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Prototype-based methodology for the statistical analysis of local features in stereotypical handwriting tasks

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Abstract

A three steps methodology is proposed to derive consistent sets of local features which may be easily compared between the different samples of a stereotypical human handwriting movement, allowing the statistical analysis its local variability. This technique is illustrated using the Sigma-Lognormal modeling of on-line triangular trajectory patterns obtained from a standardized neuromuscular task. The overall approach can be adapted and generalized to the analysis of the end-effector kinematics of many planar upper limb movements.

1. Introduction

On-line handwriting analysis and processing has been a major topic in pattern recognition since the very beginning of the discipline, particularly for applications dealing with character, symbol or word recognition [1-3] as well as signature verification [4]. Apart from these two main streams, several research projects have been conducted over the years to transfer part of this knowledge and methodologies to track various problems in education, forensic sciences, anthropomorphic robotics, psychology, and medicine.

In these latter two fields, handwriting has been exploited, among other things, to analyze the neuromotor control of patients with Alzeimer's [5] or Parkinson's diseases [6] and to design neuropsychological [7] and rehabilitation [8] tests for stroke patients. Most of these studies rely, directly or indirectly, on a human motor control model that serves as the corner stone upon which research hypotheses are investigated. Then, researchers use different features extracted from movements gathered from standardized tests to run statistical analyses and develop recognition algorithms. Typically, these features can be considered as either global or local. Although the comparison of a global feature value on different samples is most of the time a straightforward process, the situation gets more complicated when dealing with local features obtained through a heterogeneous segmentation of patterns.

In some cases, such as in neuroscience studies, it may be advantageous, to describe the main characteristics of a test movement by using a feature set which exhibit an inter-sample consistency. Such feature sets will hereafter be referred to as being *consistent*, a concept that is defined more thoroughly in section 2. Section 3 presents a prototype-based feature extraction methodology that guarantees this property. The section 4 discusses the experimental results obtained using this technique on human movement data.

2. Consistent feature set

A global feature (i.e. a parameter describing the whole movement, for example the trajectory duration) is, by nature, consistent in the sense that its value on a given sample may always be compared to its value on any other movement. These features always have an obvious, unambiguous and known 1-to-1 relationship.

This correspondence becomes more complicated when local features (i.e. parameters which describe characteristics of restricted parts of a movement, for example the local maxima of the amplitude of a pen tip speed) are considered. These features take on a variable number of values depending on the motion

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sample considered and the segmentation technique used to divide it in parts. Therefore, local features usually form an inconsistent set in the sense that no clear relationship can be established between their values across different movements. For this kind of features, there is an unobvious, ambiguous and unknown N-to-M relationship.

Although many techniques may be used to try to establish an adequate correspondence between the elements of such inconsistent sets (e.g. using dynamic programming for matching feature strings), it is still unclear how a systematic statistical analysis of these feature variations may be performed on this kind of stereotypical movement data.

In this publication, we propose to use an alternative strategy to ease the pattern analysis. That is, to extract consistent local feature sets which are characterized by an unambiguous N-to-N relationship.

3. Prototype-based consistent feature set extraction

To study the effect of various factors on the characteristics of a stereotypical class of movements, (e.g. reaching movement, circle drawing, writing of a given letter), a new feature extraction methodology has been developed. It proceeds in three steps: 1) synthesizing a movement prototype, 2) scaling and time-shifting this prototype to a real movement, 3) and optimizing the curve fitting between this modified prototype and the real movement.

3.1. Synthesizing a prototype

The synthesis of a movement prototype is based on prior knowledge of the task specifications and on the nature of the human movement generation process.

3.1.1. Prior knowledge on the task specification.

A priori knowledge can be derived from the task specification when the stereotypical nature of the movements is ensured through a set of rules, guiding sheets or similar apparatus. This kind of constraints is often applied, for example, in experimental study of human movements or in neuromuscular tests.

