TEMPORAL EVOLUTION IN SYNTHETIC HANDWRITING

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Highlights

- Method of synthesizing the temporal evolution of handwriting from childhood to adulthood.
- Synthesis of both online and offline handwriting.
- Parameters (E, $\varepsilon_D, \varepsilon_t, K_\sigma$) for dealing with synthesized handwriting evolution.
- Method for comparing temporal evolution of real and synthetic handwriting.

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Abstract

New methods for generating synthetic handwriting images for biometric applications have recently been developed. The temporal evolution of handwriting from childhood to adulthood is usually left unexplored in these works. This paper proposes a novel methodology for including temporal evolution in a handwriting synthesizer by means of simplifying the text trajectory plan and handwriting dynamics. This is achieved through a tailored version of the kinematic theory of rapid human movements and the neuromotor inspired handwriting synthesizer. The realism of the proposed method has been evaluated by comparing the temporal evolution of real and synthetic samples both quantitatively and subjectively. The quantitative test is based on a visual perception algorithm that compares the letter variability and the number of strokes in the real and synthetic handwriting produced at different ages. In the subjective test, 30 people are asked to evaluate the perceived realism of the evolution of the synthetic handwriting.

Keywords: handwriting; handwriting synthesis; handwriting evolution; equivalence model, kinematic theory of human movements.

1. Introduction

Handwriting is a common tool for communication between human beings. It involves both cognitive and motor skills. Following the motor equivalence model presented in [1], the handwriting process can be divided into two stages: the effector independent stage, where the text trajectory plan is build up at cognitive level and the effector dependent stage, where the handwriting is performed by the neuromuscular system. These processes are developed during childhood by repeating patterns. Once children learn the basic patterns and are able to reproduce them, they develop their own style and evolve it up to their adulthood [2].

Aging involves some changes in handwriting characteristics. It is easy to appreciate the different writing styles between child and adult writers (see Fig. 1). In children's handwriting the pen velocity is smaller and the number of strokes greater than in the adult case [3, 4]. With aging, the handwriting tends to become slower again like that of children who are starting to write [2].

Figure 1 Handwritten sample from a child (above) and an adult (below) writing the sequence a, e, I, o and u.

The research on handwriting synthesis has many motivations. Among them, is to provide large handwriting corpuses to the biometric community to evaluate automatic signature verifiers or writer identifiers and to avoid legal problems on privacy [5]. It is also worth mentioning that an accurate human like synthesis mechanism could help improve the understanding of the underlying processes in human handwriting production or even answer questions related to intra and inter personal variability, as well as to help understand the variability due to different diseases, such as Parkinsonǒs, Alzheimerǒs or ALS. In the future, artistic creation and CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) generation may have other motivations [5,6,7,8,9,10].

There are different ways to generate synthetic handwriting. Some produce duplicates of a given handwritten sample. These duplicates can be generated by simple affine distortion or stroke wise distortion, as proposed by [11,12,13,14]. A second way of generating synthetic handwriting is the glyph-based method, which records individual letters or words from one user, applies geometric deformation to simulate a new user and joins them to create a new version of the handwriting [15, 7]. Other methods generate handwriting samples by modifying the parameters of a handwriting generation model. Handwriting models have also been developed in the frequency domain [16] or from a neuromotor perspective [17, 18]. None of the above have studied the temporal evolution of handwriting nor included handwriting evolution models in the synthesizer.

This paper is aimed at synthesizing handwriting by taking into account the *graphic maturity* of the synthetic writer for emulating its temporal evolution from childhood to adulthood. Graphic maturity is defined as the time a healthy person has been practicing his handwriting [19]. Specifically, the paper tries to answer the question: how could the writing script of writers of different graphic maturity be synthesized automatically in a common framework?

Related research has been performed on age estimation from handwriting [20] and on studying the effects of aging in signature recognition [21, 22]. It is expected that studying handwriting evolution from the synthesis point of view will deepen our understanding of the human handwriting process and its influence in designing automatic writer and signature verifiers.

As the maturity process involves both the cognitive and the motor system, the synthesizer most suitable for modelling the temporal evolution of the handwriting is the one proposed in [17], which allows actions at both cognitive and motor level. Specifically, actions at cognitive level are related to the modification of the letter engram trajectories through the spatial grid, as evident in [23]. At motor level, actions to take into account the maturity modify the Plamondon Kinematic model [24].

The model presented here is verified for three important ages: 5, 10 and adult. This is because these three ages are distinct in terms of behavioural adjustment and related to the maturation process of the neuromotor system in human beings. At the age of 5, children start to learn the motor programs required to write with pre-handwriting letter patterns. The motor programs for cursive handwriting are fully developed and integrated around age 10 but need more deliberate practice [2, 4]. By the time children reach adulthood, handwriting movements are fully mastered.

