Reliability of the Kinematic Theory parameters during handwriting tasks on a vertical setup

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Word and Figure Counts:

Abstract: 191 words
Introduction through discussion: 4564 words
Number of figures: 2
Number of tables: 3
Supplementary materials: 2

Color should be used for any figures in print.

Abbreviations

CI: Confidence Interval

CV: Coefficient of Variation

ICC: Intraclass Correlation Coefficient

MDC: Minimal Detectable Change

SEM: Standard Error of Measurement

SNR: Signal-to-Noise Ratio

Figures and Tables:

Figure 1: single-column fitting image

Figure 2: two-column fitting image

Tables 1, 2 and 3: two-column fitting tables

Highlights

- ✓ Kinematic Theory has reliable test-retest parameters in all types of strokes
- ✓ The Sigma-Lognormal model reconstructs data similarly from day to day
- ✓ The Kinematic Theory offers clinical insights in the detection of fatigue
- ✓ Kinematic Theory and the Sigma-Lognormal model can be used to study shoulder fatigue
- ✓ The *mode, median* and *time delay* are effective parameters for fatigue detection

Abstract

Background: The Kinematic Theory and its Sigma-Lognormal model have been used extensively in motor control analyses. It has recently shown promise in its ability to detect neuromuscular fatigue in the shoulder. The use of an ergonomic setup composed of a vertically oriented tablet offers a good demonstration for use in future clinical applications. However, parameters' reliability of this theory needs to be evaluated. The aim of this study is to assess the test-retest reliability of these parameters in the specific case of fatigue detection.

Method: Forty participants performed two sessions of fast strokes handwriting (simple strokes, triangles, horizontal and vertical oscillations) on a tablet placed at shoulder's height. Reliability was assessed using the intraclass correlation coefficient (ICC), their relative standard error of measurement (SEM) and coefficient of variation. The minimal detectable change was also reported.

Findings: In general, a moderate to excellent reliability was denoted in the main parameters of each test (ICC: 0.54-0.91). The parameters related to shoulder fatigue detection had good to excellent reliability (ICC: 0.77-0.90) with low SEM (SEM: 4.75-6.99%).

Conclusion: Most of the parameters have good test-retest reliability, and the setup seems adequate for shoulder fatigue detection.

Keywords: Sigma-Lognormal model; Kinematic Theory; Reliability; Shoulder; Muscle fatigue; Fatigue detection.

1. Introduction

Muscle fatigue corresponds to a decline in strength production during a task [1], and results in atypical stresses, which can possibly lead to musculoskeletal injuries over time [2]. Those injuries are omnipresent in the population, especially in the shoulder [3]. Overuse injuries affect quality of life and are expensive to treat, requiring physiotherapy treatments over a period of years [4]. It is then essential to detect shoulder muscle fatigue before the onset of an injury. In the long pathway of assessing a test as clinically usable, an important step is to evaluate its diagnostic accuracy [5]. To that extent, screening tests have to be reliable with sensitive and specific data, but must also be affordable and easy to implement [6]. According to Weir [7], the Intraclass Correlation Coefficient (ICC) and the Standard Error of Measurement are powerful metrics in the quantification of data reliability.

Current methods can detect shoulder fatigue, but unfortunately have limitations that prohibits their use in a clinical environment [8]. A common method includes questionnaires such as the Borg's Rating of Perceived Exertion Scale, which represents a participant's subjective level of exertion during exercise [9]. However, studies correlating this rating with physiological variables of exertion are not always consistent [10, 11], as the rating depends on motivation and is subjective. Objective measures can be used, such as biomarkers, but their assessment is often invasive [12]. Less invasive biomarkers such as those obtained from surface electromyography may be used, where the analysis of the signal amplitude and power spectrum density can be used to detect fatigue [13-15]. This is a reliable measure for fatigue detection [8, 16], as the median and mean power frequencies tend to be greatly reliable (Intraclass Correlation Coefficient > 0.80) [17]. However, a good electrode placement is essential to avoid cross-talk and maintain a good reliability [18, 19]. The post-collection data processing is also time-consuming, which is a disadvantage for clinical evaluation. Other methods, such as mecanomyography, sonomyography or near-infrared spectroscopy can also be used to detect fatigue. However, they are combined most of the time with electromyography, which is difficult to implement in clinics [8].

Recently, a new method for shoulder fatigue detection has been settled using the Kinematic Theory of Rapid Human Movements [20, 21]. More broadly, the Kinematic Theory has been utilized to assess patients with Parkinson's disease [22], concussion [23], attention deficit hyperactivity disorder [24], as well as aging phenomena [25], and stroke risk factors [26]. This theory assesses behavior through their end-effector kinematics [27, 28] (see section 2.3). The movement velocity is described as the synergy of impulse responses from neuromuscular systems generating the movement. Each response is modeled through a lognormal equation whose parameters describe the participant's motor control conditions [29]. The ideal movement is known and a change in the parameters baseline highlights neuromuscular problems, such as shoulder neuromuscular fatigue [20, 21]. Theoretically, identified parameters may be related to the central or the peripheral nervous systems (as well as to the agonistic or antagonistic systems) and to the motor program execution, as described in Appendix A. The specificity of the Kinematic Theory has therefore a prescreening potential that could be used by medical professional in their diagnoses. To characterize the cranio-caudal sequence of turning while walking [30], we know that the reliability in the kinematic parameters is moderate to good (Intraclass Correlation Coefficient = 0.64-0.81). However, to the best of our knowledge, the reliability of handwriting tasks for clinical applications has never been assessed. In the specific example of shoulder fatigue, handwriting data were recorded on a vertical setup [20], an ergonomic and easy to use tablet, and has shown potential for clinical applications [5]. After the onset of fatigue, the parameters related to motor program execution increased significantly, but their reliability was not assessed in this study.

The objective of this study is then to assess the test-retest reliability of the parameters extracted through Kinematic Theory from handwriting movements recorded with a vertically oriented digitizing tablet. A characterization of the reliability of these parameters will allow a better comprehension of the parameters' reproducibility and of their measurement errors for motor control studies.

2. Materials and methods

2.1. Participants

Forty healthy active adults participated in the study (18 males and 22 females, age: 24.8±4.3 years, height: 173.3±9.8 cm, mass: 69.6±12.6 kg, dominant hand 6 left-handed and 34 right-handed). Participants were excluded if: *(i)* they had upper-limb musculoskeletal disorders; *(ii)* neurological problems or *(iii)* history of shoulder surgery in the past years. The study was approved by Polytechnique Montréal research ethics committee (CER-1819-23 v.3).

2.2. Protocol

Fast stroke kinematics were recorded on a Wacom Cintiq 13HD tablet (sampling frequency: 200 Hz) during two test sessions. The tablet was positioned at the participant's shoulder height, as measured while standing (Figure 1). The tablet was positioned so that the participant's fingertip was touching the bottom of the tablet with a shoulder flexion of 90°. The same tablet height was used for all tests for each individual. They were also asked to stand at a comfortable distance from the tablet. Four series of fast strokes were drawn on the tablet with the participant's dominant hand in a random sequence: 30 simple strokes, 30 triangles, 10-second horizontal oscillations and 10-second vertical oscillations at their maximal speed. A training period of five to seven fast strokes was given before simple strokes and triangles. The current test is part of a larger study, which fully describes the procedure of collecting data [20]. Test and retest were recorded by a single tester with a minimum of one-day interval (up to two months).

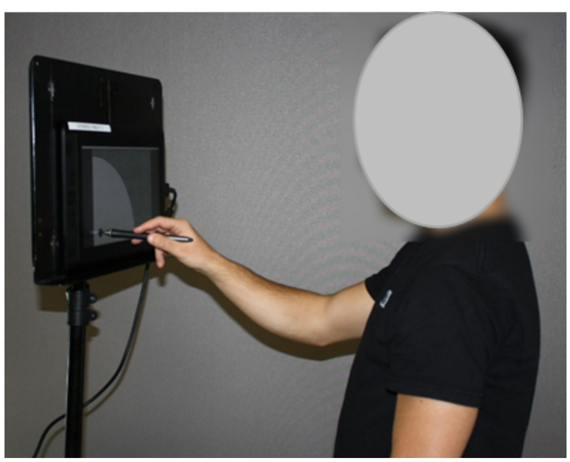

Figure 1: Position of the participant while drawing strokes. The tablet was positioned at the shoulder's height.

