GLoBD: Geometric and Learned Logic Algorithm for Straight or Curved Handwriting Baseline Detection

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Abstract: *This paper presents a developed geometric and logic algorithm of on-line Arabic handwriting baseline detection. It consists of two stages: the geometric first stage detects sets of nearly aligned points candidates to support the baseline by considering the accordance between the alignment of the trajectory points and their tangents directions. While the logic second stage uses topologic conditions and rules specific to the Arabic handwritten script in order to evaluate the relevance of each one of the three most extended sets of points from the extracted groups to be recognized as a baseline and then to correct the first stage detection result which is based only on the size of the group of points. The system is also designed to be able to extract the baseline of inclined and/or irregular aligned short handwritten sentence thanks to the flexibility of the used method for the constitution of sets of nearly aligned points. The iterative application of this last method in a relatively short neighborhood window sliding on a long and curved handwritten line script permits to extract its curved baseline.*

Keywords: *Online Arabic handwriting, baseline detection, topologic conditions, baseline correction, curved baseline extraction.*

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1. Introduction

Handwriting is an essential human talent since it is one of the most familiar communication media. The large diffusion of mobile computer devices with touch screen and pen based interface has increased the interest on handwriting modeling and recognition over the last decades with the aims to offer a very easy and natural data entry way [14]. Nowadays the recognition of on-line Arabic handwriting becomes increasingly an open lexicon problem. Indeed Besides the use of the Arabic characters for the inscription of Persian, Kurdish, Uyghur and other indo-european languages, we note also the diffusion among electronic device young users of the transcription of names, designation of objects and slogans of European cultures with Arabic characters and vice versa while maintaining their original phonemes. In such context, the baseline may constitute an important topologic tool to discern and to segment the handwriting basic entities: characters, graphemes or visual codes [19] and to extract their parametric or structural features [12, 13, 14] which consents then to recognize the treated handwriting script [3]. On the other hand, the use of electronic ink system on a mobile devices to acquire handwritten text in a variable conditions of travel, introduce a supplementary challenge: the irregularity of the text words alignment.

The presented Geometric and learned Logic algorithm for on-line Arabic handwriting Baseline Detection abbreviated by (GLoBD) constitutes a part of a large dual online/offline Arabic handwriting recognition system [8]. Compared to the literature, the developed approach is designed to quantify the verification level of the Arabic handwriting baseline topologic rules by a detected line candidate and to be able to extract curved baseline. The algorithm combines successively geometric and neural network detection approaches. The first aims to detect groups of nearly aligned points verifying the accordance between the average direction of alignment of their elements and their tangents direction. Then the second detection stage proceed with an evaluation of the relevance of the extracted groups of points to be recognized as a baseline using an ADAptive LINear Element (ADALINE) network simple layer measuring the verification of logic rules and topologic conditions specific to the concatenation of the Arabic handwriting. The paper is organized as follows; first we present the state of art and the pre-processing step. Then in fourth section we describe the first stage of the developed baseline detection algorithm allowing the extraction of groups of point's candidates to support the baseline. The same section presents subsequently the second detection stage permitting the evaluation of the detected baseline solutions. Then we illustrate in the fifth section the approach used to enhance the aptitude of the algorithm to detect handwriting curved baseline. Finally we conclude by presenting the experimental tests results and the perspectives.

2. Related Works

By definition, the baseline is the virtual line on which cursive or semi cursive writing characters are aligned and/or joined. Indeed, it represents in writing as well as in reading, a reference for the vertical positioning of every character and ligatures graphics as well as for the distinction of the graphemes that they compose [1, 5, 10, 20]. In digital recognition process, the baseline is used principally as a reference level for handwriting segmentation and modeling. The advantage of the cursive handwriting segmentation approaches consists in the division of the problem of word recognition into several complementary sub-problems of graphemes recognition [10, 14, 18]. This makes such analytical approaches adapted to handwriting recognition in large or opened vocabulary context.

Several baseline detection methods are proposed in the literature that we can generally divide on two branches: the geometric approaches which are the oldest and the logic ones. The first are often apply on an enough large text block because they are inspired from off-line or printed script applications. The most known are the histogram method [18], the Hough transform method [11] and the entropy method.

The histogram method consists in the projection of the writing tracing points according to a predefined direction which makes it possible to detect the levels of the baselines that coincide with the local maximums of the obtained histogram [16]. It was used by Eraqi and Abdelazeem for on-line Arabic handwriting baseline and delay strokes detection [9]. However, this method is considered as very sensitive to the skew [16].

The Hough transform method proceed to the transposition of the tracing points in the polar coordinates space where the original point alignment appears in the Hough domain as agglomerations of images points intersection defining the angle of writing lines skew [11]. This method is enough expensive in calculation time and it is rather adapted for application on text blocks of several lines.

The entropy method consists to the projection of the words trajectory points according to several rotation plans. The calculation of the entropy of each of the obtained histograms permits to find the orientation according to which the word is the most compact [16]. This method has also the defect to be expensive in term of calculation time.

