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The Lognometer

A New Normalized and Computerized Device for Assessing the Neurodevelopment of Fine Motor Control in Children

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***Abstract*— Motor skills are fundamental for the development of children. Neurodevelopmental tests currently used by professionals for measuring motor control maturity exhibit several limitations. To address some of these, we have designed the Lognometer, a tablet-based device that can run computerized neuromotor tests. To normalize this tool against a representative population, we collected handwritten triangles from 780 children. We used the Sigma-Lognormal model and a prototype-based parameter estimation algorithm to analyze these movements. To ensure clinical acceptance, we developed an explainable solution relying on statistical regression. We evaluated how well the proposed lognormal decomposition captures the motor control maturation between 6 to 13 years of age by plotting the biological age versus the age estimated using movement kinematics. To provide an equivalent to growth curves, we further overlaid percentile lines that can be used by clinicians to evaluate the neuromotor development of children.**

***Keywords*— Neuromotor development; Kinematic Theory; Lognormality Principle; Human Motor Control; Normalization; Sigma-Lognormal Model; Parameter Extraction.**

I. Introduction

Motor skills are crucial in the development of children. They allow them to explore their environment, engage in games, initiate social interactions and develop their basic academic skills [1]. According to [1], exploring the environment requires two essential processes: perception, which relies on sensory functioning, and action, which depends on motor control. The theory of embodied cognition also places great importance on the sensorimotor exploration of the environment for the development of the child [2]. Its proponents argue that the development of different cognitive processes such as conceptualization, categorization, and ideation is possible through sensorimotor exploration of the surrounding world. This theory has been supported by various studies showing that the motor areas of the brain are activated during different cognitive tasks, such as lexical decision [3] or action-related sentence comprehension [4]. Taken together, these studies suggest a significant contribution of the motor system in the development of the child.

Analysis of motor control in children is a central aspect in the assessments of several neurodevelopmental conditions, according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). Among these stands the Attention-Deficit/Hyperactivity Disorder (ADHD), which is the most common psychiatric disorder in school-aged children (4-10%) with a male predominance (4 boys/1 girl) [5], [6]. Most children with ADHD present gross or fine motor skill problems, or both [7]. They have poorer handwriting than control participants, with less legible and slower writing [8].

The tools currently used by professionals for measuring neurodevelopmental maturity in ADHD children present several limitations [9]. Most evaluations are conventional "pen and paper" tests or are based on behavioral observations often relying on task completion time [10], [11]. Although some image-based tests have been computerized [12]–[14], most assessments cannot be administered remotely, which constitutes a major limitation in the post-pandemic context where remote medical and psychological consultations are becoming increasingly frequent. Current assessments with conventional tests are long to administer and scored manually. There is a significant lack of precision in motor assessments, and most tools have not been standardized in a large representative population. Therefore, there is an urgent need to set up digital, effective, and objective evaluation systems based on properly standardized tests. This problem is the focus of this paper.

We recently integrated into an experimental device, the Lognometer [15], the fruit of many years of research on the design of objective tools for measuring fine motor skills. This system has proven to be one of the most innovative and efficient tools for performing fundamental exploratory research on many problems and phenomena related to neuromotor control. Its software, running on a high-end digitizing tablet (Wacom Cintiq 13HD) connected to a microcomputer, extracts lognormal kinematic parameters from simple gestures. These parameters describe the central and peripheral neuromotor state of a person. We have collected data from 780 children aged 6 to 13, which allowed us to normalize the Lognometer and

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produce curves of neuromotor maturation as a function of age. Our long-term objective with this study is to establish standards for measuring fine motor skills in elementary school children. The aim of this article is to describe the methodology used to perform this standardization. We first describe the Lognometer and briefly review the theoretical ground on which this technology has been designed. We then present the protocol used to build our reference database. The description of the various statistical analyzes used to standardize the Lognometer follows. We discuss and conclude after presenting our normalization curves.

II. The Lognometer

The Lognometer [15] is an experimental tool composed of a Wacom Cintiq 13HD digitizer connected to a portable computer and operated by specialized software. It has a graphical interface that displays visual stimuli or audio cues to be used as starting times in psychometric tests. As depicted in Fig. 1, the interface is divided into three sections, two lateral sections displaying the visual cues and a middle section used to display a guide sheet for the task. A button in the interface allows switching between right-handed and left-handed guide sheets.