2.3. Extraction of kinematic parameters, the Sigma-Lognormal model

Numerous models have been used over the last few decades to study human motor control: models relying on neural networks, on equilibrium points, behavioral models, coupled oscillator models, kinematic models, motor synergetic models, non-Euclidean and Rieman models as well as models exploiting minimization principles (minimization of: acceleration, energy, time, jerk, snap, torque changes, and sensory-motor noise), sensory-motor optimal control models (see Plamondon [31] for an exhaustive list of references). Many of these models exploit the properties of various mathematical functions to represent human movements: exponentials, second order systems, Gaussians, beta functions, splines, and trigonometric functions. Among these, Kinematic Theory [27, 28, 32, 33] and its sigma-lognormal model [34, 35] is one of the most efficient methodologies for reproducing human-like movements. It has been tested time and again over the last few decades by numerous researchers, using various input devices under various experimental (1D, 2D and 3D) conditions [36]. It has even been mathematically demonstrated that it is the ultimate minimization theory, and that the process of trajectory selection could be described as the process of recruiting a sufficient number of neuromuscular subsystems to approximate the lognormal profile [37]. For all of these reasons, we have chosen to use Kinematic Theory in the present study.

Empirical data of each stroke were modeled thanks to the Sigma-Lognormal model of the Kinematic Theory. To do so, the in-house program named Script Studio was used [34].

The key concept behind the Kinematic Theory is twofold. First, it postulates that the invariant properties of simple pointing movements can be considered as specific movement primitives [38] that reflect the asymptotic behavior of complex systems, made up of a large number of coupled neuromuscular networks, whose impulse response can be modelled using lognormal functions.

From a mathematical point of view, when a command D_i is input to a lognormal neuromuscular system at a given time t_{0i} a velocity profile is produced at the output of such a system:

$$\left|\vec{v}_i\left(t;t_{0i},\mu_i,\sigma_i^2\right)\right| = D_i\Lambda_i\left(t;t_{0i},\mu_i,\sigma_i^2\right) \tag{1}$$

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

and where the set of parameters describing a lognormal pulse Λ_i refers to

D_i : the input command, which is the intended distance to be covered with the pulse;

t_{0i} : the time occurrence of that command, as instantiated in the central nervous system (CNS);

μ_i : the log time delay (i.e., the time delay on a logarithmic time scale);

σ_i : the log response time (i.e., the response time on a logarithmic time scale).

Accordingly, the sequence of lognormal velocity patterns observed in any movements are the results of an asymptotic convergence that can be interpreted as reflecting the behavior of subjects who are in perfect control of their movements. In other words, the production of complex movements is reached through the exploitation of the Lognormality Principle, by time superimposing and summing up lognormal vectors, with the goal of minimizing their number in a given task, to produce efficient, fluent gestures, optimizing the energy required to generate these. This summation process is referred to as the Sigma-Lognormal model:

$$\vec{v}(t)=\sum_{i=1}^{N}\vec{v}_i(t;\ t_{0i},\mu_i,\sigma_i^2)=\sum_{i=1}^{N}\begin{bmatrix}cos\big(\theta_i(t)\big)\\ sin\big(\theta_i(t)\big)\end{bmatrix}v_i(t);N\geq 2 \tag{3}$$

$$v_i(t)=\ D_i\Lambda_i(t;t_{0i},\mu_i,\sigma_i^2)=\frac{D_i}{\sigma_i(t-t_{0i})\sqrt{2\pi}}exp\left(\frac{[ln(t-t_{0i})-\mu_i]^2}{-2\sigma_i^2}\right) \tag{4}$$

where $$\theta_i(t)=\theta_{si}+\frac{(\theta_{ei}-\theta_{si})}{D_i}\int_0^t v_i(\tau)d\tau \tag{5}$$

and where θ_{si} and θ_{ei} stand respectively for the starting and ending angular direction of each discontinuous primitive or stroke.

From a practical point of view, what is interesting is that Kinematic Theory can be reverse engineered to decompose any movements into its lognormal constituents using specific software [34, 36, 39-41] that provide a set of central and peripheral parameters describing the neuromuscular state of the subject who has produced a given movement. Each lognormal function describes the impulse response of a neuromuscular component involved in the movement execution (Figure 2A). All lognormals are scaled in time (t_{0i}) and space (D_i) (2). Under a physiological point of view, t_{0i} (s) represents the time at which the brain send the command to execute the movement of the *i-th* lognormal; and D_i (mm) is the amplitude of a lognormal. In case of an oscillatory movement, it is possible to calculate the time difference between two consecutive t_0 ($\Delta(t_0)$, s) to get the rhythmicity of a command sent during the test. All lognormals also have their own distribution, defined by the mean (μ_i) and the standard deviation (σ_i) of the normal distribution associated. These two parameters are related to the timing properties of the neuromuscular system: μ also called the log-time delay (s) and σ the log-response time (s). Nevertheless, as the reconstruction is performed for a complex movement with a change in direction (*e.g.* when drawing a triangle), the notion of trajectory is important. Each lognormal describes a trajectory part of the action plan. When all of the lognormals are combined, they form the complete action plan and thus the overall trajectory of the movement. In consequence, each lognormal has a starting (θ_s) and ending angle (θ_e) to define its own trajectory. The number of lognormal functions (*NbLog*) depends on the movement and its fluidity. The optimization of the reconstruction relies on the Signal-to-Noise Ratio (*SNR*), which is considered to be excellent if higher than 25 dB. For more details regarding the Theory and the extraction of parameters, can be found in [27], Plamondon, Feng and Woch [32], [34].

Aside from the eight main parameters (*i.e.* t_0, D, θ_s, θ_e, μ, σ, *NbLog*, *SNR*), six derived parameters were calculated as follows [32, 42]: *(i)* the *mode* (s) which corresponds to the time when the maximum velocity of the lognormal is reached; (*ii)* the *median* (s) that is the time when half the value of the lognormal integral is attained; (*iii)* the *time delay* (s) which corresponds to the response command rapidity of a given system; (*iv)* the *response time* (s) which evaluates the impulse response spread; (*v)* the *asymmetry* (no units) which describes the general shape of the lognormal; and (*vi*) the *SNR/NbLog* that depicts the motor control quality. The *reaction time* (*RT*), a classical parameter that is not otherwise part of the Theory, was also extracted in order to calculate the *conduction time (s)*, which represents the duration of the command propagation [43]. The supplementary material (APPENDIX A) of the present study provides a more detailed explanation of these parameters and their physiological meaning.

2.4. Data processing

Simple strokes were divided into their largest *agonist* and *antagonist* components (Figures 2B). When only one lognormal described the stroke, it was automatically labeled as *agonist*. Lognormals with parameters outside of the mean±3SD were rejected. For the *NbLog*, the *SNR*, the *SNR/NbLog*, the *reaction time* and the *conduction time*, no distinctions between *agonist*/*antagonist* components were made, as they refer to global stroke properties. The mean value of each parameter was calculated.

Triangles were split into the *agonist* components explaining the three main strokes (Figures 2C). Outliers were manually removed when the action plan of the reconstruction was found to be incorrect. Finally, lognormals with parameters outside of the mean±3SD were rejected. The mean value of each parameter was calculated, except for t_0 as only the first one was considered.

For the horizontal and vertical oscillations (50-160 mm long), only lognormals extracted from a stable phase were analyzed (*i.e.* from 2 to 10-s oscillations). Each stroke of the oscillatory movement was considered as *agonist* (Figure 2D). Lognormals with an amplitude below 50 mm and with parameters outside of the mean±3SD were considered as artefacts, therefore rejected. The mean value of each parameter was calculated, except for the *reaction time*, the *conduction time*, the *SNR* and the *SNR/NbLog*, since only a single value per test and participant can be recorded.

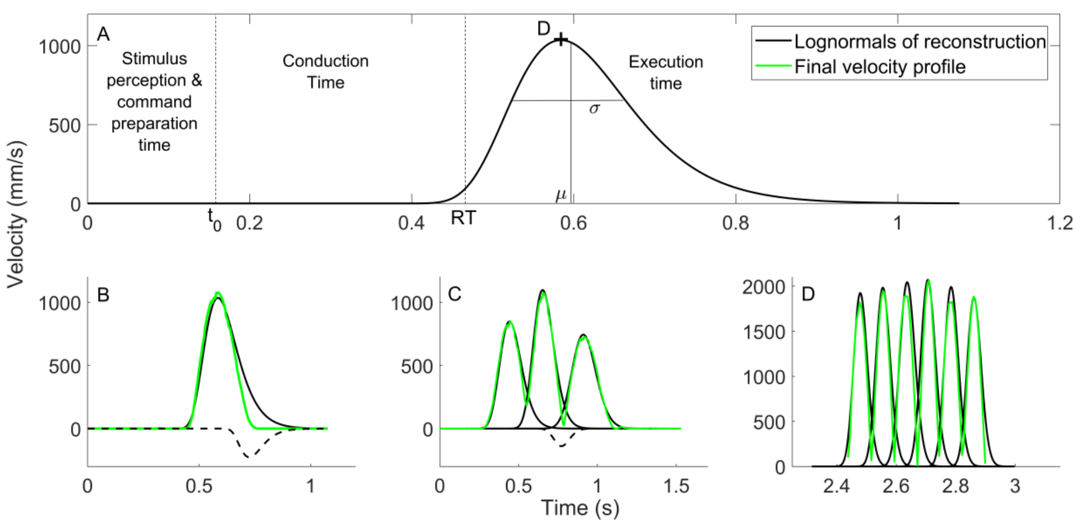

Figure 2: Reconstruction of the different types of strokes. (Green) is the final velocity profile and (black) are the lognormals used for reconstruction referred as *agonists* (solid lines) or *antagonists* (dashed lines). (A) is a vizualisation of the parameters on a lognormal. (B) is the reconstruction of a simple stroke. (C) is the reconstruction of a triangle. (D) is an example of a signal portion reconstruction for the oscillations.