The logic approaches of baseline detection apply a logic analysis of the handwriting script topology to discern or to select relevant points or stroke of the trajectory supporting the searched baseline.

The algorithm proposed by Oliver *et al.* [12] considers the position of handwriting loops as a reference to detect the local maximum of the handwriting horizontal density. Indeed in Arabic words, the loops are close to the baseline and the ligature lines are characterized by very low frequency variations of the signal. Thus, the detection of the inter-characters connection lines is obtained by the analysis of the frequency variations of the trajectory useful signal [12]. Stahlberg and Vogel [17] proposes to detect dense foreground stripes in Arabic handwriting text line to ensure an accurate positioning of the baseline while AL-Shatnawi [2]. uses Voronoi diagrams, thresholds limits and logic conditions to select points estimating the baseline of offline handwriting text.

Pechwitz and Märgner [13] present a method based on the polygonal approximation of the handwriting skeleton or trajectory. For each trajectory point, the algorithm extracts features to discern relevant baseline points. Then it proceeds to a linear regression analysis on the selected relevant points to define the straight line representing the baseline.

The approach presented by Schenk *et al.* [15] permits to identify the script guide lines in on-line handwritten whiteboard note recognition. First, the system extracts spatial extreme points, local minima and local maxima from the text line. Then it performs an assignment between the detected extreme points within a fraction of a text line and the script line by applying the Viterbi algorithm in order to find the least costly path through a trellis built by the algorithms.

For online Arabic handwriting systems, Baseline detection is a step principally used for delay strokes detection or removal [7, 9] or character segmentation and features extraction [5, 8]. Moreover, many segmentation techniques are involved in such systems and they were discussed by Abuzaraida and Zeki [1].

At the level of baseline detection, the geometric and logical approaches represent two different scales of view. Indeed in the first case we consider a window of global vision on the entire manuscript composed of one or more script lines, while the second approach considers a window of local vision for analyzing the shapes of the characters trajectories. However, the two vision windows are complementary considering the context of an irregular handwriting and various writing styles. Thus we chose to address a mixed approach in developing the presented baseline detection algorithm which is based on the examination of the geometric global characteristics of the handwriting trajectory strokes linking on a sliding neighborhood and the verification of other local topological conditions.

3. Conception and Pre-Processing

3.1. System Overview

The developed baseline detection algorithm is applied on online Arabic handwriting. The handwriting trajectory is captured by digital tablet, or similar digital ink device. It may represent short messages, replies to an electronic form, notes on electronic agenda, lesson, e-mail.

Since the baseline represents the horizontal level on which characters of a cursive script are joined by ligature valley, it can be generally identified as the least curved line which extendedly overlaps the handwriting trajectory on closely aligned neighborhood strokes. This general geometric definition is subject to restrictions rules specific to the used writing alphabet.

Based on this observation, we designed our baseline detection algorithm as a two-stage system (see Figure 1). The first stage detects for each entered new online handwritten word, the trajectory points checking low trajectory inclination angle that it assigns or decomposes into groups of nearly aligned points and accorded tangent direction. The extracted groups of points considered as candidates to mark out the baseline are ordered according to their size in term of number of elements. The second stage executes a topologic evaluation on the most extended groups (candidates) to correct the first detection result.

The two steps are applied successively on a limited sliding window of trajectory to follow the curvature of the handwritten text line. The detection of a new line induces the reset of all extracted groups of points as shown in Figure 1.

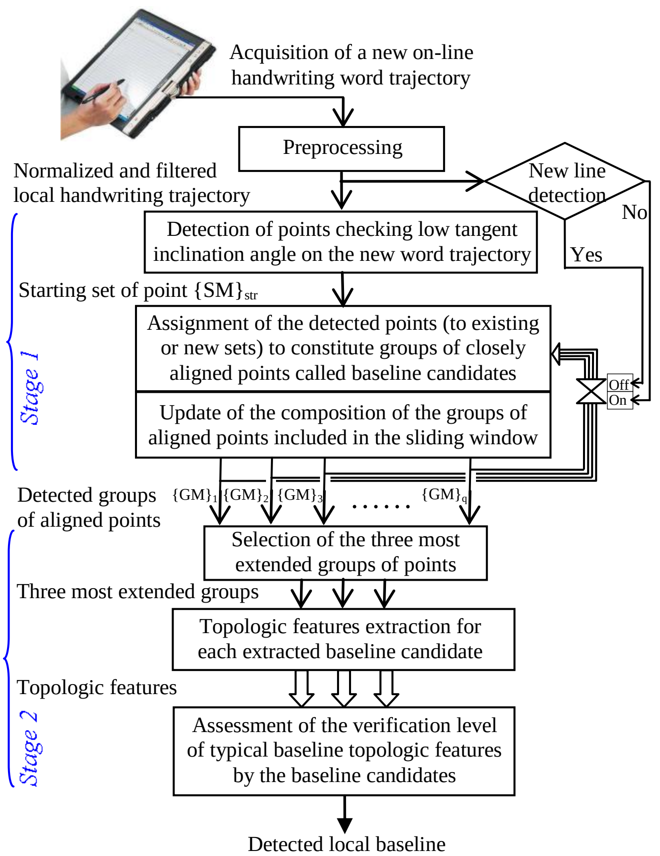


Figure 1. Overview of the baseline detection process.