3.1.2. Prior knowledge on human movement.

A priori hypotheses can be derived from a human motor control theory. In this work, we used for that purpose the Sigma-Lognormal model [9] derived from the Kinematic Theory of rapid human movements. It considers a movement as the product of the synergistic interaction of multiple neuromuscular components. The end-effector velocity ($\vec{v}$) is modeled mathematically through the vectorial summation of the speed (v_{ti}) and the direction (ϕ_i) of the individual components.

$$\overrightarrow{v(t)} = \sum_{i=1}^{N} \mathrm{v}_{\mathrm{ti}}(\mathrm{t}) \begin{bmatrix} \cos(\phi_i(t)) \\ \sin(\phi_i(t)) \end{bmatrix} \tag{1}$$

The speed $\mathrm{v}_{\mathrm{ti}}(\mathrm{t})$ of a component follows a lognormal profile - characterised by its usual μ and σ parameters - which is scaled and time shifted respectively by the parameter D and t_0 whereas its direction $\phi_i(t)$ is defined in such a way that it has a circle arc trajectory starting at an angle θ_s and ending in the direction θ_e.

$$\mathrm{v}_{\mathrm{ti}}(\mathrm{t}) = \frac{D_i}{\sigma_i(t-t_{0i})\sqrt{2\pi}} \exp\left(\frac{[\ln(t-t_{0i})-\mu_i]^2}{-2\sigma_i^2}\right) \tag{2}$$

$$\phi_i(t) = \theta_{\mathrm{si}} + (\theta_{\mathrm{ei}} - \theta_{\mathrm{si}}) \int_0^t \mathrm{v}_{\mathrm{ti}}(\tau)\, d\tau \tag{3}$$

3.2. Scaling and time-shifting the prototype

The global time scaling (i.e. setting a shorter or a longer duration) and shifting (i.e. setting an earlier or a later onset) of a stereotypical human movement account for a large part of its variability [10], as long as its duration is kept relatively short. Fortunately, such transformation may be easily manipulated to adjust the prototype to a real movement by finding the value of a scaling factor (C_s) and of a time-shifting parameter (t_s) such that the curve fitting between the modified prototype and the real movement is optimal.

It can be shown that a proportional stretching and a time shifting of a Sigma-Lognormal equation only necessitate the modification of the μ_i and the t_{0i} parameters such that the scaled values (μ_{is} and t_{0is}) are related to the original values (μ_i and t_{0i}) through the scaling factor C_s and the time-shifting parameter t_s.

$$t_{0is} = C_s t_{0i} + t_s \tag{4.a}$$

$$\mu_{is} = \mu_{is} + \ln(C_s) \tag{4.b}$$

3.3. Optimizing the parameters

The scaled and time-shifted prototype can be used as a starting solution to be refined further through any non-linear optimization technique. In this work, a custom algorithm based on the generalized pattern search algorithm [11] has been used.

4. Experimental results

4.1. Data collection

The previous technique has been applied to movements acquired in the context of a project aiming at developing tools for the prevention of neuromuscular disorders. The test movements where performed by 120 subjects from both genders, being between 25 to 85 years old and having variable health conditions (some had stroke and about half of them had at least one the following stroke risk factor: diabetes mellitus, hypertension, hypercholesterolemia, obesity, cigarette smoking, and cardiac problems).

Each subject was asked to draw a triangle passing through two intermediary targets and ending on a third target (which was the starting point). A guiding sheet was given to specify the target geometry to the subject[1]. The pattern had to be performed as fast as possible in response to an audio stimulus. Two repetitions were collected, for three different triangle sizes and for both clockwise and counterclockwise directions. Hence, each one of the 120 subjects made 12 movements for a total of 1440 samples.

4.2. Prototype definition

Since the movement was constrained by the task specifications, it was assumed that the task was executed as a series of three straight and sequential but time overlapping target reaching movements. Moreover, it was hypothesized that each reaching movement was constituted of two neuromuscular components, one agonist to the movement (aiming at the target) and one antagonist (stopping the movement to avoid overshooting). Table 1 gives the values of the Sigma-Lognormal parameters used to generate the prototype of the smaller clockwise triangle. Using these parameter values with equations (2) and (3) any investigator could reproduce the prototype used in our analysis. The choice of these parameter values is heuristically derived from prior knowledge discussed in the current paragraph and in section 3.1.

TABLE I: ΣΛ PARAMETERS FOR SMALL CLOCKWISE TRIANGLE

No log.	t_0 (s)	D (mm)	μ	σ	θ_s (rad)	θ_e (rad)
1	0.1	50	-1.65	0.34	2π/3	2π/3
2	0.1	5	-1.37	0.16	- π/3	- π/3
3	0.3	50	-1.65	0.34	0.0	0.0
4	0.3	5	-1.37	0.16	π	π
5	0.5	50	-1.65	0.34	-2π/3	-2π/3
6	0.5	5	-1.37	0.16	π/3	π/3

The other triangle prototypes were obtained by multiplying by 2 or 3 the D parameters (i.e. which is equivalent to multiplying the size of the triangle by the same factor) and by adjusting the angular parameters to reverse the direction for the counterclockwise triangles.

