Modeling Handwriting Style: a Preliminary Investigation

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Abstract

We present a study for modeling handwriting styles that derives from handwriting generation studies, according to which handwriting is a temporal sequence of elementary movements. Hence, handwriting style results from the way those movements are actually performed and sequentially executed to reach fluency. We conjecture that handwriting styles depend on two main factors: the shape of the traces corresponding to the elementary movements and the way these traces are connected. To prove this conjecture, and the handwriting style model we have derived from it, we have designed an experiment in which handwriting samples are described by only two parameters and then clustered. The experimental results show that, despite its simplicity, the proposed method is able to capture the distinctive aspects of handwriting styles behind the handwriting samples, even when the writers deliberately attempts to modify it, and therefore corroborate our conjecture.

1. Introduction

Studies on motor control have shown that handwriting is a learned, complex motoric task, composed of elementary movements, or strokes, arranged in a temporal sequence. Fluency, then, emerges when these movements are executed in such a way to minimize the writer's energy consumption [1, 2]. At beginning of handwriting learning, each stroke aimed at reaching the target point that has been visually selected is executed independently from the previous or the following one. Such a stop-and-go writing modality is slow, because after reaching a target point the next one needs to be selected and the appropriate motor commands planned, and expensive, because of both the cognitive load for planning and the need to overcome the inertia for executing each stroke. By repeated practice, the sequence of target points becomes familiar to the writer, as well as the sequence of motor commands needed to execute them, so that the next movement can start before the current one terminates. This anticipation allows for a faster and cheaper writing, because of the elimination of both the pauses between successive strokes and the corresponding inertias. When the learning completes, fluency is achieved, in that the whole sequence of motor commands has been learned and stores in such a way that it is resorted from memory and the corresponding movements executed automatically with proper timing and without any visual and proprioceptive feedback, as it were an elementary movement [3, 4].

According to those findings, what we call handwriting style results from the sequence of target points, the movements to reach them and the timing for their execution. We conjecture that all those aspects are embedded into the ink trace and can be estimated by looking at the actual shape of the ink. To prove this conjecture, we propose a model for handwriting styles that envisages only two parameters. To validate the model, we designed an experiment in which a standard K-means clustering algorithm is used in the model parameter space for recognizing handwriting style across a set of samples.

The remaining of the paper is organized as it follows. In Section 2 we describe the rationale behind our conjecture and derive the model for characterizing handwriting styles. In Section 3 we present the method we have designed for estimating the model parameter. In Section 4, we present the experimental validation of the model and discuss results. Eventually, we draw some preliminary conclusions and outline the future work.

2. A model of handwriting style

To illustrate the rationale behind our conjecture, let us consider a very simple task: to reproduce the shape of in fig. 1a. At the beginning of the learning, the writer will visually select the target points A_v and M_v, and then will draw a stroke for connecting them. Once the point M_v has been reached, the writer will select the target point B_v and draw the second stroke, as depicted in fig. 1b. The repeated practice of the task leads the writer to know that,

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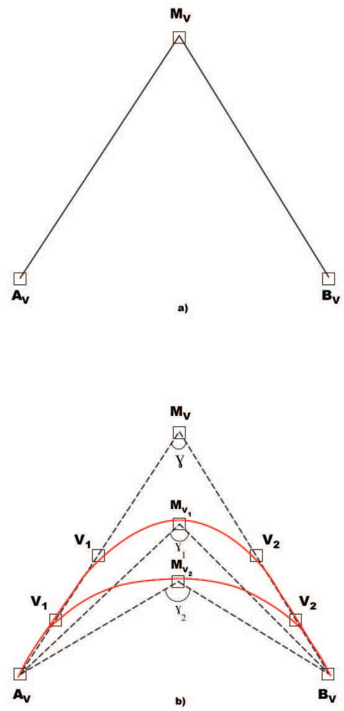

Fig.1. Handwriting style formation. a) A simple shape to be reproduced. and the estimated sequence of visual targets: A_v, M_v and B_v. b) The effect of time superimposition between the stroke going from A_v, to M_v and the following ones, connecting M_v to B_v. As the amount of time superimposition increases the point V_1 (V_2) get closer to A_v (B_v) and so the part of the strokes that is not affected by the drawing of the successive (previous) one decreases. As a consequence, the target M_v will not be reached, and the segmentation points between the first and the second strokes, M_{v1} or M_{v2} in the figure, will be located along the arc V_1V_2, in correspondence of the curvature maximum. Eventually, the angle g becomes larger as the time superimposition between the two strokes increases, thus providing an estimate of the time superimposition amount used by the writer to produce a sequence of strokes for reproducing the given shape.

