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Omega-Lognormal Analysis of Oscillatory Movements as a Function of Brain Stroke Risk Factors

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Abstract.
The development of predictive tools has been commonly utilized as the most effective manner to prevent illnesses that strike suddenly. Within this context, investigations linking fine human motor control with brain stroke risk factors are considered to have a high potential but they are still in an early stage of research. The present paper analyses neuromuscular features of oscillatory movements based on the Omega-Lognormal model of the Kinematic Theory. On a database of oscillatory movements from 120 subjects, we demonstrate that the proposed features differ significantly between subjects with and without brain stroke risk factors. This promising result motivates the development of predictive tools based on the Omega-Lognormal model.

1. Introduction

A brain stroke, or cerebrovascular accident, is characterized by the sudden manifestation of combined cerebral circulatory disorders that negatively affect the vasculature of the brain. A brain stroke episode results in necrosis of certain brain cell types, which causes irreversible damage to an array of neurological functions in 22% to 25% of the patients and death within one year for 25% of the patients [1]. Approximately 795.000 people experience a new or recurrent stroke annually. Therefore, on average, someone dies of a stroke every 4 minutes [2].

Furthermore, brain strokes are sudden events and most of the time they occur unexpectedly. An effective method of addressing this medical issue is therefore prevention through the development of predictive tools. Handwriting recognition tools have emerged as one such possible solution [3, 4]. It is not the first time that pattern analysis of fine motor control is employed in disease prevention. Noticeable results have been achieved previously in the prevention of other diseases, such as Parkinson disease [5] or Schizophrenia [6].

It has been reported recently that some brain stroke risk factors can be associated with the deterioration of several cognitive psychomotor characteristics [7], which are obtained from the lognormal handwriting model of the Kinematic Theory [8, 9, 10]. In this paper, we focus on one of the movement modalities suggested in [7], namely oscillatory movements at maximum frequency, and investigate the feasibility of developing predictive tools in more detail. The study and analysis of oscillatory movements has a strong history in human motor control, from a theoretical and model perspective [11, 12, 13] to applications in various field [13, 14].

To achieve our goal, a database containing the handwriting movements of 120 subjects with and without brain stroke risk factors is analysed using the Omega-Lognormal model [7]. We propose a set of seven neuromuscular features based on the model and demonstrate with ANOVA tests that four of these differ significantly between subjects with and without risk factors. The results obtained can be considered as an initial step towards the development of a tool to determine if the performer of oscillatory movements has brain stoke risk factors or not.

The remainder of this paper is organized as follows. First, the experimental protocol for the acquisition of oscillatory movements is detailed in Section 2. Then, the data analysis based on the Omega-Lognormal model and the proposed neuromuscular features are presented in Section 3. Finally, experimental results are provided in Section 4 and conclusions are drawn in Section 5.

2. Experimental Protocol

For the assessment of the proposed method, a database containing digitized information of oscillatory movements from 120 subjects was used. Within the database, 57 subjects considered as healthy are mixed with 63 exhibiting some of the following brain stroke risk factors (abbreviation, number of subjects affected): diabetes mellitus (DM; 15), obesity (OB; 10), hyper-tension (HT; 40), hypercholesterolemia (HC; 28), cardiac disease (CD; 24), and cigarette smoking (CS; 13). From these 63 participants, 25 had only one risk factor, 18 had two, 12 had three, 7 had four, and 1 had five. In order to evaluate a

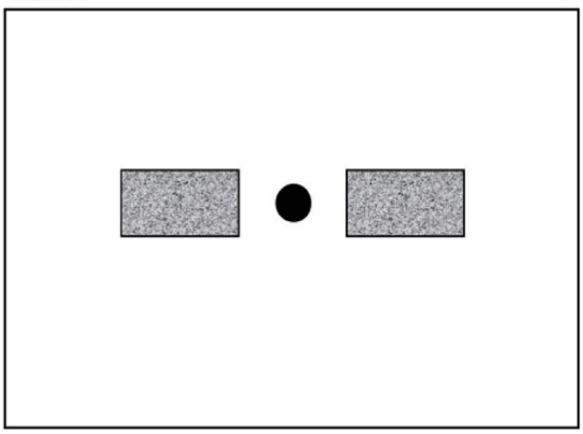

Figure 1 | Guiding sheet for the oscillatory movements test. The black circle and the gray areas indicate respectively the starting and the target zones

wide age rage, 27 of the participants are between 25 and 39 years old, 31 are between 40 and 54, 33 are between 55 and 69 and 29 are between 70 to 85 years old. Moreover the distribution among genders is almost balanced as the sample contains 68 women and 52 men.
During the performance of the trial, a Wacom Intuos2 tablet was used to digitize the 2D Cartesian coordinates of the pen tip at a sampling frequency of 200 Hz.
To accomplish the trial, the subjects were asked to perform oscillatory movements with the pen tip as fast as possible between two targets during ten seconds, after a start signaled by an auditory cue. Additionally, guiding sheets were used to indicate to the participants the starting position and the targets to hit as illustrated in Figure 1. The movements were performed with the dominant hand. 112 participants reported themselves as right-handed.
It is also important to mention that no practice or learning period was allowed before the exercise and only one acquisition of data was permitted. After removing outliers, 115 subjects were kept in the database. More information about the database can be found in [7].