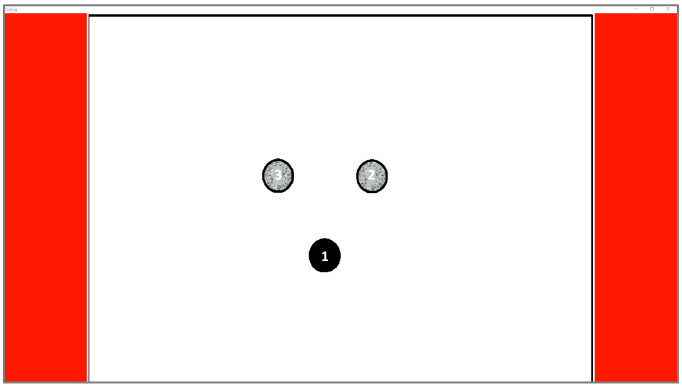

Fig. 1. Example of stimulus. The lateral sections blink red to signal that the system is ready for a new trial. The middle portion displays the guiding sheet. In this example, we show the guiding sheet used for the triangular drawing test.

To standardize the system, a battery of five tests was created from tests previously developed in our laboratory [15], [16]. This battery included, in order of presentation, 1) fast reaching movements initiated following an auditory or 2) a visual stimulus, 3) fast reaching movement with a choice of direction, 4) triangular drawing, and 5) maximal frequency oscillations. These tasks were developed in collaboration with a neurologist and are based on classic experimental psychology paradigms used to measure well-studied psychophysical properties (e.g., visual, auditory, and choice reaction times). However, these tasks were also adapted to allow contrasting simple ballistic motions with more complex sequences of movements (e.g., triangular drawings) and to characterize the maximal speed of motion (maximal frequency oscillations). Importantly, these tasks are accessible to a wide range of individuals (i.e., their simplicity is inclusive), and they are easy to understand and execute by school children.

All tests are following the same timeline: Red color flashing on both sides invites the subjects to put their pen on the black starting dot. Once the pen is in position, the two sides become black for a random period (between 1 and 10 s). Then, the two sides become green to signal "go" (visual condition), or they remain black and a beep signal is emitted (auditory condition). When the subjects perceive the start signal, they must perform the requested task as quickly as possible. Since preliminary analyses showed the highest sensitivity (true positive rate) and specificity (true negative rate) for the triangle drawing task (e.g., when attempting to classify children by age or by a medical condition such as ADHD), we report only the results of our analyses for this task. This test consisted in drawing a triangle by linking the 3 points displayed on the guide sheet starting from point 1 and returning to it at the end (Fig. 1). This test used an auditory stimulus and had 30 repetitions.

As shown in Fig. 2, the interface also shows, in real-time, on the tablet and the computer screen, the stroke being executed by a subject as well as its velocity profile. The various neuromuscular tests present in our database are embedded in the system [17].

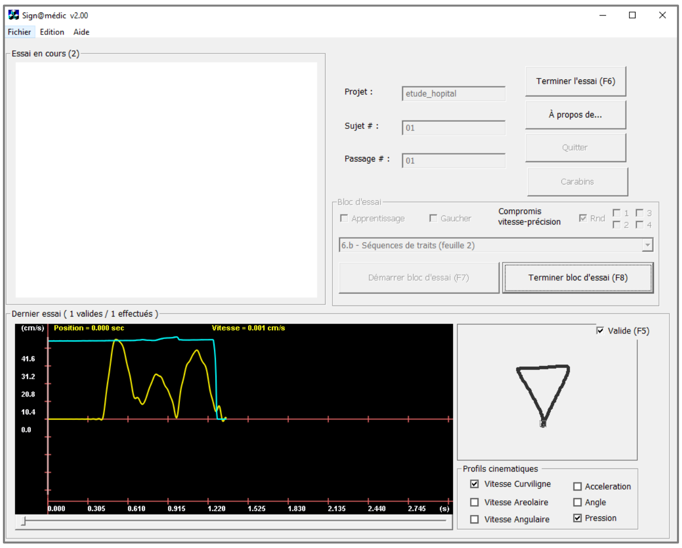

Fig. 2. Interface showing in real-time the trajectory and velocity of the digitized movement.

