Arabic Handwriting Recognition Using Restored Stroke Chronology

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Abstract

In this paper we present a system of the off-line handwriting recognition. Our recognition system is based on temporal order restoration of the off-line trajectory. For this task we use a genetic algorithm (GA) to optimize the sequences of handwritten strokes. To benefit from dynamic information we make a sampling operation by the consideration of trajectory curvatures. We proceed to calculate the curvilinear velocity signal and use the beta-elliptical modeling which is developed in on-line systems to calculate other characteristics. Our approach is validated by Hidden Markov Model (HMM) Tool Kit (HTK) recognition system using IfN/ENIT database.

1. Introduction

The automation of the off-line handwriting recognition is a challenging problem which is presented largely in literature. Many applications have been released us the recognition of signatures, the automatic sorting of mail, the automatic treatment of the administrative files, investigations forms, accounts - bank checks, digitalization and saving of written heritage, etc. In fact, the conversion of the printed or handwritten documents into numeric information facilities the different analysis steps and saving process.

In OCR field three steps are considered: modeling or features extraction, learning and classification. The global performance of the systems is depending essentially on the first step.

The features are classified in two categories: structural and statistical. The first one is based on geometrical and topological method for form description [7, 9]. These features present elementary strokes of the trajectory, orientation variability, etc. The second approach of modeling is based in statistical features and pattern description by a measures set [1, 4]. These parameters contain: zoning, loci features, crossing, invariant moments, etc.

The extracted features have a large dependency with a writing variability (printed, handwritten, degraded, etc.) and the acquisition method (on or off-line).

The on-line handwriting is presented us a mono-dimensional signal composed of a succession of points. The position of points depends on time. Therefore, the dynamic information us temporal order of points, pen velocity can be used for dynamic features extraction. Also, the pen trajectory coordinates offer static features. In the case of the off-line system, we have a static image which has lost its dynamic information. Many works in literature are developed to the temporal order restoration off the off-line trajectory and benefit from one of dynamic information [12, 14]. The most of these works are based on classical method without thinking about velocity and acceleration signals. In this paper, we present a new approach of the off-line handwriting modeling based on temporal order reconstruction. Six sections are described. In the second section we present the module of the temporal order restoration. Section three is developed to describe the module of trajectory signal sampling.

We describe the beta-elliptical modeling in section four. Section five presents the characteristics extraction. Finally, section six is developed to the experimentation of our approach which is based on HTK development in order to recognize the Arabic words extracted from IfN/ENIT database.

2. Temporal Order Restoration

A follow-up algorithm permits to determine the skeleton segments of each connected component. These segments

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are classified according to three categories.

For a related component having n segments there will be $n! = 1 \cdot 2 \cdot \ldots \cdot n$ possible permutations of these segments to traverse all these segments. If number n increases, the number of possibilities becomes more and more important.

For that, to seek the best permutation we will use GA for each connected component [6].

On the basis of a number of random permutations m lower than $n!$ and by applying the genetic operations, GA converges towards the optimal solution after a certain number of generations without testing all $n!$ permutations.

The used GA is inspired from the one used to solve the problem of the commercial traveler.

GA seeks to find a permutation which minimizes the evaluation function value (Fitness).

3. Restorated Signal Sampling

Signal have a succession of equidistant points. This signal doesn't explain the pen velocity when writing. A study made on the neuronal and muscular effect shows that the pen velocity decreases at the begin and end strokes and in significant angular variations of the curve. This phenomena is remarkable, if one observes the on-line signal acquired by a graphic tablet for example. Since the on-line signal is acquired in real time and taking into account the resolution (the saving time) of a graphic tablet, it is noticed well that these points are not distributed in a same manner. One observes points concentrations at the beginning and at the end of the strokes; and at the curves. This information is used in on-line systems to calculate the velocity and the acceleration.

It appears thus obvious that a sampling of the rebuilt trajectory must be proceeded according to its intrinsic topological characteristics. Indeed, when this trajectory dynamic sampling is carried out, the signal becomes equivalent to on-line handwriting. We can so apply the panoply of the Beta-elliptic extractor tools to benefit from all advantages of on-line modeling.

3.1. Correspondence Trajectory - Velocity: The Law of Two Thirds ($\frac{2}{3}$)

A correspondence is observed between the curvilinear velocity pace of a cursive handwritten trajectory and that of its curvature radius.

Studies established initially by Lacquaniti and al. [11], then by Viviani and al. [15], showed the existence of a correlation between the angular velocity $V_\theta(t)$ and the curve $C(t)$ (or between curvilinear velocity $V_\sigma(t) = \frac{V_\theta(t)}{C(t)}$ and the curvature radius $R_C(t) = \frac{1}{C(t)}$). This correlation is named the law of two thirds power. Its form suggested by Viviani and Schneider [16] is given by:

$$V_\sigma(t) = K\left[\frac{R_C(t)}{1+\alpha R_C(t)}\right]^{1-\beta} \qquad (1)$$

where K is the factor of velocity gain depending on the duration of the stroke, β is a parameter having a low value and intervening only in the trajectory inflection and $0 < (1-\beta) < 1$ is the logarithmic coefficient of the proportionality. In order to keep a constant velocity gain K along a stroke, the value of the parameter β is evaluated into $\frac{2}{3}$ in experiments.