2.5. Statistical analysis

An analysis of variance (ANOVA) based on intraclass correlation coefficients (ICC) was performed (Matlab, the Mathworks Intraclass Correlation Coefficient (ICC) version 1.3.1.0 of Arash Salarian) to get the test-retest reliability. ICC were calculated by parameters at 95% confidence intervals using a two-way mixed effects model based on absolute agreement [44]. An average measurements model was used for mean values whereas a single measure model was used for single values (*i.e. reaction time*, *conduction time*, *SNR* and *SNR/NbLog* in the oscillations). The scores were interpreted in line with the scale used in Koo and Li [44]: poor (<0.50), moderate (0.50-0.75), good (0.75-0.90) and excellent (>0.90) reliability. As explained in Bartko [45], a value of zero was set in case of negative ICC. The absolute and relative standard error of measurement (SEM), the coefficient of variation (CV) and the minimal detectable change (MDC) were also reported to estimate the measurement errors. These measurements are the gold standards in reliability analyses of movement science [46, 47]. Bland-Altman plots were also drawn (see APPENDIX B) to display the degree of agreement of the intra-participant measurements for *SNR*, *asymmetry*, σ and *conduction time*.

3. Results

Data are expressed as mean±SD. In the simple strokes (Table 3.1), the time t_0 had good reliability, both for the *agonist* (ICC=0.80) and *antagonist* components (ICC=0.89). The coefficient of variation was higher in the *agonist* than in the *antagonist* components (respectively 36.81% and 25.51%). Regarding σ, the ICC was moderate with a value of 0.62 for the *agonist* components and 0.69 for the *antagonist*. Their CVs were 18.12% and 23.27% respectively. The *mode*, *median*, *time delay* and *response time* had good to excellent reliability, ranging from 0.85 to 0.90 in both components, with a low SEM (5.44 - 14.11%) and a minimal detectable change (MDC) of 0.10 s. Parameters describing the global state of the neuromotor system (*NbLog*, *SNR* and *SNR/NbLog*) had a moderate ICC ranging from 0.56 to 0.73 with low SEM values (from 2.35% to 5.41%). The *conduction time* had a moderate ICC (0.67) with a high CV (38.78%).

Table 1: Test-retest reliability of kinematic parameters extracted from simple strokes with the Sigma-Lognormal model. Red, orange, green and blue respectively represents poor, moderate, good and excellent reliability.

Parameter	Test	Retest	ICC (95% CI)	SEM	SEM (%)	CV (%)	MDC
			***Agonist* component**				
t_0	0.24 ± 0.11	0.26 ± 0.09	0.80 (0.63-0.90)	0.04	16.29	36.81	0.11
D	206.40 ± 20.75	208.40 ± 23.31	0.86 (0.74-0.93)	7.74	3.73	9.96	21.46
μ	-1.34 ± 0.26	-1.40 ± 0.19	0.76 (0.54-0.87)	0.10	7.44	15.05	0.28
σ	0.27 ± 0.07	0.27 ± 0.05	0.62 (0.28-0.80)	0.03	11.19	18.12	0.08
$\lvert\cos(\vartheta_s)\rvert$	0.79 ± 0.09	0.78 ± 0.09	0.91 (0.82-0.95)	0.03	3.17	10.32	0.07
$\lvert\cos(\vartheta_e)\rvert$	0.94 ± 0.04	0.95 ± 0.03	0.83 (0.66-0.91)	0.01	1.47	3.53	0.04
Mode	0.51 ± 0.09	0.51 ± 0.10	0.85 (0.71-0.92)	0.04	6.99	17.83	0.10
Median	0.53 ± 0.10	0.52 ± 0.10	0.86 (0.73-0.93)	0.04	6.72	17.89	0.10
Time Delay	0.54 ± 0.10	0.53 ± 0.11	0.87 (0.75-0.93)	0.04	6.60	17.99	0.10
Response Time	0.07 ± 0.02	0.07 ± 0.02	0.84 (0.67-0.92)	0.01	10.10	25.02	0.02
Asymmetry	0.10 ± 0.05	0.09 ± 0.04	0.51 (0.09-0.74)	0.03	29.24	41.81	0.07
			***Antagonist* component**				
t_0	0.46 ± 0.12	0.45 ± 0.13	0.89 (0.79-0.94)	0.04	8.59	25.51	0.11
D	30.11 ± 6.00	29.69 ± 7.42	0.70 (0.44-0.84)	3.22	10.76	19.80	8.92
μ	-1.80 ± 0.18	-1.84 ± 0.24	0.19 (0.00-0.57)	0.14	7.86	8.71	0.40
σ	0.37 ± 0.10	0.36 ± 0.10	0.69 (0.41-0.84)	0.05	12.98	23.27	0.13
$\lvert\cos(\vartheta s)\rvert$	0.94 ± 0.05	0.96 ± 0.05	0.00 (0.00-0.46)	0.03	3.41	3.39	0.09
$\lvert\cos(\vartheta_e)\rvert$	0.89 ± 0.10	0.91 ± 0.07	0.86 (0.74-0.93)	0.03	3.17	8.55	0.08
Mode	0.64 ± 0.11	0.63 ± 0.11	0.88 (0.77-0.94)	0.04	5.64	16.14	0.10
Median	0.66 ± 0.11	0.65 ± 0.12	0.89 (0.79-0.94)	0.04	5.49	16.59	0.10
Time Delay	0.67 ± 0.12	0.66 ± 0.12	0.90 (0.81-0.95)	0.04	5.44	16.97	0.10
Response Time	0.06 ± 0.02	0.06 ± 0.02	0.81 (0.64-0.90)	0.01	14.11	32.13	0.02
Asymmetry	0.21 ± 0.11	0.20 ± 0.11	0.66 (0.37-0.82)	0.05	26.49	45.75	0.15
			Whole signal				
NbLog	2.28±0.27	2.19±0.25	0.73 (0.49-0.86)	0.12	5.41	10.50	0.34
SNR	30.05±1.34	30.06±1.21	0.56 (0.15-0.77)	0.71	2.35	3.53	1.96
SNR/NbLog	13.89±1.68	14.41±1.75	0.67 (0.37-0.82)	0.86	6.11	10.57	2.40
RT	0.41±0.08	0.41±0.10	0.82 (0.65-0.90)	0.04	8.55	19.90	0.10
$\lvert t_0\text{-}RT\rvert$	0.17±0.09	0.15±0.05	0.67 (0.39-0.83)	0.04	22.18	38.78	0.10

ICC: Intraclass Correlation Coefficient, CI: Confidence Interval, SEM: Standard Error of Measurement, CV: Coefficient of Variation, MDC: Minimal Detectable Change

For the triangles (Table 3.2), t_0 presented a good reliability (ICC=0.81), with a SEM of 10.41%. Parameters related to the peripheral system, μ and σ, had respectively moderate (0.68) and good (0.78) reliability, with a low value of SEM (11.69% and 8.76%). The derived parameters (the *mode*, *median*, *time delay*, *response time* and *asymmetry*) had good reliability, ranging from 0.77

to 0.79 with a low CV (10.4% - 15.8%) except for the *asymmetry* (42.2%). Their MDC was 0.11 s. The *SNR* had poor reliability (0.13) with a low SEM (1.10%) whereas the *SNR/NbLog* had moderate reliability. The *conduction time* had good reliability (0.77, 95%CI: 0.57-0.88), with a CV of 39.46%.

Table 2: Test-retest reliability of kinematic parameters extracted from triangles with the Sigma-Lognormal model. Red, orange and green respectively represents poor, moderate and good reliability. No parameters had an excellent reliability.