III. The Kinematic Theory

The Lognometer is a tool for analyzing graphomotor capabilities. It relies on solid foundations: the Kinematic Theory of human movements [18]–[21] and its Lognormality Principle [22], [23]. This theory predicts that humans in perfect control of their gestures produce overlapping sequences of lognormal speed profiles and attempt to use a minimum number of lognormals (i.e., individual motor commands) to perform a task. It has been validated experimentally using electromyography (EMG) [24] and electroencephalography (EEG) [25]. It has further been demonstrated to capture the optimal neuromuscular response under proportionality assumptions [26]. Although many alternative models have been proposed to capture the generation of human movements (an extensive list can be found in [27]), the Kinematic Theory has the advantage of offering a precise analytical representation of movements. This representation can be used to explain most basic phenomena reported in classical studies of human motor control [28] and to analyze several factors involved in fine motor control [29-31]. Further, this theory has shown its practical usefulness in various applications, such as in online signature verification [32], teaching handwriting to children [33], and health monitoring [16, 34].

Based on this theory, the Sigma-Lognormal model has been developed to allow the analysis of simple and complex rapid movements [35]. Following the description in [36], this model decomposes the speed of a movement into several lognormal components representing discrete motor commands being generated by the central nervous system. Each lognormal composing a movement is characterized by six parameters, four describing the motor command (t_0, D, θ_{start}, and θ_{end}) and two describing the dynamic properties of the neuromuscular chain producing the gesture (μ, σ). The tangential velocity (i.e., the modulus of the vectorial velocity) of such components is modeled as having a lognormal profile, scaled by a command parameter (D) and time-shifted by the time occurrence of the command (t_0) as shown in (1).

$$\begin{aligned}\left|\vec{v}_j(t;P_j)\right| &= D_j\Lambda(t-t_{0j};\mu_j,\sigma_j^2)\\ &= \frac{D_j}{\sigma(t-t_{0j})\sqrt{2\pi}}\exp\left(\frac{\left[\ln(t-t_{0j})-\mu_j\right]^2}{-2\sigma_j^2}\right)\end{aligned} \tag{1}$$

Under the assumption that this movement is made around a fixed pivot point, the angular position can be calculated as shown in (2), where the set of parameters P_j is defined in (3). The error function, erf(x), used in (2) is as defined in (4).

$$\begin{aligned}\phi_j(t;P_j) &= \theta_{sj}+\frac{\theta_{ej}-\theta_{sj}}{D_j}\int_0^t\left|\vec{v}_j(\tau;P_j)\right|d\tau\\ &= \theta_{sj}+\frac{\theta_{ej}-\theta_{sj}}{2}\left[1+erf\left(\frac{\ln(t-t_{0j})-\mu_j}{\sigma_j\sqrt{2}}\right)\right]\end{aligned} \tag{2}$$

$$P_j = \left[D_j \quad t_{0j} \quad \mu_j \quad \sigma_j \quad \theta_{sj} \quad \theta_{ej}\right]^t \tag{3}$$

$$erf(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt \tag{4}$$

A movement made up of many overlapping components can be computed as the vectorial sum (5) with P defined in (6) and the Cartesian components of the velocity defined in (7-8). If needed, Cartesian positions can be obtained from these velocities using standard numerical integration algorithms.

$$\vec{v}(t) = \vec{\Sigma}\Lambda(t;P) = \sum_{j=1}^{M}\vec{v}_j(t;P_j) \tag{5}$$

$$P = \left[P_1^t \quad P_2^t \quad \ldots \quad P_j^t \quad \ldots \quad P_M^t\right]^t \tag{6}$$

$$v_x(t;P) = \sum_{j=1}^{M}\left|\vec{v}_j(t;P_j)\right|\cos(\phi_j(t;P_j)) \tag{7}$$

$$v_y(t;P) = \sum_{j=1}^{M}\left|\vec{v}_j(t;P_j)\right|\sin(\phi_j(t;P_j)) \tag{8}$$

This model can be used to synthesize human-like movement [37, 38] or, as is the case in this paper, to analyze simple and complex gestures to characterize the fine motor control of a person [29, 30, 36]. Such an analysis gives an objective measure of the overall state of the neuromuscular system of the tested persons.

