \Delta \alpha_{k,i} < \Delta \alpha_{\text{lim}} \text{ (cl)}
\]

With \( \Delta \alpha_{\text{lim}} \) is the tolerance limit of the absolute deviation angles between the trajectory tangents. And:

\[
\Delta \alpha_{i,k} = \alpha_{n,g_{M_{n,i}}} - \text{ the slant angle of the direction } (M_{n,i}, M_k)
\]

\[
\Delta \alpha_{k,i} = \alpha_{g_{M_k}} - \text{ the slant angle of the direction } (M_{n,i}, M_k)
\]

(See Fig. 1)

Verification of the trajectory neighborhoods alignment.

Figure 1.
- Affectation criterion:
A point candidate $M_k$ verifying the validation conditions (cI) to several regroupings $\{M\}_m$, is assigned to the regrouping of index $m$: $\{M\}_m$ where agrees best its trajectory tangent direction with those of the other members as well as with the directions of interpolation ($M_k, M_m$) in accordance with the following criterion (cII):

$$\Delta \theta_{M_k}(n) = \text{Min} \left\{ \Delta \theta_{M_k}(n) \right\}_{n=1,...,q}$$

with:

$$\Delta \theta_{M_k}(n) = \frac{1}{N_n} \cdot \sum_{i \in \{M\}_m} \Delta \alpha_{i,k}$$

Where $N_n$ is the initial size of the $\{M\}_m$ regrouping and $m \in \{1, ..., q\}$.

A new points regrouping is initialized when the point candidate $M_k$ is not included in any already constituted regrouping.

The baseline detection at this stage, consist in looking for the most numerous regrouping among the points regroupings that are constituted (see Fig. 2).

![Figure 2. constitution of the points regroupings.](image)

The examination of baseline detection errors shows that they are classified in two cases [16]:
- Confusion of the baseline with the lower limit line for the cases of words composed essentially or exclusively of isolated character or of legs as ‘، ‘، ‘، ‘ (example see Fig. 3).
- Confusion of the baseline with the median zone line, or the superior limit line, due to the writing style or to the presence of particular calligraphic effects.

![Figure 3. Examples of baseline detection errors.](image)

To discern and to treat the baseline detection errors we opted for a function of assessment considering the first three most extended in order to optimize the detection result. This cost function excels the size of the points regrouping (npt) and penalize:

- The average angle $\theta_{\alpha,bl}$ of intersection between the upward trajectory and baseline.
- The average angle $\theta_{m,\text{Curv}}$ of graphemes absolute curvature.
- The bending on the left (bbl) of the barycentre of the set of contact points between segmented graphemes and baseline (see Fig. 3).

The function of assessment $S$ is assimilated to the output of an ADALINE network simple layer trained according to the 'least mean square error' rule.

Fig. 4 shows the result of the correction step of the baseline detection error obtained in Fig. 3.

![Figure 4. Example of baseline correction (green).](image)

III. THE CRISP GRAPHEME SEGMENTATION

A grapheme is a distinctive unit of the handwriting that represent a whole character or a section of its tracing. Example: several Arabic characters as ‘، ‘، ‘، ‘ include one or several graphemes named 'nabra' ‘،

A. Particular Points Detection

The segmentation of the Arabic pseudo – words (PAW) in graphemes is based on the detection of two types of topologically significant points $M_{PP}$ [16] (see Fig. 5):

- The bottom of the valleys: the point of an inter – grapheme ligature adjoining the baseline with a horizontal tangent.
- The angular points: the extremum point of a vertical trajectory turn back.