Parameter	Test	Retest	ICC (95% CI)	SEM	SEM (%)	CV (%)	MDC
t_0	0.25 ± 0.06	0.25 ± 0.07	0.81 (0.64-0.90)	0.03	10.41	23.67	0.07
D	151.87 ± 8.36	154.15 ± 9.05	0.54 (0.14-0.75)	4.92	3.21	4.72	13.63
μ	-0.75 ± 0.17	-0.77 ± 0.19	0.68 (0.40-0.83)	0.09	11.69	20.67	0.25
σ	0.20 ± 0.04	0.19 ± 0.04	0.78 (0.58-0.88)	0.02	8.76	18.51	0.05
Mode	0.79 ± 0.08	0.77 ± 0.10	0.77 (0.57-0.88)	0.04	5.08	10.61	0.11
Median	0.82 ± 0.09	0.79 ± 0.10	0.77 (0.57-0.88)	0.04	5.02	10.47	0.11
Time Delay	0.82 ± 0.09	0.80 ± 0.10	0.77 (0.57-0.88)	0.04	5.00	10.42	0.11
Response time	0.08 ± 0.02	0.08 ± 0.01	0.79 (0.43-0.91)	0.01	7.28	15.84	0.02
Asymmetry	0.06 ± 0.03	0.05 ± 0.02	0.78 (0.58-0.88)	0.01	19.99	42.19	0.03
NbLog	5.43 ± 0.65	5.09 ± 0.50	0.78 (0.25-0.91)	0.25	4.82	10.27	0.70
SNR	26.78 ± 0.41	26.97 ± 0.45	0.13 (0.00-0.52)	0.30	1.10	1.18	0.82
SNR/NbLog	5.12 ± 0.63	5.47 ± 0.51	0.74 (0.19-0.90)	0.27	5.03	9.95	0.74
RT	0.42 ± 0.07	0.43 ± 0.09	0.85 (0.71-0.92)	0.03	7.01	17.84	0.08
$\lvert t_0\text{-}RT \rvert$	0.17 ± 0.07	0.19 ± 0.08	0.77 (0.57-0.88)	0.03	18.82	39.46	0.09

ICC: Intraclass Correlation Coefficient, CI: Confidence Interval, SEM: Standard Error of Measurement, CV: Coefficient of Variation, MDC: Minimal Detectable Change

Parameters were categorized similarly for the horizontal and vertical oscillations (Table 3.3), except for the *reaction time* and the *conduction time*. Δt_0 had good reliability (ICC=0.79 and 0.80) and a low SEM (horizontal oscillations: 5.07%; vertical oscillations: 6.92%). Poor reliability was observed for σ, *asymmetry* and *SNR*. The *SNR/NbLog* had moderate reliability, ranging from 0.64 to 0.70 (95% CI: 0.29-0.82). The *mode*, *median*, *time delay* and *response time* had an ICC considered as good (horizontal oscillations: 0.83; vertical oscillations: 0.79-0.80). The *conduction time* had poor reliability in the horizontal oscillations and moderate in the vertical oscillations, with a low SEM (horizontal oscillations: 17.60%; vertical oscillations: 19.49%). The *NbLog* was exactly the same for every participant for both the horizontal or vertical oscillations.

Table 3: Test-retest reliability of kinematic parameters extracted from horizontal and vertical oscillations with the Sigma-Lognormal model. Red, orange and green respectively represents poor, moderate and good reliability. No parameters had an excellent reliability.

Parameter	Test	Retest	ICC (95% CI)	SEM	SEM (%)	CV (%)	MDC
			Horizontal oscillations				
$\Delta(t_0)$	0.09 ± 0.01	0.09 ± 0.01	0.79 (0.52-0.90)	0.00	5.07	11.04	0.01
D	119.74 ± 22.42	116.30 ± 20.94	0.86 (0.73-0.92)	7.72	6.54	17.25	21.39
μ	-0.75 ± 0.13	-0.79 ± 0.10	0.83 (0.62-0.92)	0.05	5.91	14.39	0.13
σ	(0.06 ± 0.83)E-03	(0.06 ± 1.33)E-03	0.07 (0.00-0.50)	3.51E-04	0.61	0.63	9.73E-04
Mode	0.57 ± 0.08	0.54 ± 0.06	0.83 (0.59-0.92)	0.03	4.75	11.38	0.07
Median	0.57 ± 0.08	0.55 ± 0.06	0.83 (0.59-0.92)	0.03	4.75	11.38	0.07
Time Delay	0.57 ± 0.08	0.55 ± 0.06	0.83 (0.59-0.92)	0.03	4.75	11.38	0.07
Response Time	(30.0 ± 3.67)E-03	(30.0 ± 2.71)E-03	0.83 (0.63-0.92)	1.22E-03	4.54	11.16	3.39E-03
Asymmetry	(3.36 ± 0.25)E-03	(3.43 ± 0.72)E-03	0.03 (0.00-0.48)	4.19E-05	1.27	1.29	1.16E-04
RT	0.48 ± 0.11	0.45 ± 0.10	0.36 (0.00-0.66)	0.07	14.43	18.06	0.18
$\|\Delta(t_0)$-RT|	-0.38 ± 0.10	-0.36 ± 0.10	0.33 (0.00-0.64)	0.07	17.60	21.51	0.18
SNR	28.21 ± 1.20	28.62 ± 0.97	0.00 (0.00-0.26)	0.77	2.71	2.64	2.13
SNR(dB)/NbLog	0.23 ± 0.04	0.22 ± 0.03	0.70 (0.44-0.84)	0.02	7.04	12.83	0.04
			Vertical oscillations				
$\Delta(t_0)$	0.10 ± 0.02	0.09 ± 0.01	0.80 (0.49-0.91)	0.01	6.92	15.38	0.02
D	116.04 ± 21.12	114.44 ± 22.21	0.84 (0.69-0.91)	8.12	7.05	17.41	22.52
μ	-0.68 ± 0.17	-0.75 ± 0.14	0.81 (0.49-0.91)	0.06	8.86	20.11	0.18
σ	(0.06 ± 4.74)E-04	(0.06 ± 2.82)E-03	0.25 (0.00-0.60)	0.0013	2.30	2.66	3.60E-03
Mode	0.61 ± 0.11	0.57 ± 0.08	0.79 (0.47-0.90)	0.04	6.80	14.87	0.11
Median	0.61 ± 0.11	0.57 ± 0.08	0.79 (0.47-0.90)	0.04	6.80	14.87	0.11
Time Delay	0.61 ± 0.11	0.57 ± 0.08	0.79 (0.47-0.90)	0.04	6.80	14.87	0.11
Response Time	0.03 ± 0.01	0.03 ± 0.004	0.80 (0.50-0.91)	0.00	6.57	14.84	0.01
Asymmetry	(3.30 ± 0.06)E-03	(3.55 ± 1.56)E-03	0.06 (0.00-0.50)	0.00	22.40	23.14	2.13E-03
RT	0.46 ± 0.15	0.43 ± 0.10	0.55 (0.16-0.76)	0.07	15.61	23.25	0.19
$\|\Delta(t_0)$-RT|	-0.37 ± 0.14	-0.34 ± 0.10	0.53 (0.12-0.75)	0.07	19.49	28.56	0.19
SNR	28.00 ± 1.43	28.07 ± 1.30	0.45 (0.15-0.67)	0.86	3.07	4.14	2.39
SNR(dB)/NbLog	0.25 ± 0.05	0.23 ± 0.04	0.64 (0.29-0.82)	0.02	10.26	17.10	0.07

ICC: Intraclass Correlation Coefficient, CI: Confidence Interval, SEM: Standard Error of Measurement, CV: Coefficient of Variation, MDC: Minimal Detectable Change

4. Discussion

The aim of this study was to assess the test-retest reliability of fast strokes' kinematic parameters drawn on a tablet using a vertical setup. They were extracted according to the Sigma-Lognormal model with the aim of using the setup for clinical applications in fatigue detection. Overall, most of the parameters from the four tests seem to present sufficient reliability for clinical applications.

4.1. Reliability of the four tests

In general, the four series of tests seem to present an adequate level of reliability. The movement execution with the dominant hand enables one to attain superior levels of motor control quality, and have less variability in the gesture [48]. As found by Smits, Tolonen, Cluitmans, van Gils, Zietsma, Tijssen and Maurits [49], a zigzag graphical task (*i.e.* a combination of simple strokes) had already been assessed as good, with an ICC of 0.89 for its movement time and of 0.82 for its mean error. Other handwriting tasks were considered to have excellent reliability (ICC=0.927) in their average absolute velocity [50], meaning that the overall kinematics of handwriting seems to be reliable from day to day for an individual. This result is reflected in the kinematic parameters for each test. When analyzing <u>simple strokes</u> through the theory, the parameters describing the action plan (t_0, D, θ_s and θ_e) of the *agonist* system seem to be more reliable than for the *antagonist* (*e.g. D agonist* ICC=0.86, *D antagonist* ICC=0.70; $|cos(\theta_s)|$ *agonist* ICC=0.91, $|cos(\theta_s)|$ *antagonist* ICC=0.00). The parameters of the *agonist* system are reliable as the strokes are equally oriented each time thanks to the guiding sheet. However, as determined by Plamondon and Djioua [35], glitches at the end of the movement, can change the velocity profile of the stroke. Those glitches do not occur in the main orientation of the movement, *i.e.* the *agonist* system, and can therefore enlarge the variability of the *antagonist* system. Even if glitches were partly rejected during the data processing, they could have still influenced the reliability of the *antagonist* parameters and also explain the poor ICC value of μ *antagonist*. A detailed comparison with a Delta-Lognormal extraction (*i.e.* simple strokes defined only by two Lognormals) could help to determine the most appropriate and accurate extraction method for simple strokes [51]. When analyzing more complex movements, such as the <u>triangles</u> or the <u>oscillations</u>, a good reliability is also denoted in general. Except for the logresponse time σ in the oscillations, the intrinsic parameters of a lognormal (t_0 or $\Delta(t_0)$, D, μ, σ) are reliable from day to day. In fact their ICC values may be lowered by the very low inter-participant variability, as explained in Weir [7]. This explanation could also be relevant for the *SNR,* which has a poor ICC for every test. As a stopping criterion for the reconstruction program Script Studio is for the *SNR* to attain 25dB, the *SNR/NbLog* should be analyzed instead when evaluating the motor control quality [25, 52]. The triangles, which are more complex tests than simple strokes and oscillations, may be more reliable for the assessment of fine motor control quality because the inter-session learning effect is smaller, as mentioned in Smits, Tolonen, Cluitmans, van Gils, Zietsma, Tijssen and Maurits [49]. The Sigma-Lognormal model seems to reconstruct the data similarly each time it is deployed, whether for a simple stroke or a complex movement, leading to parameters with sufficient reliability.