When using this model to represent a digitized movement, we characterized fitting accuracy using a signal-to-noise ratio (SNR). This SNR index the lognormality of the movement, and, therefore, indicates its fluidity [39]. The parameters extracted for the Sigma-Lognormal model and the SNR are defined as follows:

- **SNR** (dB): This parameter represents how well the software reproduces the recorded movement. It is defined as follows:

$$SNR = 10log_{10}\left(\frac{\int |V_a(t)|+|V_n(t)|dt}{2\int |V_a(t)-V_n(t)|dt}\right) \tag{9}$$

  with $V_a(t)$ and $V_n(t)$ being the vectorial velocity from the fitted model and the digitized movements, respectively, and |...| standing for the Euclidean norm. The higher the SNR, the better the reconstruction. An SNR greater than 20 dB is considered good.

- **t_0** (s): The time required for the brain to send the motor command with respect to a reference at t=0 (e.g., the time of the "go" stimulus). t_0 should not be confused with the reaction time measured by the moment when the child begins to move the pen. t_0 represents the moment when a population of neurons sends a motor command. Therefore, it happens after the start signal, since the central nervous system must perceive the stimulus before sending the command, but before the reaction time, since a delay is necessary for the motor command to propagate and recruit enough muscle cells to initiate the movement [29]. The higher the t_0, the longer the pre-motor delay (i.e., the delay before the motor command is issued). This parameter is therefore expected to index processes such as attention.

- **D** (mm): The amplitude of movement associated with each motor command. Larger D values indicate a greater range of motion for the corresponding movement primitives.

- **μ**: The neuromuscular time delay (on a logarithmic scale) associated with the reaction of the neuromuscular system to a command, i.e., the logarithm of the time it takes to reach halfway through the movement. It is therefore expected to be associated with the overall response speed of the neuromuscular system to the neural command.

- **σ**: The response time (on a logarithmic scale) of the neuromuscular system. It constitutes an estimate of the duration of the movement component.

- **θ_{start}**: Angle at the start of the movement primitive.
- **Θ_{end}**: Angle at the end of the movement primitive.

The theory has been used in numerous studies to describe and characterize the movements of the fingers, hand, wrist, forearm, eyes, head, trunk, and most recently speech [23]. These parameters have been analyzed by us and our collaborators to study: the handwriting learning in kindergarten and elementary school children; the course of concussions in children; the effects of physical and mental fatigue in children, adults, and athletes; the actions of people with Parkinson's or Alzheimer's diseases; the risk of cerebrovascular accidents (brain stroke); and monitoring of rehabilitation following stroke. The first chapter of a recent book gives a brief overview of more than 50 such studies [23].

IV. Database

To proceed with the normalization of the Lognometer, 780 children (52% boys) between the ages of 5 and 13 were recruited. These children came from three different schools, from kindergarten to grade 6. Between 120 and 135 children participated at each school level, except for kindergarten which included only 11 children.

All the acquisitions were done under the guidance and supervision of a university student who makes sure that the whole protocol, formerly approved by our institution ethical committee, was respected. For the acquisition, the children sat comfortably at their desk in front of the tablet (i.e., the Lognormeter). To provide a naturalistic use of the tool, no rigid constraints were imposed on the orientation of the tablet with respect to the body, neither on the posture or the distance between the eyes and the tablet. Children were allowed to practice a given test a few times before it was run, to make sure that they were familiar with the equipment and the protocol. Then they performed the experiment at their own rhythm, following the sequence of the five tests presented to them by the Lognometer. The order of the tests and the sequence of events during each test were as described in section II.