4.3. Evaluation of the curve fitting quality

Using the prototypes defined in section 4.2 and the methodology outlined in section 3, the features of the 1440 triangles have been extracted. The quality of these extractions was evaluated using the signal-to-noise ratio (SNR) between the velocity of the real movements (v_{xn}, v_{yn}) and of the movements reconstructed from the extracted parameters (v_{xa}, v_{ya}).

$$SNR = 10log\left(\frac{\int[v_{xn}^2(t)+v_{yn}^2(t)]dt}{\int\left[\left(v_{xn}(t)-v_{xa}(t)\right)^2+\left(v_{yn}(t)-v_{ya}(t)\right)^2\right]dt}\right) \quad (5)$$

Figure 1 compares the distribution of the SNR obtained using this technique with what has been obtained using the RX_0 parameter extractor [12]. The average fitting SNR is respectively 22.05dB and 20.75dB for the RX_0 and the prototype-based (PB) extraction, with a larger variability for the PB extractions. This is nevertheless a very acceptable performance for the PB extraction method considering its simplicity and the fact that it always use 6 lognormal components (i.e. it extracts consistent parameter sets) whereas the RX_0 extraction method derived a variable number of components (i.e. it extracts inconsistent parameter sets) with an average of 9.1 lognormals.

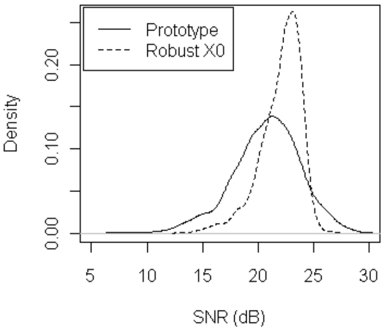

Figure 1 Distribution of the reconstruction SNR obtained with the RX_0 and the PB extractor.

4.4. Using a consistent parameter set for movement analyses

The availability of consistent local parameter sets for the different movements allows the statistical analysis of these parameters variability through various techniques such as ANOVA or HMM.

As a simple example, figure 2 shows the variation of two μ parameters with respect to the age of the

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[1] These sheets had three circular targets with a 15mm diameter placed at the apex of equilateral triangles with three vertex size: 135mm, 90mm or 45mm.

participants for the small clockwise triangle drawing task. Apart from its obvious increase with age, it shows that these features seem to be most discriminating of the age for movements that the subject directs toward himself. Indeed, as a function of age, the variations of μ_5 (associated with the agonist component of the inward last target reaching), is greater than the variations of μ_1 (associated with the agonist component of the outward first target reaching). This shows that inward movement seems to be more influenced by the age than the outward movement, at least for the μ parameter. This is an example of a phenomenon that might not have been observed without the use of the present technique. Such a phenomenon might have a practical relevance in some psychophysical analysis of handwriting.

A more thorough example of application can be found in [13] where these triangular drawings have been analyzed using this technique to study the relationship between fine motor control characteristics and the presence of brain stroke risk factors.

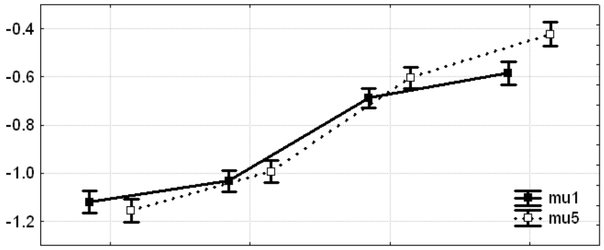

Figure 2 Example of analysis of the variance of a local feature (μ_1 and μ_5) as a function of the age. Whiskers indicate the 95% confidence interval.

5. Conclusion

In this paper, we have presented a method of analysis, based on movement prototypes, that can be used to study statistically the local variations of human movements as a function of some factor (e.g. age, health condition, fatigue). This pattern analysis technique allows to model complex standardized motions with a relatively few parameters while still achieving high quality curve fitting. An important characteristic of this technique is that it uses a consistent parameter set (e.g. the set of 36 features used in our example) which allows easier analysis of local movement variability. This paper has highlighted its use for the analysis of triangle drawings in a neuroscience study. However, the methodology described here is applicable to many other types of human movements involving the kinematic of an end-effector and it is transferable to other fields interested in characterizing human movements such as the biomedical engineering, the experimental psychology and the writing education.

Finally, although in this study we exclusively focused on handwriting analysis for psychophysical analysis, this technique may be applicable to handwriting recognition applications, although this topic is beyond the scope of the present paper.

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