4.2. The setup as a new clinical tool for the detection of shoulder fatigue

The vertical setup was specific to shoulder neuromuscular fatigue detection [20, 21] and its clinical relevance still needs to be assessed. As explained in Van den Bruel, Cleemput, Aertgeerts, Ramaekers and Buntinx [5], any tool being used to assess neuromuscular fatigue clinically needs to be easily implementable with quickly accessible data. The tablet linked to the computer offers numerous advantages as the whole process is integrated [53]. However, triangles had to be manually verified, because some reconstructions presented inaccuracies in their trajectory. As Script Studio optimizes the reconstruction on the velocity profile, a trajectory offset can be observed [34, 54]. The use of "iDeLog", a new algorithm that optimizes parameters based on both speed and trajectory may avoid outliers and speed up the data formatting process [40]. This will be the subject of a follow-up study. Nevertheless, the simplicity of the use of the tablet and the possibility of improvements in algorithm optimization leads us to believe that the setup will soon be capable of meeting the requirements for clinical implementation.

In addition to this, clinical guidelines require data to be reliable with high sensitivity and specificity [6]. As shown in Laurent, Plamondon and Begon [20], the *mode, median* and *time delay* present the most significant differences pre and post shoulder fatigue in internal and external rotation. Their reliability on all tests was good to excellent, ranging from 0.77 to 0.90. In comparison, goniometers and inclinometers, have a reliability ranging from moderate to excellent in external and internal rotation (goniometer: ICC from 0.64 to 0.91, inclinometer: ICC from 0.63 to 0.97) [55, 56]. The latter are tools that are currently used in clinics for the evaluation of the articular amplitude, which may be used as to assess shoulder neuromuscular disorders [57].

These disorders can also be assessed with a muscular force evaluation. To that extent, stationary dynamometers have high reliability with ICC ranging from 0.87 to 0.94 [58]. However the minimal detectable changes (MDC) were not reported [58, 59], or had high values (21 to 43% MDC) [60] limiting their assessment of sensitivity to changes. In our study, the MDC were higher than the mean difference pre and post fatigue [20]. However, the effect sizes of the pre and post fatigue differences always ranged from moderate to good, indicating that the observed phenomenon of variation was high and that a clinically relevant change has still occurred. The MDC might be too severe in the assessment of the sensitivity to changes in our study. Further studies need to be undertaken to specify the sensitivity and specificity after internal and external rotation fatigue using Kinematic Theory. For clinical requirements, these values tend to have to be excellent, as in medical imaging (sensitivity and specificity>0.85) [61, 62]. Otherwise, a combination of several tests with different values of sensitivity and specificity is also possible, as is done with physical tests [63, 64]. Tests with a high sensitivity will correctly identify persons who have a pathology, while tests with a high specificity will correctly reject those without the pathology [65]. The theory is reliable from day to day and its use in shoulder fatigue detection could be clinically relevant, when sensitivity and specificity are assessed.

4.3. Further clinical applications

Kinematic Theory has been used in many applications for motor control evaluation. A tablet is an ergonomic and standardized method [53], which has already shown many interesting results in studies such as Parkinson's disease [22], concussion [23], attention deficit hyperactivity disorder [24], aging phenomena [25], stroke risk factors [26]. Contrary to the present study, these data were recorded on a setup horizontally oriented, with sitting participants. Another study from Fischer, Plamondon, O'Reilly and Savaria [66] reconstructed handwriting from a whiteboard, in a vertical orientation. Portnoy, Rosenberg, Alazraki, Elyakim and Friedman [67] postulated that whether on a vertical or horizontal surface, the graphic product performance level during handwriting will not be affected. However, without efficient support from the table as in a horizontal set-up, upper-limb muscles have higher amplitude activation [68, 69]. Moreover, the handwriting kinematics on horizontal surfaces seems more fluid than on vertical surfaces [70]. A better reliability may thus be expected on horizontal surfaces with sitting participants than on vertical surfaces with standing participants. As simple strokes and more complex tasks (*i.e.*

triangles and oscillations) were reliable after the Sigma-Lognormal model analysis, it can be expected that the parameters extracted from any kind of well-specified movement are reliable from one day to another.

4.4. Limitations

A first limitation to our study is that participants were not constrained when executing their strokes. The distance between the participant and the tablet in-between days was not controlled in this study. Although differences in posture might affect the kinematics, forcing a given posture might have created biases in the results of some participants who might have been obligated to use strategies that were not optimal for them. We thus chose to prioritize a comfortable, self-selected posture, which is important during a clinical test involving maximal speed. As a result, different strategies were used by the individual participants, especially for the vertical oscillations. However, postural difference between test days for the participants could have affected the kinematics [71] and could therefore lead to decreased reliability in some tests, especially the vertical oscillations. A standardization of the distance between the participant and the tablet, and the standing posture could be means by which to increase the intra-participant reliability, but would add complexity to the setup for clinical testing. Further studies evaluating the parameters' reliability with comparison of self-selected *versus* controlled posture could help improve the reliability of handwriting tasks for clinical application. In addition, tiredness and boredom could be observed in such studies. As the model describes the neuromotor condition of the participant [33, 72], it could be of interest to add a fatigue scale or a subjective scale to know if the participants were tired [73]. Performing the study at the same moment of the day (whether always the morning or afternoon) could also heighten the reliability as handwriting speed could be affected by circadian variations [74]. The use of neurostimulants should also be documented, as they have an effect on fatigue [75]. Furthermore, a learning process can be observed between two sessions as the velocity in handwriting can be affected by familiarity and practice of the test [76]. Despite the training period at the beginning of each session, kinematic profiles appeared faster on the second day in our study, as in Smits, Tolonen, Cluitmans, van Gils, Zietsma, Tijssen and Maurits [49], and parameters for the second day showed more variability. To diminish the inter-session variability, additional training sessions could be assigned at least one day before the recording session. For clinical reasons, the same study should be performed on fatigued participants. Despite the need for some improvements, the method in the present study seems appropriate for fatigue detection and with these improvements should be feasible for clinical use.

5. Conclusion (89)

Most of the parameters have good test-retest reliability in the four series of tests presented. Both agonist lognormals and more complex movements were modelled by parameters that presented high reliability. The *mode, median* and *time delay* had good to excellent reliability supporting their use in shoulder fatigue detection. However, the minimal detectable change may need to be refined. Nevertheless, the theory has many other applications and its use on a horizontal surface (*e.g.* in a sitting position) leads us to believe that the reliability of the data could be even better for other applications.

Acknowledgements

This research was conducted as part of the TransMedTech Institute's activities and the first author was funded in part by the Canada First Research Excellence Fund. This work was also partly supported by NSERC CANADA Discovery Grants RGPIN-2015-06409 to Réjean Plamondon and RGPIN-2019-04978 to Mickaël Begon.

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential competing interest. Any research group interested to extend this study by performing model comparison with their own software should contact the authors for planning a non-commercial collaboration.

Author contribution

Anaïs Laurent: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – Original Draft. **Réjean Plamondon and Mickaël Begon:** Conceptualization, Methodology, Supervision, Writing – Review & Editing.

References

[1] D.B. Chaffin, G. Andersson, B.J. Martin, Occupational Biomechanics, Fourth Edition ed., Wiley2006.

[2] S. Kumar, Theories of musculoskeletal injury causation, Ergonomics, 44 (2001) 17-47.

[3] U.S.B.a.J. Initiative, The Burden of Musculoskeletal Diseases in the United States (BMUS), Third Edition ed., Rosemont, IL, 2014.