In addition, 185 children (24%) were neuroatypical (ADHD: 117, attention deficit disorder (ADD): 45, other: 23) of which 132 were medicated (ADHD: 91, ADD: 35, other: 6). Other conditions included disorders such as anxiety disorder, oppositional defiant disorder, autism spectrum disorder, Asperger's syndrome, epilepsy, Tourette syndrome, Down syndrome, tic disorders, impulsivity-control disorder, intellectual disorder, muscular hypotonia, or coordination disorders. Neurodevelopmental issues were reported through questionnaires filled by parents and were not validated by a neuropsychologist or a medical doctor. In this context, to normalize the Lognormeter with respect to a neurotypical baseline, we included only the healthy neurotypical subjects in our analyses. Following these selection criteria, 579 participants were considered.

V. Statistical analysis

A. *Lognormal parameter estimation*

A prototype-based approach [30] has been adopted to estimate lognormal parameters from digitized movements by fitting a predefined sigma-lognormal model (i.e., the prototype) using least-square optimization. The prototype we used to set the initial condition for optimization in this study describes a stereotypical triangular movement as six lognormal components, themselves being grouped as three overlapping agonist/antagonist pairs of motor commands (see Table 1 for parameter values). This is based on the idea of decomposing the triangular motion into a sequence of three ballistic motions, each being the result of an agonist motion pushing the end effector toward its target and an antagonist motion breaking the movement to avoid overshooting. In this prototype, the same values are used as starting and ending angles of individual lognormal components (i.e., the trajectory of these components is straight). The amplitude of all components is given as a proportion of a single $\tilde{d}$ value, with all agonist components being equal to 100 mm and all antagonist components being equal to 10% of the amplitude. The value of $\tilde{d}$ defines the overall size of the equilateral triangle.

The optimization procedure was implemented as a two-stage grid search algorithm. The first stage optimized global time offset (i.e., a common offset being added to all t_0) and amplitude scaling parameters (i.e., a common scaling parameter being multiplied to all D parameters) to minimize the square difference between the tangential velocity profile of the model and the digitized movement. The second stage optimized all 36 parameters to minimize the sum of squared differences between the vectorial velocity of the modeled and digitized movements. For this second step, the search space was bounded such that $t_0 \in [-1, 20]$ s, $D \in [\tilde{d}/100, 3\tilde{d}]$, $\mu \in [-10, -0.01]$, $\sigma \in [0.01, 2]$, $\theta_s \in [-4, 4]$, and $\theta_e \in [-8, 8]$. This two-stage strategy was used to simplify the fitting procedure by improving the starting solution of the second stage using a simple (in two dimensions) adjustment of two meta-parameters having a global and predictable impact over the whole velocity profile.

TABLE I. Parameter values for the prototype of triangular movement used for prototype-based optimization. Angles are specified for a clockwise and counterclockwise triangular movement. For this study, $\tilde{d}$=100 mm.

No.	**t_0 (s)**	**D (mm)**	**μ**	**σ**	**θ_s and θ_e (rad)**	
					Clockwise	***Counterclockwise***
1	0.1	$\tilde{d}$	-1.1	0.5	π/3	2π/3
2	0.2	$0.1\tilde{d}$	-0.5	0.2	4π/3	-π/3
3	0.7	$\tilde{d}$	-1.1	0.5	π	0
4	0.8	$0.1\tilde{d}$	-0.5	0.2	0	π
5	1.3	$\tilde{d}$	-1.1	0.5	5π/3	-2π/3
6	1.4	$0.1\tilde{d}$	-0.5	0.2	2π/3	π/3

TABLE II. PERCENTAGE OF LOGNORMAL COMPONENTS REJECTED WHEN APPLYING, IN TURN, THE UNIVARIATE OUTLIER REJECTION TO EVERY PARAMETER. THE SECOND TO LAST COLUMN SHOWS THE PROPORTION OF LOGNORMALS REJECTED FOR EACH OF THE SIX MOVEMENT PRIMITIVES. THE LAST COLUMN LISTS THE MEAN ± STD [MIN, MAX] NUMBER VALID LOGNORMALS PER SUBJECT.