after reaching point M_v he has to reach B_v, i.e. to learn the complete trajectory of the intended movement. The learned spatial sequence is then converted into motor commands. At this point, the sequence of targets having been learned, the movement can be executed without visual feedback, with a precision in estimating the relative position of A_v, M_v and B_v as well as in reaching the targets that depend on the fine motor skill of the writer, thus accounting for the actual shape variations observed when the task is performed by different subjects, and that will improve as the learning proceeds.

Simultaneously, to avoid stopping when reaching M_v, the writer will anticipate the starting of the second stroke. This anticipation will allow for a less expensive and faster movement, but will determine a change in the shape of the trace, because the command to draw the second stroke is issued when the hand is still involved in executing the first one. As the second command is issued, the pen-tip is subject to two competing accelerations: a negative one, because the first movement, still in place, is reaching the target and should stop, and a positive one, since the second command requires to move the pen-tip from the current position towards the target. As a matter of fact, M_v will be displaced in correspondence of the curvature maximum along the ink between V_1 and V_2. As the time superimposition between the two commands increases, the portion of the first stroke that will be drawn without interference from the following one decreases. Consequently, the actual positions of V_1 and V_2 change, as in fig. 1.b, and so will the curvature along the ink trace between them and, consequently, the position of M_v. Eventually, when the time superimposition becomes greater than a given amount, the two strokes will merge into a single one, as it can be observed in fast writing, when the time constraints force the writer to eliminate some of the stroke in quest for speed.

The actual shape of the trace, then, is the result of such a complex interaction, which involves motor planning (which accounts for the relative position of the targets and the amount of anticipation) and motor execution (which accounts for the variations of the actual shape of the trace in different executions depending on the actual conditions of the effector system when the execution starts). The intertwining between the two explains why the ink traces produced by the same writer at different times to execute a learned sequence of movements may vary considerably [5]. Thus, modeling handwriting requires to describe the shape of the strokes and the amount of time superimposition between following ones.

As with regards to the description of the shape of the stroke, among the many models proposed in the literature [6-10], in this study we have adopted the one that assumes that the best curve for describing the shape of a single stroke is an ellipse [10]. We have chosen such a model because of both its simplicity and effectiveness in providing robust descriptions. Given a stroke, then, its description is provided by estimating the three parameters of the ellipse that best fit the stroke: the half-length of both the major and the minor axis, and the angle θ between the major axis of the ellipse and the baseline. Of the three of them, the first two are rotation invariant and size dependent. This means that they will not help to discriminate among rotated strokes, that we wish because the slant is a relevant characteristics of the handwriting style, while introducing size-dependent variation, that we won't wish because the relative position of the target points already encodes such information. Thus, we include in the model only θ.

In order to estimate the amount of time superimposition between a pair of successive stroke, fig. 1 shows that as the amount of time superimposition increases, the angle γ between the segment A_vM_{v1} and the segment $M_{v1}B_v$ increases too, and therefore can provide an estimate of such a dynamic feature of handwriting.

Summarizing, an handwritten trace composed of N strokes will be associated with the following sequences:

$\Theta=(\theta_1, \theta_2, \dots, \theta_n)$;
$\Gamma=(\gamma_1, \gamma_2, \dots, \gamma_{n-1})$.

The final model $\mathcal{M}$ is achieved by averaging the values of each sequence: $\mathcal{M} = (\Theta_{avg}, \Gamma_{avg})$.
In the following section we will describe a method we have implemented for measuring these parameters from a scanned image of the trace.

3. Measuring handwriting style

To measure the model parameters we need to preliminary extract from the trace the sequence of strokes, i.e. to recover the writing order and to locate the segmentation points between successive strokes.

3.1. Writing order recovery

The methods proposed in the literature can be divided in two broad categories: local line tracing and global graph search [11]. Local line tracing methods are generally simpler and require a low computational cost, even if they exhibit some limitations because it is difficult to find robust heuristic criteria for selecting the optimal direction that can be applied to various handwriting styles. On the other hand, global graph search methods overcome some of the limitations of local tracing ones, but generally require a very huge computational cost and the definition of effective criteria for selecting, among equivalent paths, those allowing a better reconstruction of the original script.