3.2. Pre-Processing

The digital sampled trajectory of the pen is represented as a function of time of its points coordinates. Since the verification stage of the baseline detection process uses metric features as the input of a learned assessment function, a pre-treatment applied to handwriting trajectory becomes imposed. The stage of pre-processing aims to normalize the handwriting size and to eliminate the noise. First, the vertical height l_v of the original handwritten sentence is resized to a normalized value L_{V_norm} and its horizontal length l_h is adjusted with the same scale of resizing to obtain a normalized size script (l_H, l_V).

$$L_V = L_{V\_norm} = 128 \quad \text{and} \quad L_H = l_h \cdot \frac{L_{V\_norm}}{l_v} \qquad (1)$$

Then we apply a Chebyshev second type low pass filter with a cut-off frequency of f_{cut}=12Hz, on the normalized trajectory to eliminate the noise introduced by temporal and spatial sampling as shown in Figure 2.

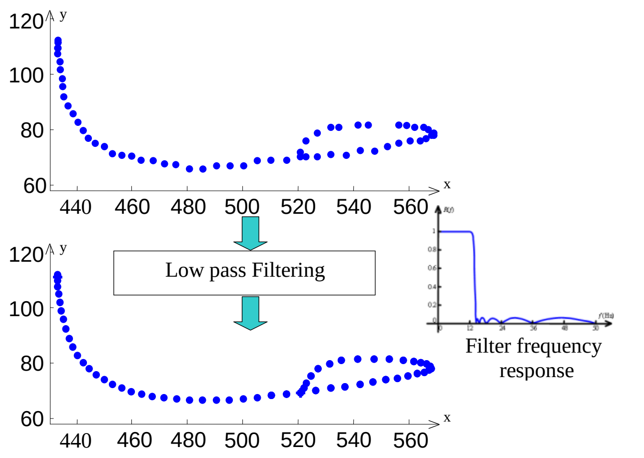


Figure 2. Low-pass filtering for noise elimination and trajectory smoothing.

4. Baseline Detection Procedures

The developed algorithm demarcates the baseline by set of points selected from the handwriting trajectory $M_i(x_i,y_i)$ considering geometric and topologic characteristics. It takes in account that the baseline can be slanted of a variable angle α_{BL} that we suppose limited in order to alleviate the calculation load:

$$-\alpha_{lim} \leq \alpha_{BL} \leq \alpha_{lim} \qquad (2)$$

4.1. Aligned Points Sets Detection

To detect the set of handwriting trajectory points marking the baseline we reduce first the trajectory point candidates by forming a starting set $\{SM\}_{Str}$ composed of points M_i verifying a low absolute tangent inclination angle α_M inferior to the adjustable limit α_{lim}:

$$|\alpha_M| \leq \alpha_{lim} \qquad (3)$$

The starting set $\{SM\}_{Str}$ is then decomposed in q groups of points, $\{GM\}_{1,\ldots,q}$, representing the virtual guidelines of the Arabic handwriting, by assigning a point candidate $M_k \in \{SM\}_{Str}$ to the already constituted group $\{GM\}_m$, $m \in \{1,...,q\}$ which minimizes the geometric measure *Daff* of an affectation criterion or initializing a new group (composing its first element) if it is not validate to integrate any existing group.

In practise, Let *Daff*(M_k, *m*) the geometric measure representing the distance between the point candidate M_k and a group of points $\{GM\}_m$. The algorithm affects the point M_k to the group of points index *m* if it verifies the two following criteria:

Validation criterion:

$$Daff(M_k, m) \leq Daff_{Max} \text{ or } q=q_{Max} \tag{4}$$

Affectation criterion:

$$m = \underset{n \in \{1,...,q\}}{\operatorname{Arg\,min}} \left[Daff\left(M_k, n\right) \right] \tag{5}$$

However, if there is no yet initialized group of points (*q*=0) or if the validation criterion is not verified, the point candidate M_k is assigned to initialize a new group of points incrementing consequently the total number of groups: $q=q+1$.

Two types of geometric measures are tested for both validation and affectation criteria: an angular measure of tangent deviation angle and a metric distance between line and point.

- *Tangent Deviation Angles Respect to the Interpolation Line*: In this method, the used measure *Daff* in the criteria of validation and affectation of a point M_k to the n^{th} group of points $\{GM\}_m$, is computed as 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 and M_i, for all already points members $M_i \in \{M\}_n$ of this group as shown in Figure 3:

$$Daff\ \left(M_k, n\right) = \frac{1}{N_n} \cdot \sum_{M_i \in \{GM\}_n} \left\{ \Delta\alpha_{M_k, M_i} + \Delta\alpha_{M_i, M_k} \right\} \tag{6}$$

Where $\Delta\alpha_{M_k, M_i} = \left| \alpha_{M_k} - \text{the slant angle of the straight line } (M_k, M_i) \right|$,

$\Delta\alpha_{M_i, M_k} = \left| \alpha_{M_i} - \text{the slant angle of the straight line } (M_k, M_i) \right|$

and N_n the current size of the n^{th} group of points $\{GM\}_n$.