[4] P. Duguay, F. Hébert, P. Massicotte, Les indicateurs de lésions indemnisées en santé et en sécurité du travail au Québec : analyse par profession en 1995-1997, in: IRSST (Ed.), 2003.

[5] A. Van den Bruel, I. Cleemput, B. Aertgeerts, D. Ramaekers, F. Buntinx, The evaluation of diagnostic tests: evidence on technical and diagnostic accuracy, impact on patient outcome and cost-effectiveness is needed, Journal of clinical epidemiology, 60 (2007) 1116-1122.

[6] A. Ljungqvist, P. Jenoure, L. Engebretsen, J.M. Alonso, R. Bahr, A. Clough, G. De Bondt, J. Dvorak, R. Maloley, G. Matheson, W. Meeuwisse, E. Meijboom, M. Mountjoy, A. Pelliccia, M. Schwellnus, D. Sprumont, P. Schamasch, J.-B. Gauthier, C. Dubi, H. Stupp, C. Thill, The International Olympic Committee (IOC) Consensus Statement on periodic health evaluation of elite athletes March 2009, British Journal of Sports Medicine, 43 (2009) 631-643.

[7] J.P. Weir, Quantifying test-retest reliability using the intraclass correlation coefficient and the SEM, Journal of Strength and Conditioning Research, 19 (2005) 231-240.

[8] M.R. Al-Mulla, F. Sepulveda, M. Colley, A Review of Non-Invasive Techniques to Detect and Predict Localised Muscle Fatigue, Sensors, 11 (2011) 3545-3594.

[9] G. Borg, Borg's perceived exertion and pain scales., Human kinetics1998.

[10] Å. Dedering, G. Németh, K. Harms-Ringdahl, Correlation between electromyographic spectral changes and subjective assessment of lumbar muscle fatigue in subjects without pain from the lower back, Clinical Biomechanics, 14 (1999) 103-111.

[11] M.J. Chen, X. Fan, S.T. Moe, Criterion-related validity of the Borg ratings of perceived exertion scale in healthy individuals: a meta-analysis, Journal of Sports Sciences, 20 (2002) 873-899.

[12] J. Finsterer, Biomarkers of peripheral muscle fatigue during exercise, BMC Musculoskeletal Disorders, 13 (2012) 218.

[13] R.H. Edwards, Human muscle function and fatigue, Human muscle fatigue: Physiological mechanisms1981, pp. 1-18.

[14] L. Lindström, R. Kadefors, I. Petersén, An electromyographic index for localized muscle fatigue, Journal of Applied Physiology: Respiratory, Environmental and Exercise Physiology, 43 (1977) 750-754.

[15] Y. Kai, M. Gotoh, K. Nagata, N. Shiba, Infraspinatus fatigue during resisted arm elevation with isometric contraction: an electromyographic study, Journal of Shoulder and Elbow Surgery, 21 (2012) 1104-1109.

[16] M. Cifrek, M. Medved, S. Tonković, S. Ostojić, Surface EMG based muscle fatigue evaluation in biomechanics, Clinical biomechanics, 24 (2009) 327-340.

[17] B. Larsson, C. Karlberg, J. Elert, B. Gerdle, Reproducibility of surface EMG during dynamic shoulder forward flexions: a study of clinically healthy subjects, Clinical Physiology, 19 (1999) 433-439.

[18] H.J. Hermens, B. Freriks, C. Disselhorst-Klug, G. Rau, Development of recommendations for SEMG sensors and sensor placement procedures, Journal of Electromyography and Kinesiology, 10 (2000) 361-374.

[19] D. Farina, R. Merletti, B. Indino, T. Graven-Nielsen, Surface EMG crosstalk evaluated from experimental recordings and simulated signals, Methods of information in medicine, 43 (2004) 30-35.

[20] A. Laurent, R. Plamondon, M. Begon, Central and Peripheral Shoulder Fatigue Pre-screening Using the Sigma–Lognormal Model: A Proof of Concept, Frontiers in Human Neuroscience, 14 (2020).

[21] A. Laurent, R. Plamondon, M. Begon, Pre-screening for Central or Peripheral Shoulder Fatigue using the Sigma-Lognormal Model, International Graphonomics Society - Your brain on artCancun, 2019.

[22] A. Nadeau, O. Lungu, A. Boré, R. Plamondon, C. Duchesne, M.-E. Robillard, F. Bobeuf, A.-L. Lafontaine, F. Gheysen, L. Bherer, J. Doyon, A 12-Week Cycling Training Regimen Improves Upper Limb Functions in People With Parkinson's Disease, Frontiers in Human Neuroscience, 12 (2018).

[23] N. Faci, N. Désiré, M.H. Beauchamp, I. Gagnon, R. Plamondon, Analysing the Evolution of Children Neuromotor System Lognormality after Mild Traumatic Brain Injury, The Lognormality Principle: Applications for e-Security, e-Health and e-Learning.2020.

[24] N. Faci, H.T. Nguyen, P. Laniel, B. Gauthier, M.H. Beauchamp, M. Nakagawa, R. Plamondon, Classifying the Kinematics of Fast Pen Strokes in Children with ADHD using different Machine Learning Models, The Lognormality Principle: Applications for e-Security, e-Health and e-Learning., in Press World Scientific Publishing, New York, Singapore, 2020.

[25] R. Plamondon, C. O'Reilly, C. Rémi, T. Duval, The lognormal handwriter: learning, performing, and declining, Frontiers in Psychology, 4 (2013).

[26] C. O'Reilly, R. Plamondon, L.-H. Lebrun, Linking brain stroke risk factors to human movement features for the development of preventive tools, Frontiers in Aging Neuroscience, 6 (2014).

[27] R. Plamondon, A kinematic theory of rapid human movements. Part I. Movement representation and generation, Biological Cybernetics, 72 (1995) 295-307.

[28] R. Plamondon, A kinematic theory of rapid human movements. Part II. Movement time and control, Biological Cybernetics, 72 (1995) 309-320.

[29] R. Plamondon, C. Feng, M. Djioua, The convergence of a neuromuscular impulse response towards a lognormal, from theory to practice, 2008.

[30] K. Lebel, H. Nguyen, C. Duval, R. Plamondon, P. Boissy, Capturing the Cranio-Caudal Signature of a Turn with Inertial Measurement Systems: Methods, Parameters Robustness and Reliability, Frontiers in Bioengineering and Biotechnology, 5 (2017) 51.

[31] R. Plamondon, The lognormality principle: a personalized survey, THE LOGNORMALITY PRINCIPLE AND ITS APPLICATIONS IN E-SECURITY, E-LEARNING AND E-HEALTH, World Scientific2021, pp. 1-39.

[32] R. Plamondon, C. Feng, A. Woch, A kinematic theory of rapid human movement. Part IV: a formal mathematical proof and new insights, Biological Cybernetics, 89 (2003) 126-138.

[33] R. Plamondon, A kinematic theory of rapid human movements: Part III. Kinetic outcomes, Biological Cybernetics, 78 (1998) 133-145.

[34] C. O'Reilly, R. Plamondon, Development of a Sigma–Lognormal representation for on-line signatures, Pattern Recognition, 42 (2009) 3324-3337.

[35] R. Plamondon, M. Djioua, A multi-level representation paradigm for handwriting stroke generation, Human Movement Science, 25 (2006) 586-607.

[36] A. Fischer, R. Schindler, M. Bouillon, R. Plamondon, Modeling 3D Movements with the Kinematic Theory of Rapid Human Movements, THE LOGNORMALITY PRINCIPLE AND ITS APPLICATIONS IN E-SECURITY, E-LEARNING AND E-HEALTH, World Scientific2021, pp. 327-342.

[37] M. Djioua, R. Plamondon, The limit profile of a rapid movement velocity, Human Movement Science, 29 (2010) 48-61.

[38] A. Woch, R. Plamondon, Using the Framework of the Kinematic Theory for the Definition of a Movement Primitive, Motor Control, 8 (2004) 547-557.

[39] M. Djioua, R. Plamondon, A new algorithm and system for the characterization of handwriting strokes with delta-lognormal parameters, IEEE Transactions on Pattern Analysis and Machine Intelligence, 31 (2008) 2060-2072.

[40] M.A. Ferrer-Ballester, M. Diaz, C. Carmona-Duarte, R. Plamondon, iDeLog: Iterative Dual Spatial and Kinematic Extraction of Sigma-Lognormal Parameters, IEEE Transactions on Pattern Analysis and Machine Intelligence, 42 (2020) 114-125.

[41] S. Chidami, M. Archambault-Caron, R. Plamondon, The Delta-Lognormal model in 2.5D, ICPRAI 2018 First International Workshop on the Lognormality Principle and its Applications, Montréal, Canada, 2018, pp. 737-747.

[42] N. Faci, S.P. Boyogueno Bidias, R. Plamondon, N. Bergeron, A New Experimental Set-up To Run Neuromuscular Tests, International Conference on Pattern Recognition and Artificial Intelligence, C. f. Intelligence (Éd.), 2018, pp. 753-757.