In this study we use a hybrid approach we have developed in previous work [12]. Basically, it uses local criteria to formulate hypothesis on traversing each intersection, and global search for the final selection. It also incorporates criteria for finding the beginning and the end of each fragment and to deal with movements including pen-lifts but still resulting in a single connected component, as it may happen when a the letter “d” is produced by drawing the loop, then lifting the pen to reach the top of the ascender, and then drawing the ascender in such a way it touches or even intersects the loop. The resulting implementation is based on the Fleury’s algorithm for graph traversal, incorporates rules derived from handwriting generation modeling for both selecting the beginning and the end of each fragment and to deal with the pen-up possibly present, and eventually resorts to good continuity criteria when alternative solutions at intersections are still possible after the previous processing. At the end of this step, thus, the ink of each fragment has been unfolded according to the reconstructed writing order.

2.2. Stroke segmentation

The strokes are generally hidden in the ink due to both noise and anticipatory effects. The noise originates from several sources, from the digitizer to erratic hand or finger movements. The anticipatory effect originates from time-superimposition of strokes that allows starting a new stroke before the end of the previous one, leading to the fluency of the handwriting movements and the smoothness of the ink. Those are the reasons why the segmentation of handwriting into strokes is believed to be among the most challenging step for cursive script analysis and recognition. In this study, we adopt the algorithm we have developed in a previous work by exploiting the concept of saliency introduced for modeling visual attention shift [13]. Following this approach, the electronic ink represents the scene the system is looking at, and its curvature represents the feature whose saliency is estimated. Thus, segmentation points correspond to the highest values of the saliency map. The obtained segmentation is much more invariant with respect to locally prominent but globally non-significant changes of curvature and compares favourably even with those exploiting changes in the writing speed as they are available in the on-line case.

3.2. Model parameter estimation

Given the sequence of strokes provided by the previous steps, we proceed by fitting each stroke with ellipses by the least square linear regression, thus obtaining the values of θ_i, $i= 1..n$, and eventually by computing the value of γ_j, $j= 1..n-1$, for each pair of successive stroke. Then, we compute the average values for each of them across all the strokes of the sequence. By this processing, each sequence s is eventually associated with its model, represented by the pair $(\Theta^s_{avg}, \Gamma^s_{avg})$.

4. Experimental validation

To validate the model we have designed an experiment in which traces produced by an unknown number of writers are clustered together according to the values of the pair (Θ^s_{avg}, Γ^s_{avg}) associated to each of them. We would expect that traces produced by the same writer would be clustered together, so that each cluster corresponds to a writer.

The data set used in the experiment was not collected by us, but made available within a larger project on writer identification by Forensic Document Examination. For this reason, some of the subjects were requested to produce a disguised handwriting, i.e. a handwriting in which they consciously modify it with respect to the genuine one. None of the subject was a skilled forger, but they were allowed to practice for 15 minutes before producing the disguised document. The complete data set is composed of the digital images scanned at 300 dpi of 32 documents produced by 18 subjects. It contains 3 documents (1 genuine, 2 disguised) written by a single writer, 12 pairs of documents (1 genuine 1 disguised), each produced by a different writer, and 5 documents (either genuine or disguised), each produced by 5 different writers. Each form contains the same text composed of 92 words, a summary of a children tale well-known to the writers. Samples of the handwritten text extracted from the documents we have used in the experiments are shown in fig. 2, while Table 1 reports the authors of each document.

Let us recall that handwriting style refers to the execution of a sequence of strokes that have been previously learned by the writers, so that they are produce automatically and thus fluently when writing a given word. Apparently, then, we should compare the traces associated to the same word. But, after the learning, every writer has developed his own way of writing the word, which may also include pen-down's and pen-up's movements. So, the same word can be written with different sequences of pen-down' and pen-up's. On the other hand, our conjecture is that handwriting style can be evaluated by looking at the shape of the traces. It follows that movements executed without leaving a trace on the paper, as it happens during pen-up's, are beyond the limits of our analysis. Thus, we consider only the fragments of the words containing traces drawn without lifting the pen and corresponding to the same sequence of characters. Those fragments need to be manually extracted from the words in order to avoid the errors introduced by both the writing order recovery and the stroke segmentation step, so in the experiments reported below we have extracted 1,503 fragments from 6 different documents, corresponding to 23 different sequences of character. Among them, the shortest sequence contains 2 characters, the longest 7. Eventually, each fragment was processed as before to compute the pair (Θ^s_{avg}, Γ^s_{avg}).

