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Modeling Reaction Time in the Ankle

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Abstract—**We are examining whether robust behavioral laws, initially designed to describe sensorimotor control of the upper extremities, can also describe lower extremity movements. Herein, we present our initial results of our research on measuring ankle reaction time (RT). We show that RT measured in ankle dorsiflexion (DP) and inversion-eversion (IE) of 7 healthy young subjects followed a γ distribution, a typical finding in the upper limb response modalities. We propose that the low-order statistics (mean and variance) of the best-fit γ function can be used to concatenate RT across subjects with similar performance and create super-subjects (SS). We then show that the most widely used model of RT cognitive processes, the Ratcliff diffusion model, is adequate to describe ankle RT in an SS. The combination of experimental data analysis with diffusion modeling of ankle RT proposed that at least two cognitive components of RT are accounted for a difference in mean RT observed between DP and IE, namely the speed of information accumulation and the non-decision time that includes, among others, the time for motor response encoding and execution. These results show a great potential to inform our adaptive assist-as-needed robotic therapy delivered to the lower limbs of children with Cerebral Palsy.**

I. Introduction

SINCE Hebb's theoretical work [1] on activity-dependent plasticity and its experimental support [2, 3], the recognition that the adult brain undergoes plastic changes has become mainstream and spurred experiments on motor learning and recovery in patients with neurological injury. We and others reasoned that the motor experience in physical therapy as delivered by clinicians could be replicated and perhaps augmented by robotic technology [4]. Accumulated evidence for its effectiveness led the American Heart Association to include endorsements for upper extremity robotic therapy in their guidelines for the standard of post-stroke treatment [5]. At least for stroke, outcomes were most positive when robotic systems employed interactive approaches, such as our performance-based adaptive scheme [6, 7]. Our performance-based algorithm explores concepts of motor learning including knowledge of results (e.g., hitting the targets) and knowledge of performance (e.g., in every fifth repetition of the game, performance is provided in terms of self-initiation movement counts, aiming accuracy, speed and deviation, amount of robotic help power, smoothness of movement, etc.) [8]. But to our knowledge, little is known of the design principles applicable to lower limb rehabilitation, in general, and the sensorimotor control of the ankle, in particular. We have recently shown that Fitts' law applies also to human ankle movements [9]. We now seek to examine ankle reaction time (RT) and explore its potential to use it as a tool for assessing deficiencies in sensorimotor control.

RT has been found to be influenced by many exogenous factors to the brain, including the type of stimulus, (e.g., auditory as opposed to visual [10]), stimulus intensity [11] and position in the visual field [12], as well as spatial accuracy constraints [13-15]. In addition to extrinsic, many of the brain's intrinsic factors, often associated with a diverse set of neurological diseases, affect RT. Significant delays in RT measures have been found in basal ganglia disorders such as Parkinson's disease (PD) [16-18] and Huntington's disease [19] and are commonly related to a deficit in motor planning [20, 21]. Mounting evidence is also linking RT to structural and functional brain characteristics: Increased RT variability is found to be indicative of white matter degradation [22, 23], disconnectivity in associate pathways [24], impaired top-down executive and attentional control processes [25], cognitive disorder, neurotransmitter dysfunction, fatigue, and stress [26]. Interestingly, impaired RTs appear responsive to intervention: RT has been used to quantify restoration of motor functions according to given cognitive contexts in PD patients treated with Deep Brain Stimulation [27]. In addition, exercise and practice improve simple and choice RT in both young and older adults [28-31]. In rehabilitation robotics, RTs can also be used to assess patients' attention and help increase their participation during therapeutic sessions; this appears to be of critical importance in a therapeutic intervention, particularly for the pediatric population which is easily distracted.

We have recently completed the development of the pediatric anklebot, a robotic device to deliver therapy to the ankle of children aged 5-8 y.o [7, 8, 32]. Our clinical target is Cerebral Palsy (CP), the most common developmental motor disability of children that currently affects at least 2 in 1,000 children born in the United States; numbers are

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expected to grow worldwide with the increased survival of pre-term babies. Three devices were deployed and are in pilot testing with children with CP at Blythedale Children's Hospital (Valhalla, NY), Bambino Gesu Children's Hospital (Rome, Italy), and Riley Children's Hospital (Indianapolis, IN). We chose to measure ankle RT first on the adult population where we can study it reliably; we will then refine our sensorimotor paradigms, as needed, for children. In this paper, we report our RT analysis from 7 healthy adult subjects that used our adult anklebot and present a simulation study of the cognitive processes affecting RT, using the Ratcliff diffusion model.