![Figure 5. The topologically significant points and graphemes segmentation.](image)

Each points $M_{im}$ of minimum slant of trajectory tangent, (which corresponds to a local minimum $\Delta \alpha$ of the absolute tangent deviation angle respect to the baseline), is considered as a particular point candidate $M_{PP}$. It will be kept as an $M_{PP}$ if it verifies the following topologic crisp conditions:

$$R_{\Delta y} = \frac{\Delta y}{h_{ZM}} < \frac{1}{2} \quad (3)$$

$$\Delta \alpha < \frac{\pi}{6}$$

$$\text{Dev} \theta_{\text{med}} = \frac{\theta_{\text{med}} - \frac{\pi}{2}}{\frac{\pi}{6}} < \frac{\pi}{6} \quad (4)$$

Where $R_{\Delta y}$, is the the normalized ratio that represents the position of the point $M_{im}$ respect to the baseline. $\Delta y$ is the distance between $M_{im}$ and the baseline. $h_{ZM}$ is the width of the median zone. $\Delta \alpha$ is the deviation angle of the tangent on
the $M_m$ respect to the baseline. $\Delta \theta$ is the deviation angle between the tangents direction $D_{tg}^-$ and $D_{tg}^+$ on the respective neighborhoods before and after the $M_m$ point. And $Dev_{med}$ is the deviation angle respect to the vertical of the median between $D_{tg}^-$ and $D_{tg}^+$. (see Fig. 6).

\[ |\theta_{med} - (\pi/2)| = Dev_{med} \]

\[ b/ \text{Case of a bottom of a ligature valley} \]
\[ a/ \text{Case of a vertical angular point} \]

\section*{B. Weakness of the crisp grapheme segmentation approach}

In a multi-writer context, the crisp aspect of the particular points detection criteria (3) and (4) may induce local segmentation errors which result in the fraction of a basic grapheme or in the fusion of two others (see Fig. 7).

\[ a/ \text{Fusion of the graphemes ‘١’, ‘١’ and ‘١’} \]
\[ b/ \text{Fraction of the grapheme ‘١’} \]

\section*{IV. THE FUZZY GRAPHEME SEGMENTATION}

\subsection*{A. Principle}

To overcome the problems introduced by the crisp thresholding segmentation, which lead the merger or the fraction of the basic graphemes, we propose to adopt a fuzzy segmentation of overlapped graphemes. In this approach we associate to each particular point candidate $M_m$ a fuzzy degree of confidence $D_C$ between 0 and 1 estimated by a fuzzy inference system. The rate of overlap of two adjacent graphemes depends on the confidence degree $D_C$ associated to the particular point candidate $M_m(i)$ separating them (see figure 9). The overlap is minimal when $D_C$ tends to 1 or 0. In the first case ($D_C \to 1$), the separation between the two graphemes is sharp and tends to tight around the particular point candidate $M_m(i)$. In the second case ($D_C \to 0$), the shortest of the two graphemes tends to shrink by merging in the longer one. Conversely, when the confidence level is medium ($D_C = 0.5$), the overlap of two successive graphemes is maximal. The longer of the two graphemes tends to spread by overlap compared to the shortest one.

In addition to the effect of overlapping graphemes, the new segmentation strategy introduces a degree of fuzzy membership $D_\mu$ variable between 0 and 1 in the definition of points of a segmented grapheme. The value of the fuzzy membership degree $D_\mu(i,j)$ of a point $M_i$ to the grapheme $G_j$ varies according to the position of this point relative to the fuzzy edges of the grapheme to where it belongs (see Fig. 12).

\subsection*{B. Fuzzy Estimation of Particular Points Confidence Degrees $D_C$}

The study of the graphemes segmentation problematic and the analysis of the errors obtained by its crisp version gave us the necessary expertise to develop a Fuzzy Inference System for estimating the confidence degree $D_C$ associated to a particular point candidate $M_m$. $D_C$ is calculated as the maximum of two degrees of confidence $D_{C1}$ and $D_{C2}$ estimating respectively that the point $M_m(i)$ is a back of a ligature valley or a vertical angular point (see Fig. 9).

\[ 1) \text{Fuzzy Estimation of the confidence Degree} D_{C1} \text{of a bottom of ligature valley} \]

The $D_{C1}$ fuzzy estimator includes three stages: fuzzification, inference and defuzzification.