Summing up, this paper proposes a novel procedure through the use of a synthetic handwriting model to emulate the temporal evolution of real handwriting. A review of the basic handwriting synthesizer which our method relies upon is presented in Section 2, while the proposed temporal evolution model and its integration into the basic synthesizer is described in Section 3. The performance evaluation is described in Section 4. This reports the quantitative experiments based on speed profiles and stroke distributions of real and synthetic handwriting samples at different ages. It also describes surveys on subjective opinion about the temporal evolution of synthetic handwriting. Section 5 closes the paper with the conclusions.

2. Overview of the basic synthesizer.

The basic handwriting synthesizer is founded on the equivalence model that divides human handwriting into two steps: the working out of an action plan (effector independent) and its execution via the corresponding neuromuscular path (effector dependent). Once the action plan is learnt, most of the variability arises from the effector-dependent component [25].

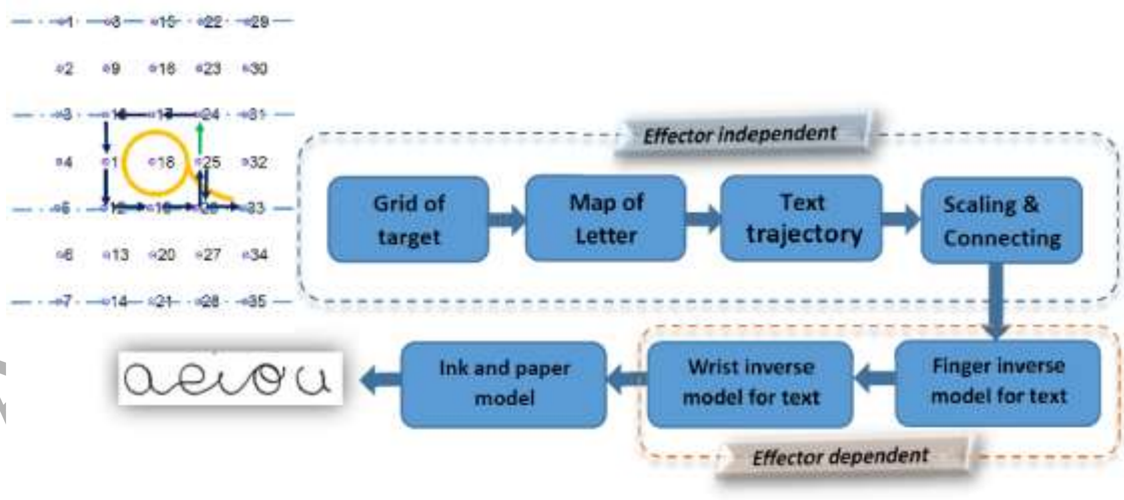

Figure 2: Motor equivalence approach to synthetic handwriting generation and the trajectory plan for the letter ‘a’

The synthesizer simulates the action plan through a trajectory plan which is a tessellation of a sequence of grid nodes. The neuromuscular path is calculated by the inverse model [26] as a sequence of kinematic filters that imitate the sequence of motor commands. Finally, an ink deposition model is applied. The block diagram of the synthesizer is shown in Fig. 2.

The trajectory plan is built by concatenating letter trajectory plans which describe the sequence of grid points necessary to write each letter. The letter trajectory plan defines the temporal order of the principal targets of the pen movement [27], emulating how letters are memorized [15]. An example of trajectory for letter ñaòis shown in Fig. 2, where each grid point is labeled with a number. For instance, the letter trajectory plan for the letter ñaòis defined as the following sequence of grid points: {25, 24, 17, 10, 11, 12, 19, 26, 25, 26 and 33}.

Once the trajectory plan is defined, an inverse model for motor control is applied to obtain a realistic human text trajectory. In short, two kinematic filters, which are heuristically related to the finger and wrist, are applied as follows:

1. the grid points of the trajectory plan are linked by straight lines and divided into strokes;
2. the finger velocity profile is estimated using the kinematic theory of rapid movements, developed in [28]. This theory shapes the velocity profile of a simple stroke with a lognormal function scaled by the variable D and time-shifted by the variable t_0:

$$|\vec{v_j}(t;t_{0j})| = D_j\Lambda_j(t;t_{0j},\mu_j,\sigma_j) = \frac{D_j}{\sigma_j\sqrt{2\pi}(t-t_{0j})}e^{\left(\frac{-\left|\ln(t-t_{0j})-\mu_j\right|^2}{2\sigma_j^2}\right)} \quad (1)$$

Table 2: p-value results from the comparison between groups of Fig. 20 (similarity value).

