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A Behavioral Model of Writing

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Abstract - In this paper we propose a new model to generate handwriting based on behavioral patterns we believe is to be found in humans when imitating a written character. The proposed algorithm has a hierarchical structure. It is consisted of two main levels. At the first level the graphical features of the written letter to be imitated are extracted. These features are the directions of movement for each stroke. To extract the strokes that shape a letter, zero crossings of vertical and horizontal spatial velocity profiles are determined. At the second part a given letter is regenerated by using the extracted directions. At this level, the letter is linearly divided into several subdivisions. After that the excursion length (step) and the slope of line-segments producing the subdivisions are estimated. In each trial of learning, trajectory points are chosen with the estimated step and a random slope. The final trajectory is produced by successive arrangement of the strokes. In each trial the slope and step of the target point has a distance less than a specified threshold from the actual path is stored in memory and others are generated again. This process will continue during different trials until the trajectory can be generated using only memory. The resulted trajectories for different letters written by different subjects are qualitatively and quantitatively similar to the actual trajectories generated by human.

I. Introduction

Handwriting stands among the most complex tasks performed by literate human beings [1]. Handwriting is a main point for several motor control problems, such as sequencing of stroke order, decomposition of movements into basic segments, characterization of mental movement coordinate systems, and the role of sensory feedback for motor planning [2]. Examination of these subjects can be done in non-invasive, inexpensive, and easily executed experiments on human subjects via the study of handwriting [2]. This study forms a very broad area that lets researches with various backgrounds to collaborate and interact with different goals [1, 3].

The study of handwriting is based on its modeling. Several modeling techniques are proposed to simulate the handwriting process [4]. There are two general methodologies of handwriting modeling. The first methodology takes into consideration computational models which are aimed to reproduce some features of human handwriting movements such as trajectory. Hollerbach oscillatory model of writing is one of these methodologies [3, 5].

The second methodology of handwriting modeling focuses on psychologically illustrative models. These methodologies consider cognitive aspect of writing such as learning and memory of the movements, which are often omitted from the first methodology, and not an aspect of trajectory formation [3, 6, 7].

Trajectory Formation is one of the basic functions of the neuromotor controller. A group of studies on trajectory formation is directly related to mechanical properties and the geometry of the muscles [6].

In this study we propose a new method that is the combination of both methodologies. We propose an algorithm to plan and generate the trajectory and also learn the trajectory of the handwriting independently of the actual joint and muscle patterns. This model relies on Arabic handwriting data. The model has a target point estimation algorithm that estimates target points and save them according to the distance that they have with the actual trajectory. This model not only generate the trajectory of a letter almost the same as human trajectory but also save the information that is needed to write the letter in working memory. So when the model learns to write a letter it can use only memory to generate the letter trajectories.

The overall approach is based upon the hypothesis that complex human movements are made up of, and can be segmented into, basic and simple parts [1, 2, 6, 8]. In other words, due to the properties of the neuromuscular system involved in a rapid writing task, there is a class of simple movements, called strokes, that are preferentially produced by such a system, once it is well-trained. More complex movements are thus generated by the vectorial addition of various strokes belonging to such a class [1].

In the case of handwriting, it is important that the model to be able to generate a script in such a way that can be recognized by almost everyone, not to try to regenerate an 'ideal' script [9].

This paper aims to show how to study and to understand the basic properties of pen-tip trajectories as produced by human subjects that perform handwriting.

This paper is organized as follows. The database is introduced in Section II. Then in section III the method that is proposed for planning and learning to write is described. The results of the proposed algorithm are then demonstrated in Section IV. The final conclusions are discussed in Section V.

II. Data Set

Handwriting data is collected using a Wacom 9 · 12 Intuos digital writing tablet with sampling frequency of 206 Hz. The data was collected from four subjects. The subjects were asked to write all the Arabic letters ten times. During every trial horizontal (X) and vertical (Y) coordinations of the pen-tip were recorded.

III. Methods

In this paper we use the hypothesis that complex human movements such as handwriting can be segmented in to some basic and simple units, called strokes. First of all we find these basic units. In Arabic letters we have both up-down and right-left strokes. So in order to find the strokes we should find vertical and horizontal zero crossings of spatial velocity. We name these estimated points stopping points. Indeed stopping points are the points in which velocity in each direction changes its sign, and also velocity became zero or near zero.