The fuzzy confidence degree $D_{C1}$ associated to the assimilation of a particular point candidate $M_m$ to be a bottom of a ligature valley is based on two physical parameters: its vertical position relative to the baseline $R_{dy}$, and its tangent deviation angle $\Delta \alpha$ respect to the baseline direction. Each physical parameter is described by 5 linguistic variables $VL$: very low, $L$: low, $M$: medium, $H$: high, $VH$: very high (see Fig. 8 and Tab.1).
The basis of inference rules is obtained by statistical tests. It is extensive and covers all possible combinations of linguistic variables representing the two input features. This choice is due to the non-correlation of these variables.

Thus, for each couple of physical input parameters \( R_{\Delta y}, \Delta \alpha \) four rules are active. We use the ‘sum–prod’ method for the inference of each rule. Then we compute \( D_{C1} \) by applying the ‘weighted–sum’ method in the defuzzification step (see Fig. 10).

### Table I. Base of Inference Rules for \( D_{C1} \) Fuzzy Confidence Degree Estimation

<table>
<thead>
<tr>
<th>( D_{C1} )</th>
<th>( R_{\Delta y} )</th>
<th>VL</th>
<th>L</th>
<th>M</th>
<th>H</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \alpha )</td>
<td>VL</td>
<td>VH</td>
<td>VH</td>
<td>H</td>
<td>M</td>
<td>L</td>
</tr>
<tr>
<td>L</td>
<td>VH</td>
<td>H</td>
<td>M</td>
<td>L</td>
<td>L</td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>H</td>
<td>M</td>
<td>L</td>
<td>L</td>
<td>VL</td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>L</td>
<td>L</td>
<td>VL</td>
<td>VL</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VH</td>
<td>VL</td>
<td>VL</td>
<td>VL</td>
<td>VL</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Thus, for each couple of physical input parameters \( R_{\Delta y}, \Delta \alpha \) four rules are active. We use the ‘sum–prod’ method for the inference of each rule. Then we compute \( D_{C1} \) by applying the ‘weighted–sum’ method in the defuzzification step (see Fig. 10).

2) **Fuzzy Estimation of the confidence Degree \( D_{C2} \) associated to the vertical angular points:** The fuzzy estimator of \( D_{C2} \) degree is analog to that used for \( D_{C1} \). Its physical input parameters are: the deviation angle \( \Delta \theta \)
between the tangents to the neighborhood before and behind the point \( M_{im} \), and the absolute inclination angle \( \text{Dev} \theta_{\text{med}} \) of the mediator direction of these two tangents respect to the vertical. Each physical input parameter is also described by 5 linguistic variables (see Fig. 11 and Tab.3).

\[
\theta_{i} = \sum_{j=1}^{5} D_{\mu_{j}} \cdot dL_{i} \quad \text{Dev} \theta_{\text{med}} = \text{abs} \left( \frac{\Delta L}{\Delta \theta} \right)
\]

Then, we introduce (5)

\[
\begin{align*}
D_{\mu_{j}} &= \frac{1}{2 \cdot \pi} \cdot \sum_{i=1}^{k} \left( D_{\mu_{j}} \cdot \theta_{i} \right) \cdot \text{dL}_{i} \\
\theta_{i} &= \frac{j \cdot 2 \cdot \pi \cdot \ell_{i}}{L_{\text{total}}} \\
b_{i} &= \frac{1}{2 \cdot \pi} \cdot \sum_{i=1}^{k} \left( D_{\mu_{j}} \cdot \theta_{i} \right) \cdot \text{sin} \left( \frac{j \cdot 2 \cdot \pi \cdot \ell_{i}}{L_{\text{total}}} \right) \cdot \text{dL}_{i}
\end{align*}
\]