The maximal value $Daff_{Max}$ of the geometric measure *Daff* used in the validation criterion is equal to the considered adjustable limit α_{lim} of the baseline inclination angle.

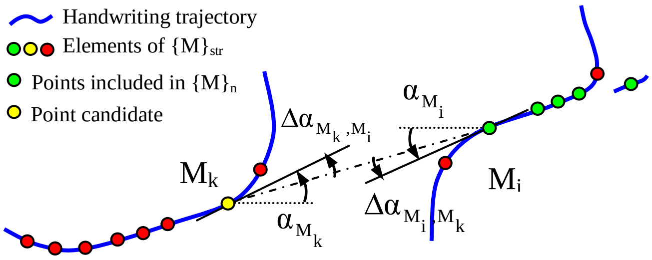


Figure 3. Tangent deviation angles $\Delta\alpha_{M_k, M_i}$ and $\Delta\alpha_{M_i, M_k}$ used for *Daff* affectation distance computing.

In order to reduce the calculation load, we change the individual representation of the group elements: points M_i in the Equation 4 by a sub-group representation. Each sub-group includes all the elements M_i of the group parent $\{GM\}_n$ belonging to a same word or Part of Arabic Word (PAW) limited between successive pen-down and pen-up actions.

Respect to a new candidate point M_k, each sub-group is represented, by its centroïde point $C_j(x_{Cj}, y_{Cj})$ provided with the average direction of the tangents to the trajectory in its point elements defined by the Cartesian equation $y=(A_{Tj}\text{-}x)+B_{Tj}$.

Thus, if the group $\{GM\}_n$ is constituted from *p* sub-groups denoted $\{\{GM\}_j\}_n$, *j*=1, ..., *p* which are composed respectively of $N_{j,\ n}$ points, the computation of the measure *Daff*(M_k, *m*) will be alleviate as:

$$Daff\left(M_k, n\right) = \frac{1}{N_n} \cdot \sum_{j=1}^{p} N_{j,n} \cdot \left\{ \Delta\alpha_{M_k, C_j} + \Delta\alpha_{C_j, M_k} \right\} \tag{7}$$

Where $\Delta\alpha_{M_k, C_j} = \left| \alpha_{M_k} - \text{the slant angle of the straight line } (M_k, C_j) \right|$,

$\Delta\alpha_{C_j, M_k} = \left| \left(\operatorname{Atan}\left(A_{Tj}\right) \right) - \text{the slant angle of the line } (M_k, C_j) \right|$.

- *Distance between Point Candidate and the Regression Line of the Examined Group*: The adopted geometric measure *Daff* to estimate the bringing of a point M_k to the n^{th} group of points $\{GM\}_n$, is computed in this second method as the average sum of two metric distances :

$$Daff\ \left(M_k, n\right) = D_{M_k\ \{GM\}_n} + D_{C_n\ T_k} \tag{8}$$

Where $D_{M_k\ \{GM\}_n}$: distance between the point candidate M_k and the regression line representing the group of points $\{GM\}_n$, $D_{C_n\ T_k}$: distance between the centroïde C_n of the group of points $\{GM\}_n$ and the tangent to the trajectory at the point candidate M_k as shown in Figure 4.

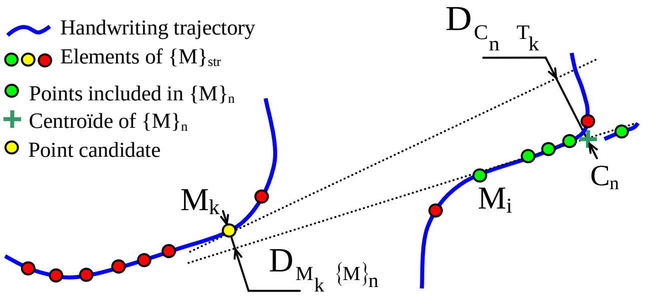


Figure 4. Metric distances considered to calculate the *Daff* geometric measure.

The calculation of the centroïdes coordinates of each group of points and the coefficients of its regression line are update every time that it includes a new candidate point $M_k(x_{M_k}, y_{M_k})$. The retained maximal value $Daff_{Max}$ of the geometric measure *Daff* used in the validation criterion is equal to:

$$Daff_{Max} = \|M_k C_n\| \cdot \sin(\alpha_{lim}) \tag{9}$$

Whatever, the adopted geometric method to compute the measure *Daff*, the baseline detection at this stage of the treatment (first stage), consists in looking for the most numerous group among the constituted sets of points as shown in Figure 5.