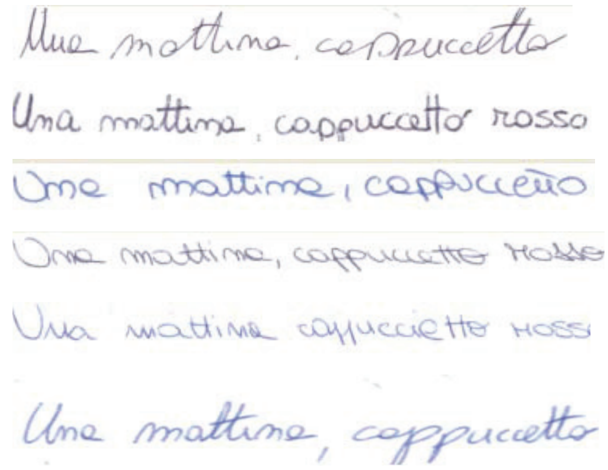

Fig. 2: Samples of handwriting extracted from the documents used in the experiments. The handwriting show belong to the documents 288, 32, 219, 707, 869 and 809, respectively.

For clustering the styles, we have used the k-means algorithm, with k equal to the number of document from which the fragments were extracted, because the number of writers is unknown. As similarity measure, we adopt the Euclidean distance between the samples. Both the algorithm and the similarity measure are standard practice in statistics. Figures 3-5 shows a few plots of the fragments in the model space. In the plots, each dot corresponds to a point, and its shape denotes the document to which it belongs. The centroids of the cluster are also shown. For the sake of clarity, in each plot we have reported only fragments extracted from 3 to 5 documents among the 6 we have processed.

After this processing, in the ideal case all the fragments extracted from the same document will be included into the same cluster. In practice, they may spread in many clusters, because it is possible that traces produced by different writers to encode some of the sequence of characters may have a very similar shape. To deal with that, we used a very simple criterion: to assign the document to the cluster that contains most of its fragments. Thus, we expect the algorithm to assign the document produced by different writers to different clusters, thus providing empty clusters when there are two, or more documents written by the same writer.

The results reported in the Tables II, III and IV, refers to the same fragments plotted in fig. 3, 4 and 5, respectively. Each entry represents the percentage of the fragments extracted from the document that are assigned to each cluster. The bold and italicised entries are those who determine the assignment of the *i-th* documents to the *j-th* cluster. The data reported in the tables compared with the ground truth reported in Table I show that documents produced by the same writer are always grouped in the same cluster, and when the number of writers *w* is smaller than *k*, i.e. there are some writers that produced two or more documents, there are *k-w* clusters containing few fragments of many writers, but not enough to have any document assigned to them.

5. Discussion and Conclusion

The data reported in the tables show that, despite its simplicity, the proposed model seems able to capture the distinctive aspects of handwriting styles. The reported performance was achieved by using the proposed model to describe handwritten samples and then by adopting a powerful but standard pattern recognition technique, namely the k-means algorithm with Euclidean distance as similarity measure, to highlight similarities (and dissimilarities) among them. The obtained clusters contained all and only the documents produced by the same writer.

It may be argued that such a conclusion has been drawn on a very limited data set, and therefore cannot be considered as reliable as one would like. While this is certainly true, we would like to highlight some aspects that may support our claim that the quality of the results does not depend on the data.

The documents used in this experiments were provided to 25 experienced FDEs participating to the project that leads to the collection of the whole data set, and only one of them was able to correctly identify the writer of each of them, confirming that the task we have addressed is very challenging for skilled human experts too. On the same set of documents, a much more complex system we have developed in a previous work [14], which adopts the CEDAR-FOX software to characterized the handwriting and the Borda count to produce the final output, was able to correctly identifying the authors of the pairs considered in both experiments, but not the writer who produced 3 documents.

