Pattern Recognition Letters 35 (2014) 225–235

Contents lists available at SciVerse ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Recent developments in the study of rapid human movements with the kinematic theory: Applications to handwriting and signature synthesis

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ARTICLE INFO

Article history:
Available online 15 June 2012

Keywords:
Kinematic theory
Human movement modeling
Sigma–lognormal model
Motor control
Signature synthesis
Gesture synthesis
Handwriting recognition
Signature verification
Customizable on-line recognition systems

ABSTRACT

Human movement modeling can be of great interest for the design of pattern recognition systems relying on the understanding of the fine motor control (such as on-line handwriting recognition or signature verification) as well as for the development of intelligent systems involving in a way or another the processing of human movements. In this paper, we briefly list the different models that have been proposed in order to characterize the handwriting process and focus on a representation involving a vectorial summation of lognormal functions: the Sigma–lognormal model. Then, from a practical perspective, we describe a new stroke extraction algorithm suitable for the reverse engineering of handwriting signals. In the following section it is shown how the resulting representation can be used to study the writer and signer variability. We then report on two joint projects dealing with the automatic generation of synthetic specimens for the creation of large databases. The first application concerns the automatic generation of totally synthetic signature specimens for the training and evaluation of verification performances of automatic signature recognition systems. The second application deals with the synthesis of handwritten gestures for speeding up the learning process in customizable on-line recognition systems to be integrated in electronic pen pads.

1. Introduction

Human movement modeling can be of great interest for the design of pattern recognition systems relying on the understanding of the fine motor control, like on-line handwriting recognition and signature verification, as well as in the development of intelligent systems involving in some way the analysis of human movements. Among other things, this general approach aims at elaborating a theoretical background for any handwriting processing application as well as providing some basic knowledge that can be integrated in the development of automatic systems.

So far, many models have been proposed to study human movement production in general and handwriting in particular: models relying on neural networks (Bullock and Grossberg, 1988; Schomaker, 1991; Gangadhar et al., 2007; Kalveram, 1998), equilibrium point models (Feldman, 1966; Feldman and Latash, 2005; Bizzi et al., 1978, 1992), behavioral models (Schmidt and Lee, 1999; Thomassen et al., 1983; van Galen and Teulings, 1983), coupled oscillator models (Hollerbach, 1981; Kelso, 1995; Zanone et al., 2005), kinematic models (Plamondon, 1995a,b; Plamondon and Djioua, 2006), and models exploiting minimization principles (Wada and Kawato, 1995; Engelbrecht, 2001): minimization of the acceleration (Neilson, 1993; Neilson and Neilson, 2005), of the energy (Nelson, 1983), of the time (Tanaka et al., 2006; Enderle and Wolfe, 1987; Hermes and LaSalle, 1969), of the jerk (Hogan, 1984; Flash and Hogan, 1985), of the snap (Edelman and Flash, 1987), of the torque changes (Uno et al., 1989) and of the sensory-motor noise (Harris and Wolpert, 1998). Finally, many models exploit the properties of various functions to reproduce human movements: exponentials (Plamondon and Lamarche, 1986), second order systems (Denier van der Gon and Thuring, 1965; Dooijes, 1983), gaussians (Leclerc et al., 1992), beta functions (Alimi, 2003), splines (Morasso et al., 1983) and trigonometrical functions (Maarse, 1987).

Among the models which provide analytical representations, the kinematic theory of rapid human movements (Plamondon, 1995a,b; Plamondon and Djioua, 2006) and its Delta- and Sigma–lognormal models have been used to explain most of the basic phenomena reported in classical studies on human motor control (Plamondon and Alimi, 1997) and to study several factors involved in the fine motricity (Plamondon and Guerfali, 1998; Plamondon et al., 2007; Djioua and Plamondon, 2008, 2009a; O'Reilly and

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http://dx.doi.org/10.1016/j.patrec.2012.06.004

Plamondon, 2010; Woch et al., 2011). Apart from these fundamental studies, the theory has been used, directly or indirectly, in many practical applications like the design of a signature verification system (Plamondon, 1994), the development of tools to help children learning handwriting (Djeziri et al., 2002), as well as of biomedical set ups to detect fine motor control problems associated with brain strokes (O'Reilly and Plamondon, 2011, 2012).

In this paper, we report on two new and original case studies dealing with the automatic generation of synthetic handwritten specimens for the creation of large databases. The first application addresses the automatic generation of totally synthetic signature specimens which may be used for the training and evaluation of the verification performances of automatic recognition systems as well as for the quality assessment of specimens. The second application regards the synthesis of handwritten gesture for speeding up the learning process in customizable on-line recognition systems to be integrated in electronic pen pads. Sections 5 and 6 reports detailed results about these two genuine applications, which at the time of the ICFHR 2010 keynote address presented by the first author, were the first trial of using the kinematic theory for the generation of synthetic trajectories to be used in signature verification and gesture recognition experiments.

To better understand these applications and estimate their potential interest, as well as making the present paper self-consistent a brief survey of the kinematic theory is presented in Section 2, two algorithms used for Sigma–lognormal parameter extraction are outlined described in Section 3 and the main results on previous studies of handwriting variability are summarized in Section 4. These sections present in a condensed and goal oriented way, the main concepts and strategies that have been explored over the years and that are necessary to understand the present applications, without coming back to these complete and often more exhaustive studies.