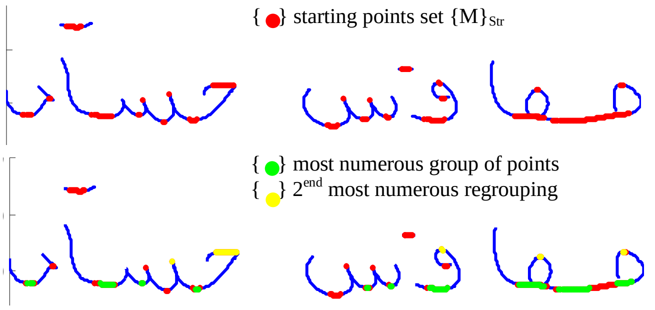


Figure 5. Detection of the starting points set and its decomposition in groups of nearly aligned points.

4.2. Verification of the Topologic Conditions

The examination of the baseline first stage detection errors shows that they are classified in two cases:

- 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 ‘ ر , و , ز , ن , ل ’ in Figures 6-a, 8-b, and 8-c).
- Confusion of the baseline with the median zone line, or the superior limit line, due to the writing style [6] or to the presence of particular calligraphic effects as shown in Figure 8-a.

A complimentary analysis of the relevance of the extracted groups of points to verify some topologic conditions specific to the Arabic handwriting baseline is then necessary to avoid such errors. Thus, the second stage of the algorithm involves an assessment function S for the first three most extended groups of points (of which the probability that one of them carries the baseline is≈100%) in order to optimize the baseline detection result in Figure 4. This function must interpret the topologic characteristics specifics to the Arabic writing baseline where it represents the most compact horizontal level of the writing that generally intersects the trajectory in tangent direction at the middles of the words. Thereby, the S function is defined so that it increases proportionally with the size of the group of points N_n and decreases in proportion to:

- The average angle φ of intersection between upward trajectory and selected baseline.
- The average angle θ_{Curv} of absolute curvature of the trajectory segments cut out by the assumed baseline.
- The rate of bending on the left bl of the centroïde of the set of contact points (coloured in bright green in the Figures 5 and 6-a) between the selected baseline and the trajectory strokes respect to their bounding box vertical limits [4] as shown in Figure 6.

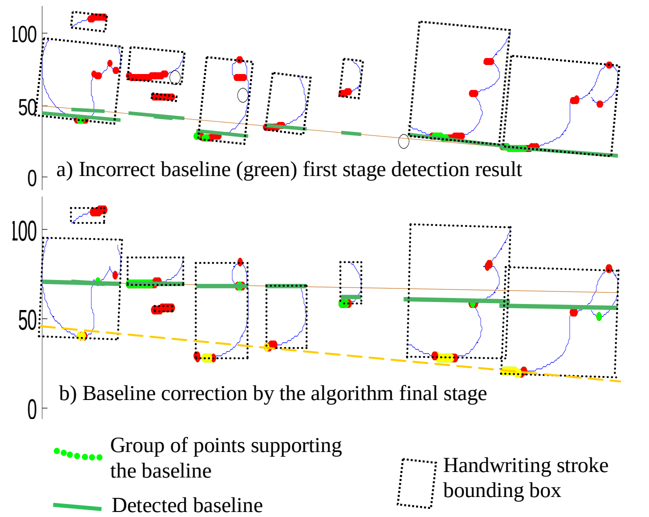


Figure 6. Example of baseline first stage detection error and final stage correction result

The function of assessment S is expressed by a linear formula that takes into account the different parameters cited above:

$$S = (\alpha_1 \cdot N_n) - (\alpha_2 \cdot \phi) - (\alpha_3 \cdot \theta_{Curv}) - (\alpha_4 \cdot bl) \tag{10}$$

In order to estimate correctly the weighting coefficients α_1, α_2, α_3, and α_4, we assimilated, at nearly a constant b, the S function to the output $S'=S-b$ of an ADALINE network simple layer trained according to the least mean square error rule. During the training phase, the system extracts, for each sample of handwritten text line, the set of parameters $\{N_n, \varphi, \theta_{Curv}, bl\}$ for every one of the detected three most extended groups of points that will be inserted in the input of the network as shown in Figure 7. On the other hand, its output value is manually assigned for every set of points as follows:

- If the examined group of points carried the true baseline then: $S'=1$.

- Else: S'=-1.

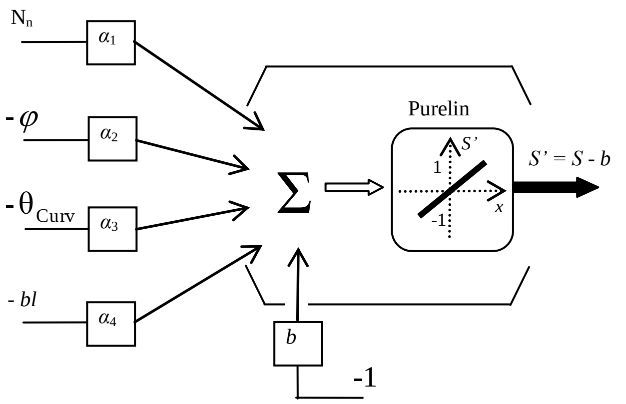


Figure 7. The ADALINE perceptron network used for the simulation of the logic function of assessment *S*'.