	5 years real	Ⱥ =100 synthetic	10 years real	Ⱥ =50 synthetic	>18 years real	Ⱥ =20 synthetic
5 years real	**1.0000**	0.0000	0.0000	0.0000	0.0000	0.0000
Ⱥ =100 synthetic	0.0000	**1.0000**	0.0000	0.0000	0.0000	0.0000
10 years real	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0006
Ⱥ =50 synthetic	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000
>18 years real	0.0000	0.0000	0.0000	0.0000	**1.0000**	**0.7385**
Ⱥ =20 synthetic	0.0000	0.0000	0.0006	0.0000	**0.7385**	**1.0000**

4.3. Perceptual evaluation

To evaluate the extent to which the modeling of temporal evolution generates samples that are perceived as produced by writers with different level of graphic maturity, we conducted a survey with 30 volunteers who were adults with a university education. The volunteers were asked to rank the handwriting from the youngest to the oldest. The handwritten samples shown to the volunteers were generated by changing only the Ⱥ value and were randomly ordered for each questioned volunteer. Once the words were ranked, the Ⱥ value of all the words with the same ranking were averaged. Fig. 21 shows the averaged result for each Ⱥ value. As can be seen, the respondents were able to sort out the graphic maturity with amazing reliability, except for the two first values of Ⱥ =80 and Ⱥ =70 which resulted in being indistinguishable.

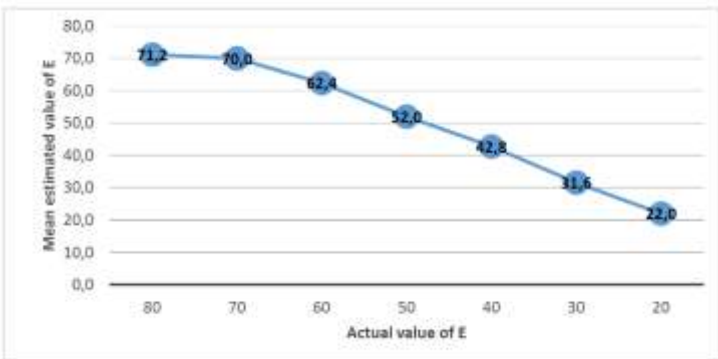

Figure 21: Mean of the E values estimated by the volunteers (Y axis) with respect of the actual E values used to generate the samples (X axis).

5. Conclusions and discussion

This paper proposes a novel methodology for including handwriting fluency evolution in a handwriting synthesizer. In the proposed method, changes to the graphic maturity from childhood to adulthood of synthetic handwriting are modeled with just four parameters (E, $\varepsilon_D, \varepsilon_t, K_\sigma$).

The initial handwriting synthesizer is based on the motor equivalence model which divides the human action into two steps: the effector dependent and the effector independent. The effector independent is approached by a hexagonal grid that spans the handwriting area. The action plan is defined as a sequence of grids. The effector dependent step is defined with inertial filters.

This paper redefines the effector dependent and independent step to allow the introduction of handwriting fluency progress into the synthesizer. Effectively, a lognormal shape profile is assigned to each segment of the action plan. The lognormal parameters are estimated through formulae that control the overlapping of the lognormals of the action plan, depending on the angle between consecutive segments and the writer's skill. The proposed synthesizer uses an initial dense action plan, appropriate for the early stages of handwriting development, and progressively selects a percentage Ⱥ of the initial set of grid points under the constraint of preserving the intelligibility of the handwriting.

Three experiments, one based on the dynamics of the synthesized handwriting, a second based on the static image of the generated trajectory and a third based on human perception of handwriting similarity, show how, by changing the percentage Ⱥ of selected grid points, it is certainly possible to generate synthetic handwriting which exhibits different level of graphic maturity.

This result seems to answer affirmatively the original question and confirm that it is possible to synthesize automatically handwriting of different maturity both in shape and dynamics in a common framework. The results show that when the E value decreases both the number of peaks and the intra-writer variability follow the real handwriting. The experimental results give measurable evidence of the similarity between real and synthetic handwriting in both shape and dynamics.

Comparing the results of both experiments (shape and dynamics), it should be noted that the number of strokes worked out in the dynamic domain is slightly greater than the number of strokes counted in the handwritten image. Strokes are not directly apparent in the image of a handwritten word because they are partially hidden in the trajectory as a consequence of the time superimposition process [11]. The dynamics evaluate spatio-temporal aspects of the handwritten word but the statics can evaluate only spatial aspects.

Nevertheless, in both shape and dynamics, the evolutional result of the synthetic handwriting is consistent with the well-known decreasing of the number of strokes with the practice [4]. The new method used to extract strokes from a static image [33] seems to be useful in analyzing the graphic maturity in the handwriting images.

The temporal evolution model based upon the tuning of the $\mathring{U}_b$ parameter is able to produce handwritten words showing the same variation around the ideal trajectory produced by children in their early handwriting [3].

The proposed methodology could be used to generate a synthetic database for improving automatic biometric writer recognition or in CAPTCHA generation.

This study opens up the possibility of further research into handwriting evolution for elderly people. In this case, it would obviously be necessary to obtain the co-operation of a medical team who should verify the state of health of any volunteers. Moreover, similar research could be carried out to characterize degenerative diseases such as Alzheimerœs, Parkinsonœs, essential tremor and so on.

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