[43] A. Woch, R. Plamondon, Rapid Movement Analysis with the ΔΛ Model: Towards a Better Understanding of Movement Generation, International Graphonomics SocietyNijmegen, 2001, pp. 165-169.

[44] T.K. Koo, M.Y. Li, A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research, Journal of Chiropractic Medicine, 15 (2016) 155-163.

[45] J.J. Bartko, On various intraclass correlation reliability coefficients, Psychological bulletin, 83 (1976) 762.

[46] P.E. Shrout, J.L. Fleiss, Intraclass correlations: uses in assessing rater reliability, Psychological Bulletin, 86 (1979) 420-428.

[47] R. Zaki, A. Bulgiba, N. Nordin, N.A. Ismail, A systematic review of statistical methods used to test for reliability of medical instruments measuring continuous variables, Iranian Journal of Basic Medical Sciences, 16 (2013) 803.

[48] Z. Pan, S. Talwar, R. Plamondon, A.W. Van Gemmert, Characteristics of bi-directional unimanual and bimanual drawing movements: The application of the Delta-Lognormal models and Sigma-Lognormal model, Pattern Recognition Letters, 121 (2019) 97-103.

[49] E.J. Smits, A.J. Tolonen, L. Cluitmans, M. van Gils, R.C. Zietsma, M.A.J. Tijssen, N.M. Maurits, Reproducibility of standardized fine motor control tasks and age effects in healthy adults, Measurement, 114 (2018) 177-184.

[50] M. Yung, R.P. Wells, Sensitivity, reliability and the effects of diurnal variation on a test battery of field usable upper limb fatigue measures, Ergonomics, 60 (2017) 923-939.

[51] A. Woch, R. Plamondon, C. O'Reilly, Kinematic characteristics of bidirectional delta-lognormal primitives in young and older subjects, Human Movement Science, 30 (2011) 1-17.

[52] P. Laniel, N. Faci, R. Plamondon, M.H. Beauchamp, B. Gauthier, Kinematic analysis of fast pen strokes in children with ADHD, Applied Neuropsychology. Child, (2019) 1-16.

[53] N. Faci, S.P. Boyogueno Bidias, R. Plamondon, N. Bergeron, An Interactive Tablet-based System to Run Neuromuscular Tests., in: Eds (Ed.) The Lognormality Principle: Applications for e-Security, e-Health and e-Learning2020.

[54] C. O'Reilly, R. Plamondon, A software assistant for the design and analysis of neuromuscular tests, 2007 IEEE Biomedical Circuits and Systems Conference, 2007, pp. 107-110.

[55] M.J. Kolber, F. Vega, K. Widmayer, M.-S.S. Cheng, The reliability and minimal detectable change of shoulder mobility measurements using a digital inclinometer, Physiotherapy Theory and Practice, 27 (2011) 176-184.

[56] S.H. Shin, D.H. Ro, O.S. Lee, J.H. Oh, S.H. Kim, Within-day reliability of shoulder range of motion measurement with a smartphone, Manual Therapy, 17 (2012) 298-304.

[57] M.J. Mullaney, M.P. McHugh, C.P. Johnson, T.F. Tyler, Reliability of shoulder range of motion comparing a goniometer to a digital level, Physiotherapy Theory and Practice, 26 (2010) 327-333.

[58] N.A. Plotnikoff, D.L. MacIntyre, Test-Retest Reliability of Glenohumeral Internal and External Rotator Strength, Clinical Journal of Sport Medicine, 12 (2002).

[59] B.G. Leggin, R.M. Neuman, J.P. Iannotti, G.R. Williams, E.C. Thompson, Intrarater and interrater reliability of three isometric dynamometers in assessing shoulder strength, Journal of Shoulder and Elbow Surgery, 5 (1996) 18-24.

[60] J.v. Meeteren, M.E. Roebroeck, H.J. Stam, Test-retest reliability in isokinetic muscle strength measurements of the shoulder, Journal of rehabilitation medicine, 34 (2002) 91-95.

[61] J.O. de Jesus, L. Parker, A.J. Frangos, L.N. Nazarian, Accuracy of MRI, MR Arthrography, and Ultrasound in the Diagnosis of Rotator Cuff Tears: A Meta-Analysis, American Journal of Roentgenology, 192 (2009) 1701-1707.

[62] J.A. Grant, B.S. Miller, J.A. Jacobson, Y. Morag, A. Bedi, J.E. Carpenter, Intra- and inter-rater reliability of the detection of tears of the supraspinatus central tendon on MRI by shoulder surgeons, Journal of Shoulder and Elbow Surgery, 22 (2013) 725-731.

[63] E. Itoi, Rotator cuff tear: physical examination and conservative treatment, J Orthop Sci, 18 (2013) 197-204.

[64] J.-S. Roy, F. Desmeules, P. Frémont, C.E. Dionne, J.C. MacDermid, L'évaluation clinique, les traitements et le retour en emploi de travailleurs souffrant d'atteintes de la coiffe des rotateurs - Bilan des connaissances, IRSST, 2015.

[65] A.K. Akobeng, Understanding diagnostic tests 1: sensitivity, specificity and predictive values, Acta Paediatrica, 96 (2007) 338-341.

[66] A. Fischer, R. Plamondon, C. O'Reilly, Y. Savaria, Neuromuscular Representation and Synthetic Generation of Handwritten Whiteboard Notes, Proceedings of International Conference on Frontiers in Handwriting Recognition, ICFHRHeraklion, Greece, 2014, pp. 222-227.

[67] S. Portnoy, L. Rosenberg, T. Alazraki, E. Elyakim, J. Friedman, Differences in muscle activity patterns and graphical product quality in children copying and tracing activities on horizontal or vertical surfaces, Journal of Electromyography and Kinesiology, 25 (2015) 540-547.

[68] A. Delisle, C. Larivière, A. Plamondon, D. Imbeau, Comparison of three computer office workstations offering forearm support: impact on upper limb posture and muscle activation, Ergonomics, 49 (2006) 139-160.

[69] M.B. Wise, T.L. Uhl, C.G. Mattacola, A.J. Nitz, W.B. Kibler, The effect of limb support on muscle activation during shoulder exercises, Journal of Shoulder and Elbow Surgery, 13 (2004) 614-620.

[70] J.G. Phillips, R.P. Ogeil, Curved motions in horizontal and vertical orientations, Human Movement Science, 29 (2010) 737-750.

[71] M. Kebaetse, P. McClure, N.A. Pratt, Thoracic position effect on shoulder range of motion, strength, and three-dimensional scapular kinematics, Archives of Physical Medicine and Rehabilitation, 80 (1999) 945-950.

[72] C. O'Reilly, R. Plamondon, M.K. Landou, B. Stemmer, Using kinematic analysis of movement to predict the time occurrence of an evoked potential associated with a motor command, European Journal of Neuroscience, 37 (2013) 173-180.

[73] K.A. Lee, G. Hicks, G. Nino-Murcia, Validity and reliability of a scale to assess fatigue, Psychiatry Research, 36 (1991) 291-298.

[74] I. Jasper, A. Häußler, B. Baur, C. Marquardt, J. Hermsdörfer, Circadian Variations in the Kinematics of Handwriting and Grip Strength, Chronobiology International, 26 (2009) 576-594.

[75] H.M. de Morree, C. Klein, S.M. Marcora, Cortical substrates of the effects of caffeine and time-on-task on perception of effort, Journal of Applied Physiology, 117 (2014) 1514-1523.

[76] R.A. Dixon, D. Kurzman, I.C. Friesen, Handwriting performance in younger and older adults: Age, familiarity, and practice effects, Psychology and Aging, 8 (1993) 360-370.

Supplementary Material, Appendix A

Equations 1 to 3: Mathematical model of movement reconstruction according to Kinematic Theory.

$$\vec{v}(t) = \sum_{i=1}^{N} \vec{v}_i(t;\ t_{0i}, \mu_i, \sigma_i^2) = \sum_{i=1}^{N} \begin{bmatrix} cos(\theta_i(t)) \\ sin(\theta_i(t)) \end{bmatrix} v_i(t) \quad (1)$$

$$v_i(t) = D_i \Lambda_i(t; t_{0i}, \mu_i, \sigma_i^2) \quad (2)$$
$$= \frac{D_i}{\sigma_i (t - t_{0i})\sqrt{2\pi}} exp\left(\frac{[ln(t - t_{0i}) - \mu_i]^2}{-2\sigma_i^2}\right)$$

where
$$\theta_i(t) = \theta_{si} + \frac{(\theta_{ei} - \theta_{si})}{D_i} \int_0^t v_i(\tau) d\tau \quad (3)$$

Table A.1: Resume of the **main parameters** extracted and their meaning

t_0	The time that it takes the brain to perceive the stimulus and emit the command to the musculoskeletal system. It refers to the moment when a population of neurons sends a motor command, and it occurs after the audible stimulus is perceived and the motor command prepared. From this parameter, we can calculate $\Delta(t_0)$, which is the elapsed time between two successive t_0. It reflects the rhythmicity of an input command, and is used in oscillation tasks only.
D	The distance covered by the resulting lognormal.
θ_s	The starting angle of the lognormal.
θ_e	The ending (terminal) angle of the lognormal.
μ	Also known as the logtime delay, it represents the time taken to reach half of the distance movement on a logarithmic scale. It corresponds to the rapidity of the reaction to a command by a system.
σ	Also known as the logresponse time, it represents the time taken from the neuromuscular system to respond to a command on a logarithmic scale. It is also linked to the movement duration and is a measure of the asymmetry of the lognormal.
Nblog	The number of lognormals required to reconstruct the velocity profile of the movement.
SNR	A measure of the quality of the movement reconstruction.