5 linguistic variables (vertical. Each physical input parameter is also described by the mediator direction of these two tangents respect to the particular points candidates \( M_{im} \) and the assignment of a fuzzy membership degree to each point of a segmented grapheme using the following model of membership function \( D_{\mu}(M_{i}) \) (see Fig. 12):

\[
\mu_{\Delta \theta}(\Delta \theta) = \begin{cases} 
1 & \text{if } 0 < \Delta \theta < \frac{\pi}{4} \\
L & \text{if } \frac{\pi}{4} \leq \Delta \theta \leq \frac{3 \pi}{4} \\
0 & \text{if } \Delta \theta > \frac{3 \pi}{4}
\end{cases}
\]

\[
\mu_{\text{Dev} \theta_{\text{med}}}(\text{Dev} \theta_{\text{med}}) = \begin{cases} 
1 & \text{if } 0 < \text{Dev} \theta_{\text{med}} < \frac{\pi}{8} \\
L & \text{if } \frac{\pi}{8} \leq \text{Dev} \theta_{\text{med}} \leq \frac{\pi}{4} \\
0 & \text{if } \text{Dev} \theta_{\text{med}} > \frac{\pi}{4}
\end{cases}
\]

Figure 11. Membership functions of \( \Delta \theta \) and \( \text{Dev} \theta_{\text{med}} \) input fuzzy sets.

**TABLE II. BASE OF INFERENCE RULES FOR \( D_{\mu} \) FUZZY CONFIDENCE DEGREE ESTIMATION**

<table>
<thead>
<tr>
<th>( D_{\mu_{2}} )</th>
<th>( \Delta \theta )</th>
<th>VL</th>
<th>L</th>
<th>M</th>
<th>H</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>VL</td>
<td>L</td>
<td>VL</td>
<td>VL</td>
<td>VL</td>
<td>VL</td>
<td>VL</td>
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<tr>
<td>L</td>
<td>M</td>
<td>L</td>
<td>L</td>
<td>VL</td>
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<td>M</td>
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<tr>
<td>VH</td>
<td>VH</td>
<td>VH</td>
<td>H</td>
<td>M</td>
<td>L</td>
<td>L</td>
</tr>
</tbody>
</table>

C. **Fuzzification of the Overlapped Boundary Edges of Graphemes**

The fuzzification of the start and end boundaries of graphemes expresses the confusion that an intelligent system can find in the delineation of their tighten borders. This fuzzification involves two steps: overlap of graphemes in proportion to the confidence degrees associated to the particular points candidates \( M_{im} \) and the assignment of a fuzzy membership degree to each point of a segmented grapheme using the following model of membership function \( D_{\mu}(M_{i}) \) (see Fig. 12):

\[
\mu_{\text{fuzz}}(x_{i}, y_{i}, D_{\mu}) = \begin{cases} 
1 & \text{if } \text{Dev} \theta_{\text{med}} < \frac{\pi}{8} \\
L & \text{if } \frac{\pi}{8} \leq \text{Dev} \theta_{\text{med}} \leq \frac{\pi}{4} \\
0 & \text{if } \text{Dev} \theta_{\text{med}} > \frac{\pi}{4}
\end{cases}
\]

**TABLE III. MEMBERSHIP OF THE OVERLAPPED BOUNDARY EDGES**

<table>
<thead>
<tr>
<th>( D_{\mu_{2}} )</th>
<th>( \Delta \theta )</th>
<th>VL</th>
<th>L</th>
<th>M</th>
<th>H</th>
<th>VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>VL</td>
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<td>L</td>
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<td>VL</td>
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<td>M</td>
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<tr>
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<td>VH</td>
<td>H</td>
<td>M</td>
<td>L</td>
<td>L</td>
</tr>
</tbody>
</table>

**V. FOURIER DESCRIPTORS FOR FUZZY GRAPHEMES MODELING**

Fourier descriptors represent one of the most accurate tools for closed contour modeling [17]. We adopted them to model the open forms of segmented graphemes and we adapted them to consider the fuzzy membership degree to the grapheme \( D_{\mu} \) of each point \( M_{i} \).