	t_0 (%)	D (%)	μ (%)	σ (%)	sin(θ_s) (%)	sin(θ_e) (%)	cos(θ_s) (%)	cos(θ_e) (%)	Total rejection (%)	# of valid lognormals per subject
1	2.06	0.00	0.07	0.02	0.70	1.16	11.78	0.50	15.7	28.1± 3.1 [6, 31]
2	1.83	0.04	0.03	0.62	7.20	0.55	14.38	2.31	24.7	24.4 ± 4.7 [1, 31]
3	1.49	0.10	0.09	0.55	0.08	0.00	12.49	6.99	20.5	26.4 ± 3.8 [5, 31]
4	1.46	0.10	0.02	0.65	0.00	0.38	12.38	0.48	15.1	27.5 ± 3.2 [4, 32]
5	1.23	0.28	0.05	0.35	13.0	2.06	9.09	0.91	24.7	25.0 ± 4.4 [1, 33]
6	1.21	0.65	0.04	0.66	8.77	2.18	0.00	0.20	13.2	24.4 ± 4.1 [3, 30]

B. Outlier rejection

We used a univariate non-parametric approach to reject outliers. The rejection thresholds were set at $Q_2 \pm 3*(Q_3-Q_1)$, with Q_X being the X^{th} quartile of the variable distribution. It was applied in turn to SNR values (rejection: 0%), to $\Delta\theta=\theta_e-\theta_s$ (rejection: 1.96%), and then, for each of the six lognormal components, to t_0, D, μ, σ, sin(θ_s), sin(θ_e), cos(θ_s), and cos(θ_e). Angles were decomposed in their sine and cosine projections for this operation because computing quartiles on the distribution of angular variables is problematic given the cyclic nature of these variables. The rejection was performed at the level of the lognormal (i.e., one lognormal parameter being an outlier was ground for rejecting for the whole lognormal component, but not the other lognormals of the same triangular movement). Table 2 gives the details regarding the percentage of rejected lognormals.

Further, to ensure a reliable estimation of the mean value for each lognormal parameter, we also rejected any participants having less than 10 valid lognormals for any of the six movement primitives used for the sigma-lognormal decomposition of their triangular movements. This criterion reduced the final number of included participants to 500.

C. Statistical modeling

To evaluate the degree to which the proposed lognormal decomposition can track motor control maturation between 6 to 13 years of age, we predicted the age of the participants using a linear model. This model was used for simplicity (i.e., Occam's razor) and interpretability, an important consideration for medical applications. To estimate this model, we used the ordinary least square regression implemented in the OLS class for the StatsModels Python package, with the logarithm of the age as the dependent variable and the within-subject average value of the 36 sigma-lognormal parameters, and the fitting SNR as predictive factors. We included the SNR as a feature because the Lognormality Principle predicts that its value increases with the mastering of handwriting. Hence, the SNR is expected to constitute a good predictor of control motor maturity. In this study, we used the traditional regression approach, and therefore did not implement a training-test split of the data as the low number of factors (37) compared to the sample size (500) and the simplicity of the model (linear regression) does not make this approach susceptible to significant overfitting.

VI. RESULTS

Our regression model captured around 60% of the age variability in our sample (R^2=0.603; adjusted R^2=0.570; $F_{37,442}$=18.16; p-value 4.15e-67). This corresponds to a Pearson's coefficient of correlation (*r*) of 0.78. For reference, a coefficient *r=0.50* is generally considered to indicate an effect size considered as "large" [40]. We noted that, since the least square optimization aims only to reduce the square difference between the biological age and the estimated age, its solution can have a systematic age bias (i.e., it tended to systematically overestimate the age of young participants and underestimate the age of older participants). To correct this bias, we further computed a robust linear regression (as implemented in the rlm function of the StatsModels Python package, using Huber's T M-estimator) between the estimated age and the biological age and used the parameters from this regression to remove any bias. A scatter plot of the biological age versus the age estimated and bias-corrected using movement kinematics is shown in Fig. 3, along with overlaid lines showing population percentiles, as is usual for analogous growth curves.

To evaluate the impact of the number of recorded movements on the precision of age estimates, we used a bootstrapping approach and sampled randomly N movements per subject (for N=1, 2, …, 10) and with 100 iterations per N value. We then computed the average absolute difference between the biological age and the estimated age and reported these results in Fig. 4. This figure illustrates the impact of using a smaller number of repetitions on the estimates shown in Fig. 3. As can be seen, although we used 30 repetitions in our normalization study, the precision of the estimates is already ceiling with N=10 repetitions. This indicates that a relatively short test with around 10 valid repetitions would suffice in practice. Overall, we obtain a median absolute difference between the biological age and the predicted age roughly between 1.1 and 1.3 years, depending on the age.