Table A.2: Resume of the **derived parameters** extracted and their meaning

Mode	The time at which the maximum value of the lognormal impulse response is reached. $$M = t_0 + e^{\mu - \sigma^2}$$
Median	The time at which the half value of the integral under the lognormal curve (50% of the covered distance) is reached. $$m = t_0 + e^{\mu}$$
Time delay	The rapidity of the neuromuscular system in response to a command. $$\bar{t} = t_0 + e^{\mu + 0.5\sigma^2}$$
Response time	A measure of the spread of the impulse response. $$s = (\bar{t} - t_0)\sqrt{\left(e^{\sigma^2} - 1\right)}$$
Asymmetry	Characterizes the shape of the lognormal. $$A_c = 1 - e^{-\sigma^2}$$
SNR/NbLog	A performance criterion that represents the motor control fluency of a gesture. The lognormality principle predicts that the ideal movement converges toward a lognormal profile. When the *SNR/NbLog* is higher, the movement is more similar to the ideal one, as postulated by the lognormal behavior.
Command propagation	The duration of the command propagation. It represents the elapsed time between the emission of the command from the brain (t_0) to the execution of the command, the reaction time (*RT*). In the present study, the reaction time was computed as the time required to reach 10% of the maximal velocity during the test. $$CP = RT - t_0$$

Note: $\Delta(t_0)$ is used instead of t_0 for the calculus in the oscillations

Supplementary Material, Appendix B

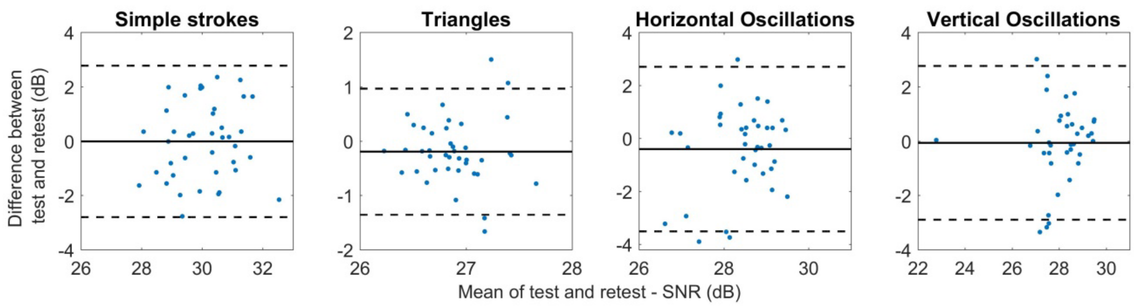

Figure B.1: Bland Altman plots of the SNR for simple strokes, triangles, horizontal and vertical oscillations with the mean difference (solid lines) and the limits of agreement (dotted lines).

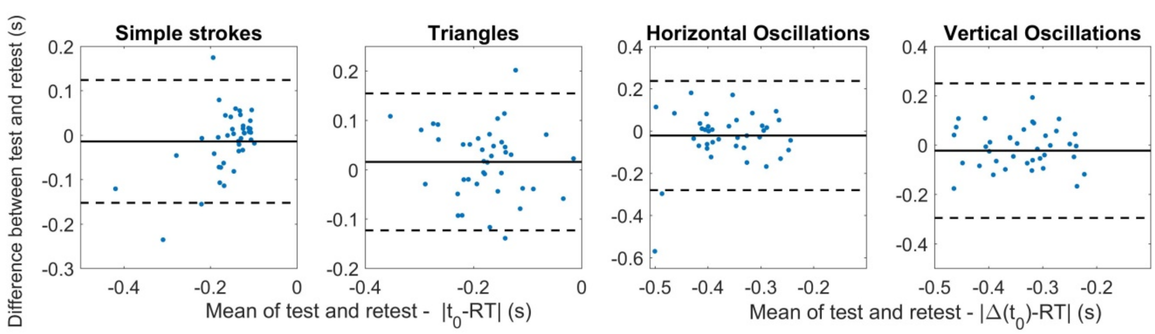

Figure B.1: Bland Altman plots of $|t_0$-RT$|$ for the simple strokes and triangles; and for $|\Delta(t_0)$-RT$|$ for horizontal and vertical oscillations with the mean difference (solid lines) and the limits of agreement (dotted lines).

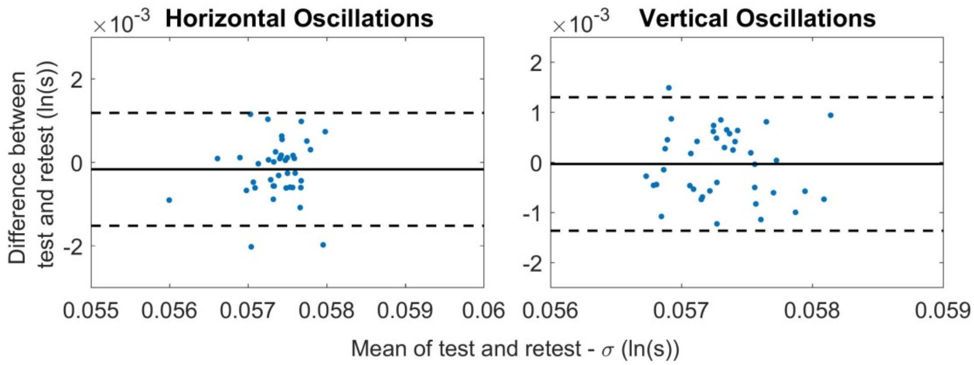

Figure B.2: Bland Altman plots of σ for the horizontal and vertical oscillations with the mean difference (solid lines) and the limits of agreement (dotted lines).

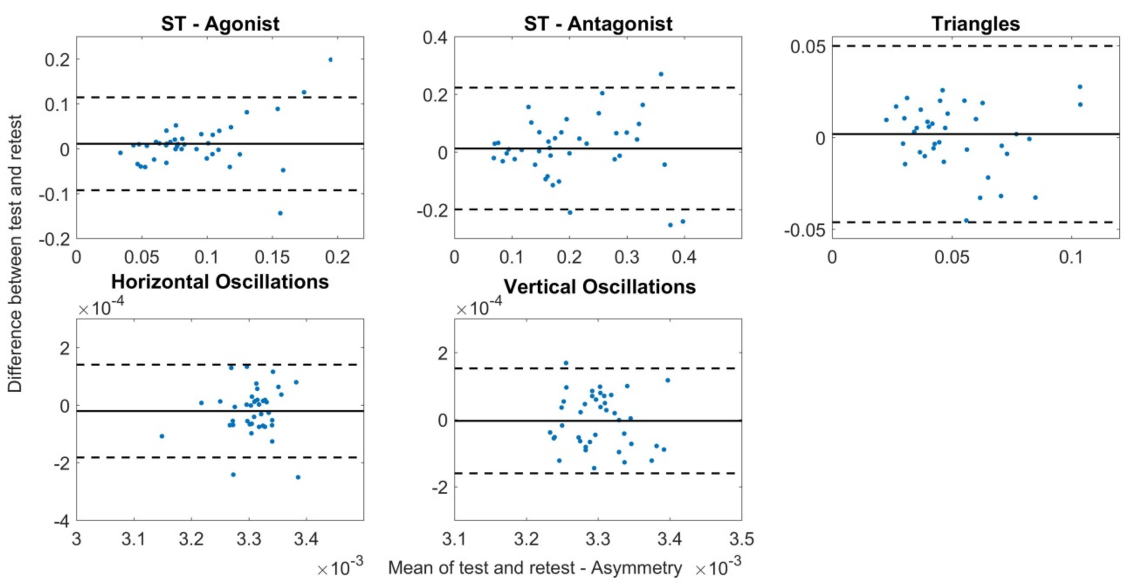

Figure B.3: Bland Altman plots of the asymmetry for the agonist and antagonist components of simple strokes (ST), triangles, horizontal and vertical oscillations with the mean difference (solid lines) and the limits of agreement (dotted lines).