At first, the grapheme trajectory is represented by the signature \( \theta_{i} = f(\ell_{i}) \) marking the variation of the inclination angle \( \theta_{i} \) of the tangent at a point \( M_{i} \) according to its corresponding curvilinear abscissa \( \ell_{i} \). Then, we introduce the parameter \( D_{\mu} \) to modulate \( \theta_{i} \) variation according to the fuzzy membership degree of \( M_{i} : (D_{\mu_{j}} \cdot \theta_{i}) = f(\ell_{i}) \) where:

\[
\ell_{i} = \sum_{j=1}^{k} D_{\mu_{j}} \cdot dL_{i} \quad L_{\text{total}} = \sum_{j=1}^{k} D_{\mu_{j}} \cdot dL_{i}
\]

and the elementary curvilinear distance \( dL_{i} = ||M_{i}, M_{i+1}|| \), \( \ell_{i} = dL_{i} = 0 \).

We calculate then the coefficients \( a_{0}, a_{j} \) and \( b_{j} \) for \( j = 1, \ldots, k \) of the Fourier series that approximates, at the \( k^{th} \) harmonic, the function: \( (D_{\mu_{j}} \cdot \theta_{i}) = f(\ell_{i}) \)

\[
a_{0} = \frac{1}{2 \cdot \pi} \cdot \sum_{i=1}^{k} \left( D_{\mu_{j}} \cdot \theta_{i} \right) \cdot dL_{i} \\
a_{j} = \frac{1}{\pi} \cdot \sum_{i=1}^{k} \left( D_{\mu_{j}} \cdot \theta_{i} \right) \cdot \text{cos} \left( \frac{j \cdot 2 \cdot \pi \cdot \ell_{i}}{L_{\text{total}}} \right) \cdot dL_{i} \\
b_{j} = \frac{1}{\pi} \cdot \sum_{i=1}^{k} \left( D_{\mu_{j}} \cdot \theta_{i} \right) \cdot \text{sin} \left( \frac{j \cdot 2 \cdot \pi \cdot \ell_{i}}{L_{\text{total}}} \right) \cdot dL_{i}
\]

**Examples:**

\[a/\] Baseline detection, \( c/\) Fuzzy segmentation result.

Figure 13. Grapheme segmentation : a/ Baseline detection, b/ Crisp segmentation result, c/ Fuzzy segmentation result.
VI. EXPERIMENTS AND RESULTS

In the evaluation phase, we applied the system on the ADAB database [7] of 937 online Tunisian names towns written in 15158 samples. We used a classifier module based on Hidden Markov Models implemented through the ‘HTK’ Toolkit as described in [18]. The used HMMs are of ‘left to right’ discrete type. The size of the codebook is 256.

We obtained the following recognition results (see Tab.3) for three ameliorated versions of the system:

**Version 2**: crisp segmentation with adjusted filtering.
**Version 3**: fuzzy grapheme segmentation and adjusted filters.

<table>
<thead>
<tr>
<th>System version</th>
<th>ADAB Set 1</th>
<th>ADAB Set 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top 1</td>
<td>Top 5</td>
</tr>
<tr>
<td>Version 1</td>
<td>57.87</td>
<td>72.84</td>
</tr>
<tr>
<td>Version 2</td>
<td>75.24</td>
<td>88.67</td>
</tr>
<tr>
<td>Version 3</td>
<td>86.39</td>
<td>96.42</td>
</tr>
</tbody>
</table>

We note the successive improvement of the recognition rates in top 1 and top 5 with the adjustment of the filters and the introduction of the fuzzy grapheme segmentation approach.

VII. CONCLUSION

We presented in this paper an online Arabic handwriting modeling system based on fuzzy graphemes segmentation. The system consists of three modules: detection of the baseline, fuzzy grapheme segmentation and features extraction. The method developed in the first module is characterized by the consideration of geometrical and topological features for the baseline detection and correction. In the second module, we use the detected baseline and topologic parameters to estimate for each vertical extremum trajectory point a fuzzy degree of confidence to be a particular point of segmentation: bottom of valleys or angular points. Thus, the segmented graphemes are then overlapped proportionally to the confidence degrees associated to the particular point that separate them. A fuzzy membership degree is then calculated for each point of graphemes. Finally the third module extracts a set of Fourier descriptors parameters adapted to describe the segmented fuzzy graphemes. The experimental results show a significant improvement in the recognition rate using the fuzzy grapheme segmentation approach.

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