The network training set consists of 3000 propositions of baseline extracted by the first stage of the developed baseline detection system for 1000 samples of handwriting text lines (composed of names of Tunisian towns from the set1 of the ADAB database and postal addresses). Among the 3000 baseline proposition, 1000 samples correspond to correct baseline detection and twice as many of different case of false solutions. In the classification phase, the system associates the baseline to the set of points maximizing the output of the *S* assessment function. Figure 8 shows the correction effect of the algorithm second stage respect to the detection error obtained considering only the geometric first stage.

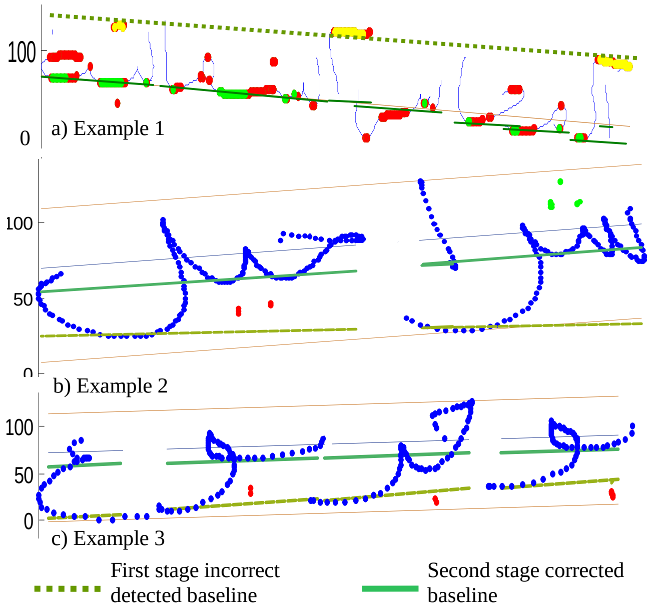


Figure 8. Example of second stage baseline correction result.

5. Curved Baselines and Newline Detections

5.1. Detection of Curved Baselines

Imposing that a handwriting line script follows a strictly straight virtual baseline is a coercive condition for the writer and not practical for a mobile electronic ink system with on-line handwriting recognition software used in a variable conditions of travel nether for off-line handwriting recognition application. Of this fact we designed our algorithm in order to be able to detect curved baselines. Indeed, the adopted baseline detection approach that consists to detect groups of points and not a straight direction has the minimum of flexibility that permit to assume irregular baseline of a short handwritten expression (see Figure 9-a). The degree of this original flexibility is proportional to the deviation angle limit α_{lim} empirically estimated to be inferior to $\pi/8$. However, to increase this flexibility in the case of a long text line sentence, a neighborhood window is defined around the current pseudo-word, on which is applied the validation and affectation criterion in Equations 3 and 4 as shown in Figure 9-b. The radius R_V of the neighborhood window is experimentally fixed to three times the normalized vertical high L_{V_norm} of the text line.

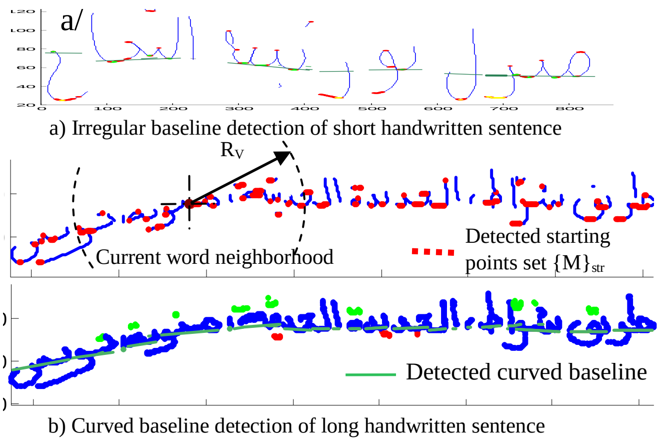


Figure 9. Irregular and curved baseline detection of short (a) and long (b) Arabic handwritten addresses.

The center of the sliding neighborhood is the midpoint (center) of the current pseudo-word bounding box. Its limits vary with the passage from a pseudo-word to another by including a new acquired pseudo-word and the exclusion of the passed one which bounding box is completely out of the neighborhood radius as shown in Figure 10.

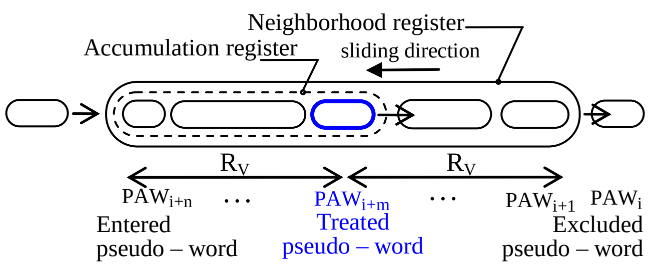


Figure 10. Evolution of the sliding neighbourhood composition by inclusion and exclusion of Successive Pseudo-Words (PAW).

An update of the composition of the different groups of points extracted by the baseline detection algorithm first stage is required for each operation of inclusion and/or exclusion of pseudo-words by executing similar operation (inclusion, exclusion) at the level of their affected points in Figure 1.