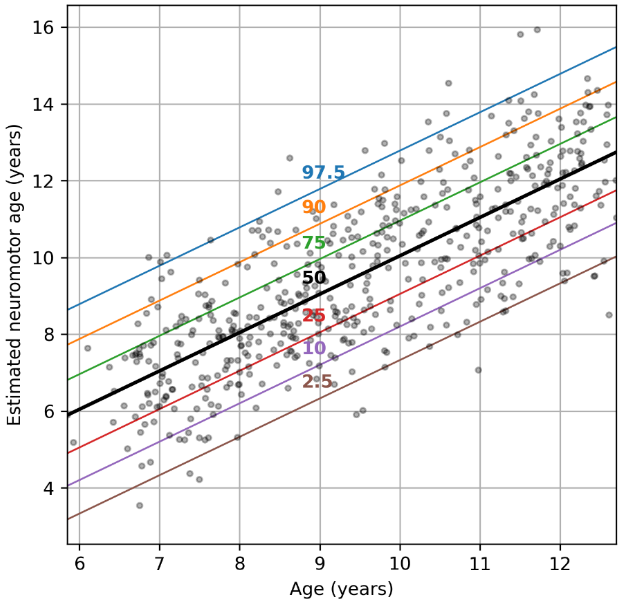

Fig. 3. Scatter plot for the biological age (in x) versus the age estimated from movement kinematics (in y) for 500 neurotypical participants between 6 and 13 years of age. Each point represents a single student. Diagonal lines show population percentiles (form 2.5th to 97.5th, as labeled). Dispersion along the y-axis is expected to be due to natural variability in the population but varies depending on the ability of the model to capture age-related differences in produced movements.

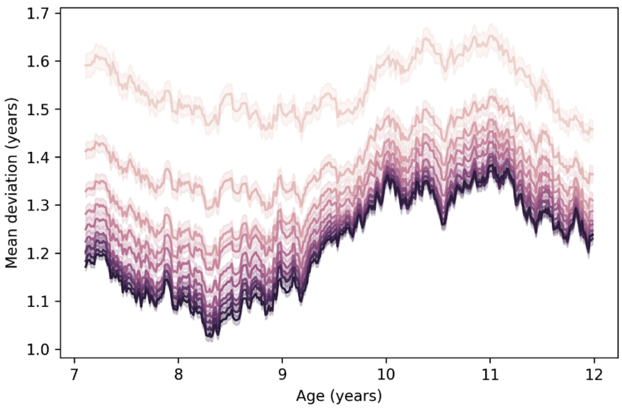

Fig. 4. Mean absolute difference between the estimated age and the biological age, as a function of the sample size (from one (light) to ten (dark) movements per child) and age. Shaded regions show the 95% confidence intervals on these estimates.

VII. Conclusion

In this paper, we reported on a methodology used to standardize the Lognometer, a computerized tool for the assessment of motor skills. The results of the various tests are obtained with no human intervention, enhancing the objectivity of this test compared to common neurophysiological tests involving subjective scoring. For example, in the Conners test used to assess ADHD symptoms, the respondents are the teachers and parents who are often affected by the negative symptoms of the unruly child. This exposure makes it very difficult for them to be objective in their assessment.

Moreover, most competing tests were validated using samples comprising less than 25 children [6], [7]. The Lognometer was standardized on a large sample of 500 children. Such a large-sample validation is an important step for establishing standards on fine motor control in elementary school children. This standardization allowed us to calibrate the tool and define the trajectory of fine motor development in neurotypical primary school children. This tool can now be used to classify and follow children according to their percentile, like growth curves are used to evaluate and monitor infants. In the end, we expect that the standardization of this diagnostic tool will allow specialists to establish a standard for each age category and determine if the motor skills of a child are indicative of a typical developmental trajectory. In the future, the sensitivity of these tests to varying cultural aspects would need to be further validated before clinical use in non-occidental cultures or populations using other alphabets than roman letters.

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