3 Data Analysis

3.1 Omega-Lognormal Model

The Kinematic Theory of rapid human movements is a set of models that describe human handwriting movements using a unique framework based on the delta-lognormal law. A basic unit representing a pen stroke is built up from lognormals. These models grant a fitting reconstruction of handwriting velocity profile [15]. Amid this set, the Omega-Lognormal model, which analyses the motion of alternating sequences of lognormals, is the most appropriate model to analyse oscillating movements in one dimension. It has already been employed in previous studies [7] and is defined by:

$$\Omega\Lambda = \sum_{i=1}^{N} D_{1i}\Lambda\left(t - t_{01i};\ \mu_{1i},\ \sigma_{1i}\right) - \sum_{j=1}^{M} D_{2j}\Lambda\left(t - t_{02j};\ \mu_{2j},\ \sigma_{2j}\right)$$

with $|\mathrm{N} - \mathrm{M}| \in \{0,1\}$ and $\Lambda(t - t_{0i};\ \mu_i,\ \sigma_i)$ defined as:

$$\Lambda = \frac{1}{\sigma\sqrt{2\pi}\,(t - t_0)}\exp\left(\frac{(\ln(t - t_0) - \mu_i)^2}{-2\,{\sigma_i}^2}\right)$$

The individual pen strokes are initialized at time t_0 and the distance covered is D. The parameters μ and σ are related to the neuromuscular execution of the pen stroke. Oscillatory movements are modelled as a sequence of alternating pen strokes in opposite direction.
For parameter extraction from the original pen trajectory, a modified version of the Robust Xzero extractor was used [16, 17]. In order to evaluate the quality of the model, the signal-to-noise ratio is computed as a measure of similarity between the original velocity v_{org} and the reconstructed velocity v_{rec} [8]:

$$SNR = 10\log\left(\frac{\int v_{org}^2\,dt}{\int (v_{org} - v_{rec})^2\,dt}\right)$$

Figure 2 shows an example of a well-fitted velocity reconstruction using the Omega-Lognormal model. In order to reach a more precise SNR, the original digitized data was first interpolated and low-pass filtered to remove high frequency components introduced during the digitization.

3.2 Outlier Removal

Since the parameter extraction software finds local minimal solutions, possible outliers or unusual values generated during the digitizing stage or the parameter extraction process have been removed.
A certain transient period at the beginning of the signal could be considered as less stable since the trials were performed without previous training. Also, the last movements of the writers could be affected and consequently altered by muscular fatigue due to the process itself. Hence, the three first and the three last lognormals were removed to minimize these fluctuations.
An approximate distance of 180 mm separated the outer limits of the two target zones. Since some writers could execute the pen strokes in a somewhat diagonal or even bending fashion, the effective distance covered by the pen could be somewhat larger than 180mm. Additionally, taking into account that the model parameter D reflects the pen stroke distance without the influence of the next pen stroke in opposite direction, a final value of 200 mm was considered as an upper bound for this parameter. Similarly, a lower bound of 45mm has been fixed, which is a bit less than the distance between the inner limits of the target zones.
Finally, a minimum SNR was required for each lognormal to be taken into account. Several reports have pointed out that a quality over 15 dB is sufficient for human movement analysis [10].
After this process 8326 lognormals remained from the original database containing 9412 (11,53% of the lorgnormals have been removed). From this percentage,

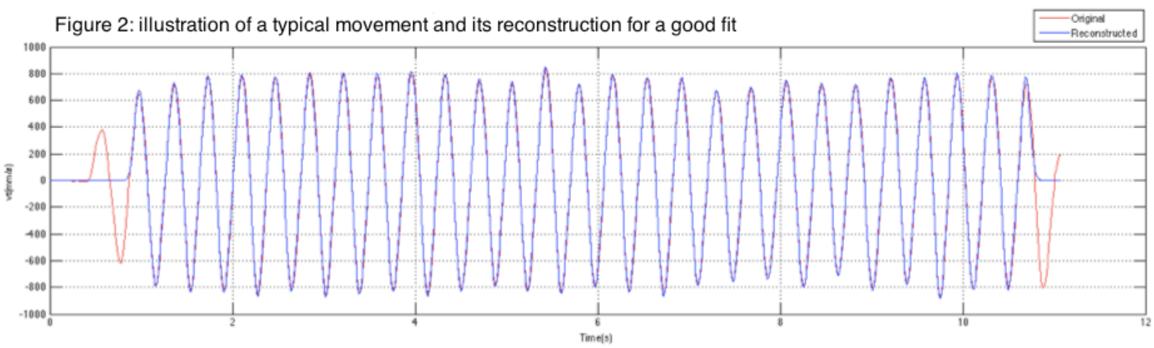

Figure 2: illustration of a typical movement and its reconstruction for a good fit

7,33% of the lognormals were removed from the extremes directly and 4,2% were removed because they did not fit within the limits mentioned above.
At the end of the cleaning process several lognormals still remain for all writers. However, if the remaining number of lognormals is low, a statistical analysis may not be reliable. This could be either due to a large number of removed outliers or due to an unusual number of pen strokes during the experiment. All writers with less than 15 lognormals (4 writers) have been excluded from the database.