After finding stopping points we should define the movement directions during each stroke. The direction of the movement changes at each stopping point. We consider four different directions: positive and negative x directions and also positive and negative y directions.

In next stage we find the slopes between every two adjacent points of the letter. Then we divide the letter into some parts in which the changes in slope is greater than a specified value. We define the slope of each part as a mean value of the slopes of every two adjacent points in that part. Then we find the length of each part and we assume these lengths as the model's steps for choosing target points in order to form the trajectory of the movement.

After the mentioned steps we run the main algorithm of learning to write. In order to find the target position (TPx, TPy) we should have the present position (PPx, PPy) and the "step" and angle of the movement toward the target. So we can calculate target position using equations (1) and (2):

$$TPx=PPx+\cos(\text{random angle})*step \quad (1)$$

$$TPy=PPy+\sin(\text{random angle})*step \quad (2)$$

We start from the first point of the letter. We choose the variable "step" the same as the "step" that we calculated in the previous stage. Then we choose a random angle according to the direction of the first stroke.

$$\text{initial random angle} = \begin{cases} 0-90 & \text{if direction} = +x,+y \\ 90-180 & \text{if direction} = -x,+y \\ 180-270 & \text{if direction} = -x,-y \\ 270-360 & \text{if direction} = +x,-y \end{cases} \quad (3)$$

Now we have calculated target position of the movement. To estimate the next point we compare the slope of the previous stage with the actual slope of the next stage and calculate the error percentage and error sign. Error sign shows the estimated slope is lower or higher than the actual one. We randomly choose the next angle according to the following rule:

$$\text{Random angle} = \text{previous random angle} \pm \begin{cases} 0-18, & \text{if } 0 \le \text{error percentage} < 20 \\ 18-36, & \text{if } 20 \le \text{error percentage} < 40 \\ 36-54, & \text{if } 40 \le \text{error percentage} < 60 \\ 54-72, & \text{if } 60 \le \text{error percentage} < 80 \\ 72-90, & \text{if } 80 \le \text{error percentage} \le 100 \end{cases} \quad (4)$$

The sign is chose according to the error sign. In each target selection at the start of each stroke we check the movement direction and preserve it up to the end of the stroke. With the composition of the produced strokes the complete trajectory will be generated.

We use the above rule and equation (1), (2) to estimate target points. After choosing each target position we check the distance between the chosen point and the nearest point in the original trajectory, if the distance is less than the specified value that depends on the accuracy that we want, we save the step and the slope of the chosen point in memory. The first trial will be completed when the comparison with the last slope is done and the last target position is chosen.

During each target selection if the slope and step that is needed to choose a target already exist in memory, these values will be used to select the target position so the movement is memory based. But if the slope and step values don't exist in memory we should choose the random angle again, but this time we choose an angle between the angle that was chosen in previous trial and the actual angle. After every trial the trajectory becomes more similar to the original trajectory and the number of the saved points in memory increase. We repeat this algorithm until all points can be chosen using only memory and so the trajectory formation become completely memory based.

IV. Results

We studied the performance of the proposed model for all the letters that can be written without taking the pen-tip off the paper, and as a sample from our simulation results we show the results for 4 letters..'Lam' that is shown in fig.1 is almost the simplest letter with comparison to other 3 chosen letters. 'Ein', 'Sin' are among the most complicated Arabic letters. Letter 'Mim' has a closed circular shape.

The best correlations between the handwriting generated by the model and the recorded data, over X and Y directions for these 4 letters are reported in table 1.

Table 1 correlations between human and model trajectory in x and y directions for 4 chosen letters shown in figures 1-4.