A. *The Ratcliff Diffusion Model*

The Ratcliff diffusion model (RDM) [33, 34] is a sequential sampling model of the cognitive processes involved in simple (single stage) and fast (average RT less than 1.5 s) 2-choice decisions. It breaks down accuracy and RT distributions into distinct processing components by separating the quality of evidence entering the decision from the decision criteria and from other, non-decision processes such as encoding the stimulus and response execution. A decision is made once sufficient evidence toward a choice has been accumulated. Accumulation is governed by two distinct processes - namely, a tendency to drift toward either of the boundaries and a stochastic component in the step size and direction on the decision dimension. The model divides the decision process into three primary processing components: the non-decision time that includes stimulus encoding, memory access, and response execution (T_{er}); the criteria used to make a decision (0 and a, starting at a point z); the quality of information extracted from stimuli (the drift rate, v) – and estimates of the trial-to-trial variability in these components. The variability parameters model participants' inability to set parameters at identical values from trial to trial: s_t is the range in T_{er}, s_z is the range of the starting point, and η is the standard deviation in the mean drift rate. All model components combined together produce traditional measures of processing speed, as well as predictions for accuracy and RT distributions for correct and error responses [34, 35]. For the mathematical details of the diffusion model, see [35].

II. METHODS

A. *Subjects*

Seven healthy young adults were enrolled into this study. Subjects were Caucasian, post-doctoral and graduate students at the Massachusetts Institute of Technology (1 female). All subjects had normal or corrected-to-normal vision and were right-foot dominant according to their preferential use of the foot during daily activities such as kicking a ball. Participants had no reported history of traumas or neuropathies to the lower limbs. All subjects were naive to the task upon enrollment and gave written informed consent according to the procedure approved by the Massachusetts Institute of Technology Committee on the Use of Humans as Experimental Subjects.

B. *Experimental Apparatus*

RT was measured for dorsi-plantarflexion (DP) and inversion-eversion (IE) ankle pointing movements using a highly back-drivable, wearable Anklebot robot (Interactive Motion Technologies, Watertown, MA). The robot is a low-friction, backdrivable device with intrinsically low mechanical impedance that allows the maximum range of motion required for the typical gait of healthy or pathological subjects in all three degrees-of-freedom of the foot relative to the shank during walking overground or on a treadmill [36, 37]. Subjects wore a modified shoe and a knee brace, to which the robot was attached. Subjects were seated and the knee brace was securely fastened to the chair to fully support the weight of the robot and to ensure that measurements were made in a repeatable posture. The chair was placed 1.5 m away from a 60-inch 1080p (Full HD), 120 Hz, 1024 x 768 Liquid Crystal TV (Sharp LC60L, Sharp Electronics Corporation) which was positioned at eye level (Fig. 1). For this study, the robot acted as a passive device and recorded simultaneously the DP and IE positions. Ankle position kinematics, with respect to the zero-angle (neutral position), were recorded at 200 Hz sampling frequency and converted to screen pixels for visualization. Visual feedback was given online to the subjects as a moving circular cursor (d = 23 pixels). A DP (IE) movement of the ankle moved the cursor vertically (horizontally); hence the cursor moved in a 2D coordinate system with the origin corresponding to the ankle's neutral position defined as the sole being at a right angle to the tibia (see Fig. 1 in [9]). Visualization software was written in TCL/TK and run on a PC equipped with Ubuntu-Xenomai operating system.

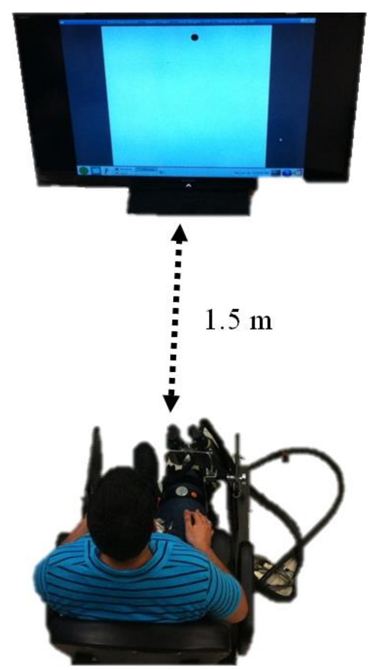

Fig. 1. Experimental Setup. Irrelevant background has been removed.

C. Experimental Protocol

The main manipulation in both experiments was direction of movement. Stimuli were black rectangles displayed against a white background on the monitor. The coordinates of the target centers were (0, ±s) and (±s, 0) in the coordinate system defined above, for DP and IE directions, respectively. Parameter s remained fixed across targets and corresponded to 0.2 rads (12°) in ankle rotation for both directions, within a comfortable range of motion for the ankle. Targets disappeared only when the cursor representing the ankle pointing movement landed inside the rectangle. An outbound target – a target away from the origin – was followed by an inbound target – a target centered in the origin – and vice versa. Outbound targets were equiprobable. The interstimulus interval between outbound target presentations ranged between 800 ms and 1200 ms.