3.3 Proposed Features

In order to potentially discriminate between subjects with and without brain stroke risk factors, we propose a set of seven neuromuscular features based on the Omega-Lognormal model:
- D, μ, σ: The first three features correspond directly with model parameters, that is the neuromuscular input command *D*, which correspond to the pen stroke distance (when executed in isolation without influence of the next pen stroke in opposite direction) and the two parameters μ and σ related to the logtime delay and the logresponse time of the neuromuscular system responding to the command.
- $\Delta t_0, f_0$: The two next features describe the frequency of the pen strokes. Δt_0 is the time difference between the t_0 parameters of two consecutive lognormals and f_0 is the dominant frequency extracted by means of fast Fourier transform (FFT). The FFT has been computed with Matlab over the reconstructed signal using 1024 points. Most of the subjects present various components in the frequency domain; f_0 corresponds to the frequency of the component with the maximum power.
- $SNR, SNR/nblog$: The final two features are concerned with the model quality. SNR is the signal-to-noise-ratio (see Section 3.1) and $SNR/nblog$ is normalized with the number of lognormals.

For the features $D, \mu, \sigma,$ and Δt_0 the mean value of the lognormals is considered for each oscillatory movement.

4 Experimental Evaluation

4.1 Statistical Analysis

In an experimental evaluation, we aim to demonstrate that the proposed neuromuscular features differ between the groups of subjects with and without brain stroke risk factors. To that end, we perform a one-way ANOVA test for each feature. The null hypothesis that the population means are the same is rejected if, for at least one of the features, the p-value is

$$p < \frac{0.05}{7} = 0.0071$$

taking into account the commonly used significance level $\alpha = 0.05$ and considering the Bonferroni correction, that is an adjustment for multiple parameter testing (7 tests in our case, one for each feature) which compensates for the fact that a significant result could be observed by chance.

4.2 Results

Table 1 displays the results obtained from the one-way ANOVA tests. Distributed horizontally in columns, the table shows all the features considered in this paper. Beneath each feature, the corresponding p-value is displayed. Likewise, the mean of the considered features is presented for subjects with and without rick factors (RF) in the table.
Significant results taking into account the Bonferroni correction are marked in bold. In four out of seven cases, the tests are significant, demonstrating that the proposed neuromuscular features, indeed, differ between subjects with brain stroke risk factors and subjects without risk factors.
The results obtained for the individual tests reveal which features are most discriminative to classify writers with respect to their brain stroke risk factors condition and which are less discriminative. Each of the three groups of features (see Section 3.3) contains at least one significant test result. The lowest p-values are reported for the second group of features related to the frequency of lognormals. The mean frequency is significantly lower for subjects with risk factors, that is they could not execute the oscillatory movements as fast as the subjects without risk factors. In the first group of features, the σ parameter of the Omega-Lognormal model has proven to be most discriminative and in the third group, the normalization of the SNR with the number of lognormals was necessary to achieve a significant result in accordance with previous studies [8, 19, 20].
In order to develop predictive tools based on the Omega-Lognormal model, these features could be pointed out as discriminative with respect to brain stroke risk factors. A combination of these features is expected to provide the best prediction result.

5 Conclusions

In this paper, we have investigated possible links between fine human motor control and brain stroke risk factors with

Table 1: ANOVA test p-values for the proposed features

	D	μ	$\boldsymbol{\sigma}$	$\boldsymbol{\Delta t_0}$	$\boldsymbol{f_0}$	SNR	$\boldsymbol{SNR/nblog}$
P-value	0.0285	0.1545	**7.21e-05**	**2.13e-05**	**2.02e-07**	0.326	**1.99e-05**
Mean without RF	124.6	-0.171	**0.041**	**0.115**	**5.0**	20.4	**0.27**
Mean with RF	116.2	-0.172	**0.059**	**0.170**	**3.5**	21.1	**0.46**

a view to prediction tools. We have focused our study on oscillatory movements at maximum frequency and proposed a set of seven neuromuscular features based on the Omega-Lognormal handwriting model that aim to distinguish subjects with risk factors from subjects without risk factors.

A database including 120 subjects, highly balanced in terms of gender, brain stroke risk factors, and age range has been analysed based on the Omega-Lognormal model. One-way ANOVA tests with Bonferroni correction have demonstrated that the features differ, indeed, between subjects with and without risk factors.

The results highlight the possibility of developing predictive tools based on some of the proposed features. The application of pattern recognition and machine learning techniques using the most discriminative features of the model seem to be the next natural step in this process.

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