Thus, the curvilinear velocity local minima $V_\sigma(t)$ correspond on the stroke to the curvature radius local minima (acute curves).

Conversely, the local maxima of $V_\sigma(t)$ corresponds to curvature radius local maxima (straight courses).

3.2. Process of the Temporal Sampling of the Rebuilt Trajectory

The sampling of he rebuilt trajectory consists in marking out its traversed stroke by a velocity (which check the law of two thirds) at moments separated by equal times intervals Δt. The envisaged instantaneous curvilinear velocity $V_\sigma(t)$ is regulated so that it is in conformity with the envisaged curvilinear velocity $V_\sigma(i)$ in each point M_i of the stroke according to the following algorithm:

1. if at the moment t the nearest rebuilt trajectory point to the current point being M_i
2. than $V_\sigma(t) = V_\sigma(i)$
3. The following current point is defined such as it is advanced to the current point by a curvilinear distance Δl on the stroke such as:

$$\Delta l = V_\sigma(t) \cdot \Delta t \qquad (2)$$

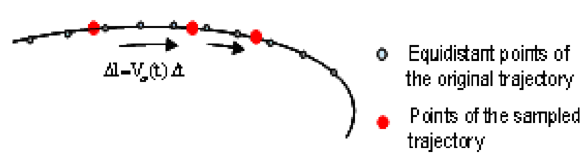

Figure 1. Temporal sampling of the rebuilt trajectory.

4. current point = following current point

This algorithm is repeated until complete the course of the trajectory. The whole of the marked points constitutes the sampled trajectory.

4. Beta-Elliptical Modeling

The act of writing is a movement which is generally produced following excitations neuromuscular exerted on the hand and the fingers. This movement implies a speed and an acceleration of the pen. Based on the geometry and the studies of kinematics in the movements of the generation of writing, we adopted a Beta-Elliptical representation of writing, [5, 2, 10].

Handwritten scripts are, then, segmented into simple movements, as already mentioned, called strokes, and are the result of a superimposition of time-overlapped velocity profiles.

The curvilinear velocity $V_\sigma(t)$ is calculated by:

$$V_\sigma(t) = \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dx(t)}{dt}\right)^2} \quad (3)$$

The curvilinear velocity of each individual strokes obeys the Beta approach. So, the generation of a complex trajectory pattern is the result of an algebraic addition of strokes velocity terms.

Each elementary component called the "stroke" is characterized in the field of space by three static parameters which overall reflect the geometrical properties of the whole of the muscles and the articulations used in a movement of writing. The parameters a and b are respectively the large one and small half axes of the ellipse, the point (x_0, y_0) represents the center of the orthogonal ellipse relating to the reference mark (O, X, Y). The angle θ represents the deviation of the elliptic portion relating to the reference mark orthogonal (O, X, Y).

5. Feature Extraction

First tests of recognition made on the IfN/ENIT multi-script database gave limited rates of recognition contrary to the results obtained by this same extractor on mono-script databases.

This result is due to the fact that the description given by beta- elliptical extractor parameters is detailed: (as far as the decomposition in strokes depends on the variation of the trajectory curvature radius) being able to arrive at the level of finding details specific to the script writing style.

The solution consists then in passing from detailed description given by beta-elliptical description of the strokes to a more general one. In this objective, we chose to pass from the stroke as unit of segmentation, to the grapheme which could include several strokes. The characteristics representing this new entity will be a global interpretation of the beta-elliptical parameters of the strokes which are included in this entity. Consequently, the obtained description will be better able to generalize the common form of a grapheme in a set of samples produced by of multiple script.

5.1. Segmentation in Graphemes

We detect the baseline using the method described in [3]. The segmentation of pseudo-words in graphemes rests on the detection of two types of points which are typographically significant:

- summits of the valleys bordering the base line with a parallel tangent
- angular points

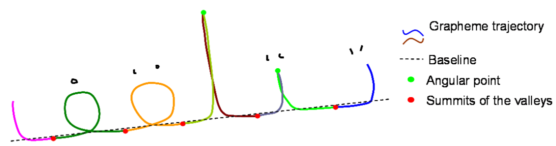

Figure 2. Segmentation in graphemes of the Arabic word تتلقف (tetelaquaf).

5.2. Extraction of the Parameters Modeling the Graphemes

Each grapheme is seen thus has a including rectangle and reference points.

In order to join the conditions of relevance and non correlation, we chose in our application context five groups of characteristics to classify the graphemes.

5.2.1 Dimensions of the Including Rectangle

The Arabic letters or graphemes can partially characterized by their dimensions (height and width). For example, the graphemes “1” and “د” are enough distinct if we consider only the dimensions of their including rectangles.