All together, those observations seem to suggest that the paramount factor in determining the reported performance is the model of handwriting we have designed. Such a model is based on observations drawn from motor control and neuroscience studies about the way handwriting is learned and executed. It represents an attempt to model handwriting not by modeling the traces, as it is customary when a pure pattern recognition approach is followed, but rather by modeling the process that generates the traces. This further level of abstraction seems to be able to explain much of the variability encountered in handwriting in a much simpler way than it is required when the traces are directly considered. Such a reduction of complexity may explain the performance of a very simple model as the one we have developed.

In the future we will extend the experiment to the whole set of documents as well as to documents from publicly available data sets.

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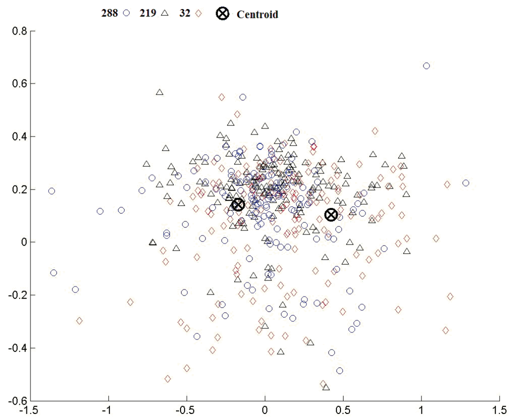

Fig 3. The plot shows the fragments extracted from 3 documents produced by 2 writers.

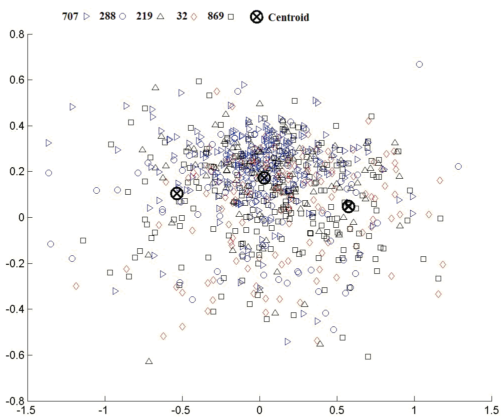

Fig. 4. The plot shows the fragments extracted from 5 documents produced by 3 writers.

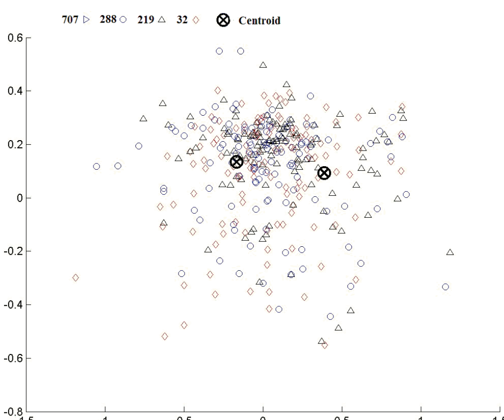

Fig. 5. The plot shows the fragments extracted from 4 documents produced by 2 writers.

TABLE I. THE AUTHORSHIP OF THE DOCUMENT

	Writer 1	Writer 2	Writer 3
Doc_id	32, 288, 809	707, 869	219

TABLE II. CLUSTERING OF THE FRAGMENTS SHOWN IN FIG. 3 AND THE FINAL CLUSTERING OF THE DOCUMENTS.

Doc_id	Cl_1	Cl_ 2	Cl_3
288	10.61	12.12	***77.27***
32	21.68	16.87	***61.45***
219	***58.90***	16.44	24.66

TABLE III. CLUSTERING OF THE FRAGMENTS SHOWN IN FIG. 4 AND THE FINAL CLUSTERING OF THE DOCUMENTS.

Doc_id	Cl_1	Cl_ 2	Cl_3	Cl_4	Cl_5
288	10.95	11.68	***40.15***	21.89	15.33
32	18.45	9.52	***30.36***	17.26	24.41
219	13.25	8.43	7.83	***36.75***	33.74
707	7.66	13.51	6.31	31.53	***40.99***
869	21.96	12.33	14.12	19.22	***31.37***

TABLE IV. CLUSTERING OF THE FRAGMENTS SHOWN IN FIG. 5 AND THE FINAL CLUSTERING OF THE DOCUMENTS.

Doc_id	Cl_1	Cl_ 2	Cl_3	Cl_4
288	15,84	13,86	4,95	***65,35***
32	12,74	9,80	24,50	***52,94***
809	8,91	17,82	6,93	***66,34***
219	16,43	8,21	***52,06***	23,29