Letter/Subject	X position	Y position
Lam/1	0.9886	0.9994
Sin/2	0.9830	0.9676
Ein/3	0.9551	0.9623
Mim/4	0.9759	0.9699

The correlations is calculated using the following equation [2, 8, 10]:

$$c(a,b)=\max_{0\le r\le R}\frac{\sum_{i=0}^{n-r}(a_i-\bar{a})(b_{i+r}-\bar{b})}{(n-r)\sqrt{\frac{1}{n}\sum_{i=0}^{n}(a_i-\bar{a})^2}\cdot\sqrt{\frac{1}{n}\sum_{i=0}^{n}(b_i-\bar{b})^2}} \qquad (5)$$

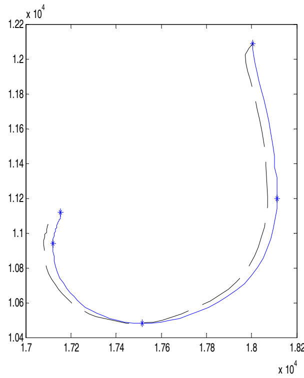

Fig. 1 Letter Lam from subject 1, recorded data (solid) and trajectories generated by the model (dash) are shown. The stars on the trajectory show the stop points which are the end of a stroke and the beginning of a new stroke.

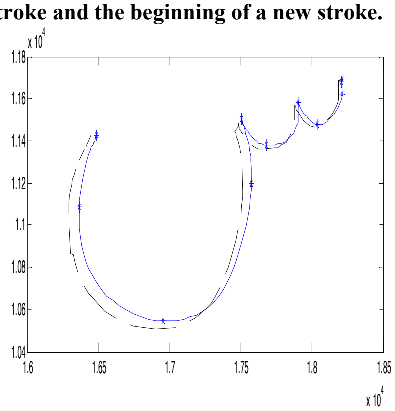

Fig. 2 Letter Sin from subject 2, recorded data (solid) and model (dash) trajectories are shown.

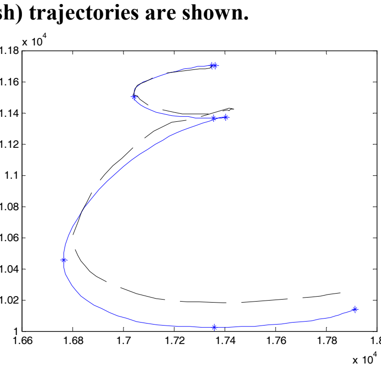

Fig. 3 Letter Ein from subject 3, recorded data (solid) and model (dash) trajectories are shown.

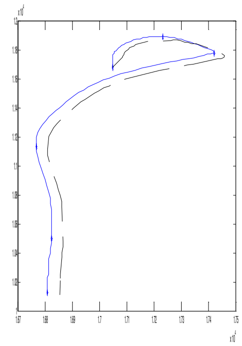

Fig. 4 Letter Mim from subject 4, human (solid) and model (dash) trajectory is shown.

We also examine the performance of the proposed model on other Arabic letters collected from the four subjects. The results show that performance of the proposed model was different among various letters, with a maximum total correlation of 0.99 (mean of x and y direction correlations) for letter 'Lam' and a minimum of 0.78 for letter 'Ein'. The reason for this observation returns to the complexity of the letter, the more complex the letter is the more the quality of performance is decreased. The model shows small variability among different subjects. Also in conditions that the generated trajectory has lower correlation with human handwriting, still the shape of the generated letter is similar to the recorded one.

V. Conclusion

In this paper we proposed a behavioral model of writing. This model can plan and learn human handwriting trajectories. This model breaks the trajectory into strokes and with the composition of these strokes the final trajectory will be generated. To form each stroke we choose some target points. These target points are chosen with a new algorithm based on human writing behavior. The strokes are generated successively. Each target point is checked to see whether it is appropriately chosen or not and according to this some information about that target point will be saved in memory. As learning proceeds over multiple trials, the memorized information becomes more complete. So after the last trial the trajectory will be generated using only memory.

This model can also generate letters with different shapes. In future work we want to examine this model on the generation of letters with different scales.

Different models are proposed for handwriting. One of these models is the Edelman and Flash (1987) minimum snap model. In this work they presented a model of trajectory formation based on dynamic minimization of jerk [8,10]. Their approach was a computational one. Another model that is proposed in modeling handwriting was AVITEWRITE which was developed by Grossberg and Paine (2000). AVITEWRITE was a physiological inspired model. The model that we have proposed is essentially inspired by human behavior during writing.

Our model although is simple, yields good correlation with recorded human handwriting data. The maximum correlation that we got for this model is 0.99 for letter "Lam" which is comparable with the results reported by

Edelman and Flash (1987) which was 1 in the best case and in the worst case the minimum correlation that our model showed is 0.78 for letter “Lam” which is better than AVITEWRITE (0.76).

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