5.2.2 The relative position of the including rectangle vis-a-vis the baseline

The vertical relative positions of the including rectangles makes it possible to discriminate three groups of graphemes. Indeed, according to their positions vis-a-vis the baseline, we distinguish from the graphemes some are written in top of the baseline, others which go down in lower part and finally the diacritic ones.

5.2.3 Positions of the references points

The references points are points of the grapheme trajectory satisfying certain geometrical or dynamic conditions. The definition of their number concerns a compromise between smoothness of the description and capability of generalization. In our application, we limited their number into three, supporting thus the capacity of generalization of the parametric description being given the multi-script context of the application. The three considered references points are:

- The starting point of the grapheme trajectory M_1.
- The point of arrival M_n.
- The minimum absolute of curvature radius or speed $M_i \in]M_1, M_n[$.

The reference point M_i is identified by analyzing the speed variation $V_\sigma(t)$ of the treated grapheme trajectory.

The positions of the points references M_1, M_n, and M_i in the including rectangle give an idea on the form of the grapheme trajectory. The three points are located compared to the left lower top of the including rectangle in the horizontal and vertical direction respectively by the ratios R_H and R_V. In the order, the parameters of location start by defining the position of the starting point, then that of the minimum of curvature radius and in the end that of the point of arrival.

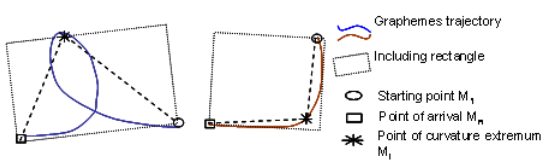

Figure 3. References points of the Arabic graphemes.

5.2.4 Direction of the trajectory on the level of the points references

To obtain even more precision on the form of the trajectory, we determine the angles of inclination θ_1, θ_n and θ_i of the tangent with the trajectory respectively at the three points references M_1, M_n, and M_i. These angles are given directly by the directions of the main axis of the ellipse arcs which model the strokes limited by these points in the beta-elliptical model.

5.2.5 Characteristics of the grapheme curvature

In order to study the curve direction of the grapheme trajectory, we measure its angles of continuous curve α_{Ct} and absolute α_{Ab} along the layout. These parameters are deduced from the beta-elliptical model characteristics, in particular from the angles of tangents inclination to the trajectory at the points limiting the stroke detected along the grapheme trajectory:

$$\alpha_{Ct} = \sum_{i=1}^{m} (\theta_{Fi} - \theta_{Di}) = \theta_{Fm} - \theta_{D1} \quad ; \qquad (4)$$

where m is the number of strokes, θ_{Fi} and θ_{Di} are respectively the inclination angles of tangents at the points of arriving and beginning of the stroke of row i.

The agreement between the values of α_{Ct} and α_{Ab} means that the grapheme trajectory did not change a curve direction. Conversely, a significant difference between the two parameters, informs about the presence of a change of curve direction. Thus the comparison of the values of α_{Ct} and α_{Ab} allows to distinguish for examples the graphemes of Arab letters "ق" and "ى" where in the first there does not exist change of curve direction contrary to the second character. Moreover, the parameter α_{Ct} who to measure the curve angle of the trajectory, allows to distinguish the occlusions ($|\alpha_{Ct}| \geq 2\pi$), the open curves ($|\alpha_{Ct}| < \pi$).

6. Experimentation and Results

We used a classifier based on the Hidden Markov Models HMM. The classifier was described in [8]. The implementation was carried out by using HMM Toolkit (HTK). HTK is a portable toolbox destiny for the system development of voice recognition. HMMs used are of type (left to right discrete HMMs). The size of the codebook is 256. The training was carried out by using sets a-d of the IFN/ENIT database.

First, we used the twenty preceding characteristics at the entry of the classifier. Then, we have to add another parameter which represents the logical position of the grapheme (at the beginning, the medium, in end, insulated).

The following table shows the obtained rates of recognition and a comparison with author systems tested in the same conditions in ICDAR 2005 Arabic Handwriting Recognition Competition [13].

Table 1. Recognition results in % with IfN/ENIT database dataset d

System	Recognition rates
Our system (with 20 features)	81.21
Our system (with 21 features)	83.71
ICRA	88.95
TH-OCR	30.13
UOB	85.00
ARAB-IFN	87.94

Table 2. Recognition results in % with IfN/ENIT database dataset e

System	Recognition rates
Our system (with 20 features)	50.01
Our system (with 21 features)	54.13
ICRA	65.74
TH-OCR	29.62
UOB	75.93
ARAB-IFN	74.69

7. Conclusions and Prospects

We presented a new approach of the off-line Arabic handwriting recognition. This approach is based on the rebuilding of the trajectory chronology. The rebuilt signal is sampled in order to calculate the curvilinear velocity. Characteristics inspired from the rebuilt dynamic information are then extracted. A Markovian classifier containing toolkit HTK is used. The preliminary results give rates of recognition which approach as of those of the systems tested with the same conditions. As these tests show that the addition of the other characteristics increase the rate of recognition. That pushes us to exploit other information already extracted to increase the rate of recognition.

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