5.2. New Line Detection and Different Modes of Script Processing

Immediately after preprocessing a new acquired pseudo-word, the algorithm performs a test for newline. The test involves two empirical thresholds: maximum normalized distances of turning back right D_{BR} and decent down D_{DW}. Simultaneous overruns of these thresholds during the passage from a pseudo-word to the next, announces the return line of the script and the introduction of a new handwriting text line. In that case the composition of the groups of points is first maintained to complete the last baseline detection and then deleted to initialize the groups of points of the new handwritten script line as shown in Figures 1 and 11.
Three modes of script treatment are proposed:

- *Deferred Processing Mode*: The user writes a multi-line text and then applies the algorithm to detect its different baselines then calls for further successive modules of grapheme segmentation, modeling and recognition to complete the treatment [5, 8].
- *Line by Line Processing Mode*: During the acquisition of the handwritten text, whenever the algorithm detects a newline, it extracts the baseline of the just been finished line of text and calls to subsequent treatments.
- *Word by Word Processing Mode:* The entered pseudo-words are successively stored in an accumulation register until its length reaches or exceeds the neighborhood radius R_V (equivalent of 2 to 4 pseudo-words). From that, the algorithm extracts the baseline corresponding to the first pseudo-word entered to the accumulation register before leaving it to pass to the neighborhood register as shown in Figure 10.

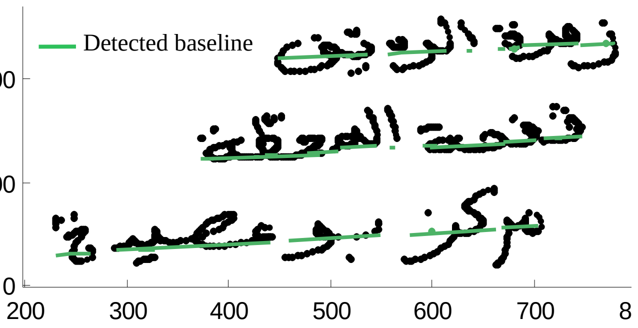


Figure 11. Baseline and newline detection in multi-line script.

6. Experiments and Results

6.1. Experimental Setup

The elaborate baseline detection algorithm is tested on 1500 samples of on-line handwritten Tunisian town and village names from the test sets 4 and 5 of ADAB database [4] and as many of chronologically reconstituted skeletons [8] of off-line samples from the IFN/ENIT database. For the tests conducted on on-line handwriting sentences, two parameters are considered to evaluate the detection results: the baseline vertical deviation distance D_{dev} and its expanse on the text horizontal length: that is partial or total deviation. An appreciation label is assigned to the baseline detection result among: good, acceptable and bad. The following table (table 1) presents the corresponding assessment label for different case of baseline deviation vertical magnitude and its horizontal expanse.

Table 1. On-line handwriting baseline detection result appreciation for different case of spatial deviation.

	Partial deviation	**Total deviation**
$D_{dev} = 0$	Good	
$0 < D_{dev} \le \left(\frac{1}{15}\right)\cdot L_{V\_norm} = 8$	Good	Acceptable
$\left(\frac{1}{15}\right)\cdot L_{V\_norm} < D_{dev} \le \left(\frac{2}{15}\right)\cdot L_{V\_norm}$	Acceptable	Bad
$D_{dev} > \left(\frac{2}{15}\right)\cdot L_{V\_norm} = 16$	Bad	

The side of the off-line handwriting, the baseline detected on the chronologically reconstituted skeleton [7, 8] of an IFN/ENIT off-line handwriting sample is returned to its original binary pixel image as shown in Figure 13 and compared to the corresponding baseline described by the database in a file having the extension .tru and the same name as the image file. This description gives in pixels the ordinates Y_1 and Y_2 of the upper and lower baseline levels. Compared to the ordinates y_1 and y_2 of the extracted baseline, we obtain the maximal deviation distance in pixels:

$$D_{dev} = \max\left(\left|Y_1 - y_1\right|, \left|Y_2 - y_2\right|\right) \qquad (11)$$

We take the same conditions see table 2 for the evaluation of the baseline detection result as in [16]:

Table 2. Off-line handwriting baseline detection result appreciation for different case of spatial deviation.

$D_{dev} < 5$ pixels	$5 \le D_{dev} \le 7$ pixels	$D_{dev} > 7$ pixels
Good	Acceptable	Bad

6.2. Results and Discussions

Statistics of the appreciation labels obtained for the baseline detection results made on respectively on-line and off-line handwriting training and test sets are presented in the following tables (Table3 and Table 4):

Table 3. On-line handwriting baseline detection result.

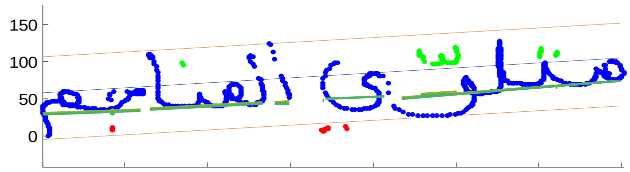
Algorithm	**ADAB Data set**	**Good**	**Acceptable**	**Bad**
Stage 1	Training set : 1000	89.7 %	4.5 %	5.8 %
Stage 1+2	samples from Set 1	96.1 %	2.7 %	1.2 %
Stage 1+2	Test set: 1500 samples	94.3 %	4.1 %	1.6 %

Table 4. Off-line handwriting baseline detection result.