2. The kinematic theory of rapid human movement and its Sigma–lognormal model

One key feature of the kinematic theory is that it relies on strong and robust mathematical grounds. All the models that are used under this paradigm are based on the lognormal function which has been proved to be the ideal curve for describing asymptotically the impulse response of a neuromuscular network made up of a large number of coupled subsystems controlling the velocity of a movement (Plamondon et al., 2003). For simple reaching or pointing gestures, a target is specified and two of these networks are needed to control a trajectory, an agonist network which is acting in the target direction and one antagonist, acting in the opposite direction. Overall, the speed profile is then described by a Delta-lognormal equation, a weighted difference of two lognormals (Plamondon, 1995a,b). When more complex trajectories have to be generated, like in handwriting or in signing, a sequence of targets has to be reached and, globally, the trajectory of the pen tip can then be described by a vectorial summation of lognormals, hereinafter called Sigma–lognormal equations, which takes into account the various changes of direction.

In this vectorial summation context, the production of a word or of a signature requires the definition beforehand of an action plan that is made up of virtual targets, which are linked in pairs with an arc of circle. This map of paired target points represents a sequence of discontinuous strokes. This plan triggers a motor command generator that produces a series of impulses activating the neuromuscular systems characterized by their lognormal impulse response (Plamondon and Privitera, 1995). For each impulse, a lognormal velocity profile is generated at the pen tip and the time superimposition of these strokes results in a smooth and well controlled trajectory. According to this representation, the original strokes are thus hidden in the signal.

Mathematically, the Sigma–lognormal model considers the velocity of the pen tip, $\vec{v}(t)$, as described by a vectorial summation of N lognormal primitives:

$$\vec{v}(t) = \sum_{i=1}^{N} \vec{v}_i(t) = \sum_{i=1}^{N} \vec{D}_i(t) \Lambda_i(t, t_{0i}, \mu_i, \sigma_i^2); N \geqslant 2 \tag{1}$$

Each lognormal in this summation defines a stroke scaled in amplitude by a command parameter (D) and time-shifted by the time occurrence of this command (t_0), any individual stroke pattern being described by a lognormal time function:

$$\Lambda(t; t_{0i}, \mu_i, \sigma_i^2) = \frac{1}{\sigma_i \sqrt{2\pi}(t - t_{0i})} \exp\left(\frac{-[\ln(t - t_{0i}) - \mu_i]^2}{2\sigma_i^2}\right) \tag{2}$$

Each of these primitives is also assumed to occur around a pivot, and the evolution of the angular position of the trajectory can be calculated using an error function (*erf*):

$$\theta_i(t) = \theta_{si} + \frac{(\theta_{ei} - \theta_{si})}{2}\left[1 + \mathrm{erf}\left(\frac{\ln(t - t_{0i}) - \mu_i}{\sigma_i \sqrt{2}}\right)\right] \tag{3}$$

where θ_{si} and θ_{ei} refer, respectively, to the starting and ending angular direction of each stroke. In Eqs. (2) and (3), μ_i and σ_i represent correspondingly the logtime delay and the logresponse time of the neuromuscular system as it reacts to the ith command (Plamondon and Djioua, 2006).

Under these conditions, the synergy produced by the interaction and coupling of many of these neuromuscular systems results in the sequential generation of a complex handwriting sample or a signature pattern.

3. Sigma–lognormal parameter extraction

To use the Sigma–lognormal model for analyzing human movements, it is necessary to have an algorithm to solve the inverse problem in a fully automatic fashion, that is, to extract the lognormal parameters that most adequately fit the experimental data. The Sigma–lognormal parameters are considered to be well estimated and fitted for statistical analysis if the SNR, defined in (4), is over 20 dB.

$$SNR = 10 \log \left(\frac{\int v_{x\_n}^2 + v_{y\_n}^2 dt}{\int (v_{x\_n} - v_{x\_\Sigma})^2 + (v_{y\_n} - v_{y\_\Sigma})^2 dt}\right) \tag{4}$$

In this equation, (v_{x_n}, v_{y_n}) are the experimental (numerical) velocity signals and $(v_{x\_\Sigma}, v_{y\_\Sigma})$ are the velocity signals of the Sigma–lognormal reconstruction.

In the last years, two complementary algorithms have been proposed to solve this nonlinear regression problem, the Robust Xzero based algorithm and the prototype based algorithm. The next subsections briefly overview the state-of-the-art regarding these parameter extractors.

3.1. The Robust Xzero based extractor

The Robust Xzero (RX0) based extractor is a powerful algorithm that provides an accurate set of Sigma–lognormal parameters describing the end-effector trajectory (e.g., the pen tip trajectory in handwriting studies) of arbitrarily complex motions without any *a priori* knowledge regarding the nature of the movement. In the following text, an outline of the algorithm is presented. A more comprehensive description can be found in (O'Reilly and Plamondon, 2009; O'Reilly, in preparation).

To implement this algorithm, sequences of five characteristic points $(t_{i\_n}, v_{ti\_n}$ $(i = 1, 2, \ldots, 5)$ must be located in the original