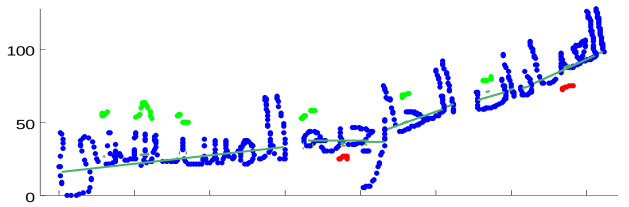
Algorithm	**IFN/ENIT Data set**	**Good**	**Acceptable**	**Bad**
Stage 1+2	Test set: 1500 samples	93.5 %	3.6 %	2.9 %

The result on the whole test set of 3000 samples of short handwritten expressions show that the baseline correct detection (Good+Acceptable) rate R_d is of 97.7%. This final result, improved in relation to the 94.2% gotten by the algorithm first basic stage, returns to the integration of the assessment function S used in the 2nd stage for the evaluation of the topologic conditions verification by the candidates set of points. The tests statistics shows also that the pseudo-words number or length of the treated text has a less influence on the baseline detection rate in the output of the evaluation function (algorithm 2nd stage) that to the output of the basic stage as to been noted in [13].

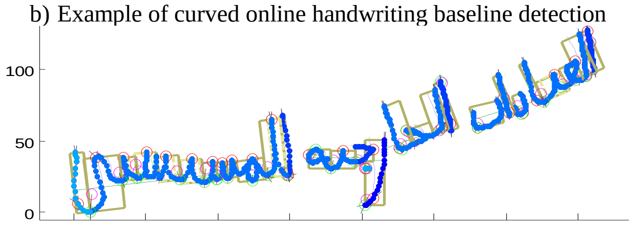
The effectiveness of a baseline detection algorithm is often considered in relation to the criteria of insensitivity to the presence of diacritical and curved legs, the inclination and the irregularity of the handwriting direction. In this evaluation, the developed algorithm is able to fulfill the first criterion thanks to its second logic processing stage that favors the baseline solution which leads to a typical segmentation of the script trajectory closely to ligature valleys in Figure 12-c. However, in front of the second criterion of handwriting skewness insensitivity, the proposed algorithm which defines a limit angle $\alpha_{lim}=\pi/8$ to the possible inclination of the baseline in order to alleviate the computational load, guarantee a correct solution only if the inclination of the handwriting direction is less than α_{lim} in Figure 12-a. This limit value can be increased detrimental to the increase of the computation time. On the other hand, the used method of sliding neighborhood window permits to tolerate the handwriting direction irregularity or partial curvature in baseline extraction in Figure 12-b.



a) Example of skewed online handwriting baseline detection



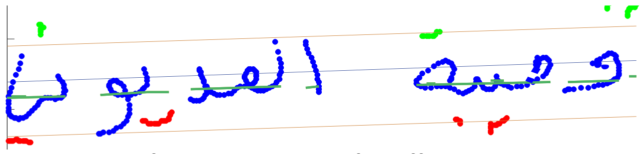
b) Example of curved online handwriting baseline detection



c) Grapheme segmentation resultant of the above detected curved baseline example (b)

Figure 12. Examples of skewed (a) and curved (b) baseline detection of online Arabic handwriting scripts and consequent graphemes segmentation result (c).

In off-line handwriting baseline detection, our algorithm is classified among the skeleton based approaches as shown in Figure 13. These are by far the most efficient approaches cited in the literature [16]. The best known among them for Arabic handwriting is the system presented by Pechwitz et al. [13] which gives a correct baseline detection rate of 95%. On the same database, our algorithm increases this rate to 97.1%.



a)Example of baseline detection of an offline handwriting reconstructed skeleton

b)Projection of the detected baseline from the reconstructed skeleton trajectory to the original handwriting binary image

Figure 13. Example of offline handwriting baseline detection.

7. Conclusions and Future Works

In this article we presented a robust algorithm of on-line or skeleton off-line Arabic handwriting baseline detection composed of two stages: The first consider the agreement between the alignment of the points and the direction of their trajectory tangents for the detection of nearly aligned group of points. The second stage evaluates the relevance of the extracted groups of points to be recognized as baseline by ordering their degree of verification of some topologic conditions specific to the Arabic handwriting baseline. The aptitude of the algorithm to detect irregular short baseline is boosted to detect long curved baselines by applying the two main stages of the algorithm in a sliding window a long the handwritten script line.

The experimental tests show first the robustness of the algorithm and the significant effect of the assessment function based on topologic parameters in detection rate improving. This advantageous result invites to adopt the algorithm in a more complete system of segmentation, modelling and recognition of online/offline handwritten short texts.

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