Subjects were instructed to point with their ankle "as fast and accurately as possible." There were 2 blocks, one in DP and the other in IE directions, each having 180 pointing movements toward targets constrained to 1D (90 outbound, 2-choice tasks and 90 inbound, simple choice tasks, per block). The presentation order of the blocks was counterbalanced across participants. Participants were allowed to take a short rest break (1 min) between the two blocks.

D. Kinematic Analysis

RT was measured as the temporal distance between the onset of a stimulus and ankle movement as defined by a velocity threshold of 5% of the peak speed [38, 39]. We excluded all non-discrete movements, i.e., those in which the ankle velocity at the onset of the target was larger than 0.001 rad/s. For each movement, we estimated the angle of the instantaneous velocity vector (approximated by the ankle velocity in the first 15 ms [3 samples] of the movement), $a_v = \tan^{-1}\left(\frac{v_{DP}}{v_{IE}}\right)$, where v_{DP} (v_{IE}) was the velocity in the DP (IE) direction. Error choices were defined as initial ankle movements away from the target. They were followed by a prominent movement correction, either as a complete stop or an abrupt change in the initial trajectory, easily identifiable by $|a_v| > \pi/4$, assuming $a_v = 0$ as the optimal (straight to the target) response.

E. Model Fitting

We used the Diffusion Model Analysis Toolbox to fit the data [40, 41]. We fit the RDM to the data using the chi-square (χ^2) method for its best balance between estimation accuracy (i.e., smallest variability in parameter estimates) and robustness to contaminants RTs [35]. Briefly, for each condition, predicted and experimental RTs were grouped into five bins, separately for correct and error responses. The bins were defined by five quintile RTs, namely, .1, .3, .5, .7, and .9. We tested the model on its ability to predict the cumulative probability of a response up to each of the RT quintiles. That gave the expected responses between adjacent quintiles and, by multiplying with the total number of observations, the expected frequency per bin. The expected and observed frequencies of response were compared, and the sums of squared differences were summed over bins to produce a χ^2 statistic for all conditions. We employed this figure as the objective function to be minimized during estimation using a SIMPLEX fitting algorithm [42].

In total, parameters for 8 models were estimated. Specifically, we experimented on the "no effect" model (all parameters constrained to be equal across conditions); models where a single parameter was allowed to vary across conditions, namely a, v and T_{er}; models where two free parameters could vary across conditions, namely {a, v}, {v, T_{er}} and {T_{er}, a}; and a model with all three parameters {a, v, T_{er}} allowed to be free. Initial parameter estimations were done using a pre-implemented algorithm (EZDIFF autogeneration).

To compare models with different numbers of parameters, we combined two statistical criteria. We used the Bayes Information criterion [43], defined as $\mathrm{BIC} = p \ln n - 2 \ln L$, where p is the number of parameters in the model, n is the sample size, and L is the maximized value of the likelihood function for the estimated mode [44]. BIC provides a penalty for the number of parameters in a model. In accord with Raftery [45], an absolute difference between two models' BIC values of [0-2], [2-6], [7-10], and >10 indicated a weak (p = [0.5-0.75]), positive (p = [0.75, 0.95]), strong (p = [0.95 – 0.99]) and very strong (p > 0.99) evidence of difference, respectively. To ensure that we did not overfit our data by supporting the equivalency of models, we additionally estimated the bias-corrected version of the Akaike Information Criterion ($\mathrm{AIC_C}$) [46]; it is defined as $\mathrm{AIC_C} = \mathrm{AIC} + 2p(n+1)/(n-p-1)$, where $\mathrm{AIC} = 2p - 2 \ln L$ [47]. We regarded models with $\mathrm{AIC_C}$ within 2 of the minimum $\mathrm{AIC_C}$ as having substantial relative support [48]. As discussed in Section III, we selected a mixture of models proposed by the different criteria to make inferences.

To obtain quintile RTs, there must be at least 5 responses per condition. Given the low error-rates [(3.0 ± 2.5) % for DP and (5.6 ± 4.7) % for IE movements], we did not have enough data to obtain the quintiles for error responses for most of the subjects. A possible solution is to create a number of "super-subjects" (SS) by combining the data from subjects with the same performance. Collapsing data across participants with similar performance to increase the data base for the RDM parameter estimation has been successfully applied before [49]. Model fits can then be performed to SS.

F. Parameter Estimation

The parameters of interest in the present study corresponded to drift rate (v), boundary separation (a), and non-decision components (T_{er}). The other parameters were important during model fitting but did not apply to our main hypotheses. Furthermore, visual inspection showed that none of them varied meaningfully across movement directions. We estimated the model's parameters by fitting the RDM to SS data (outbound movements).

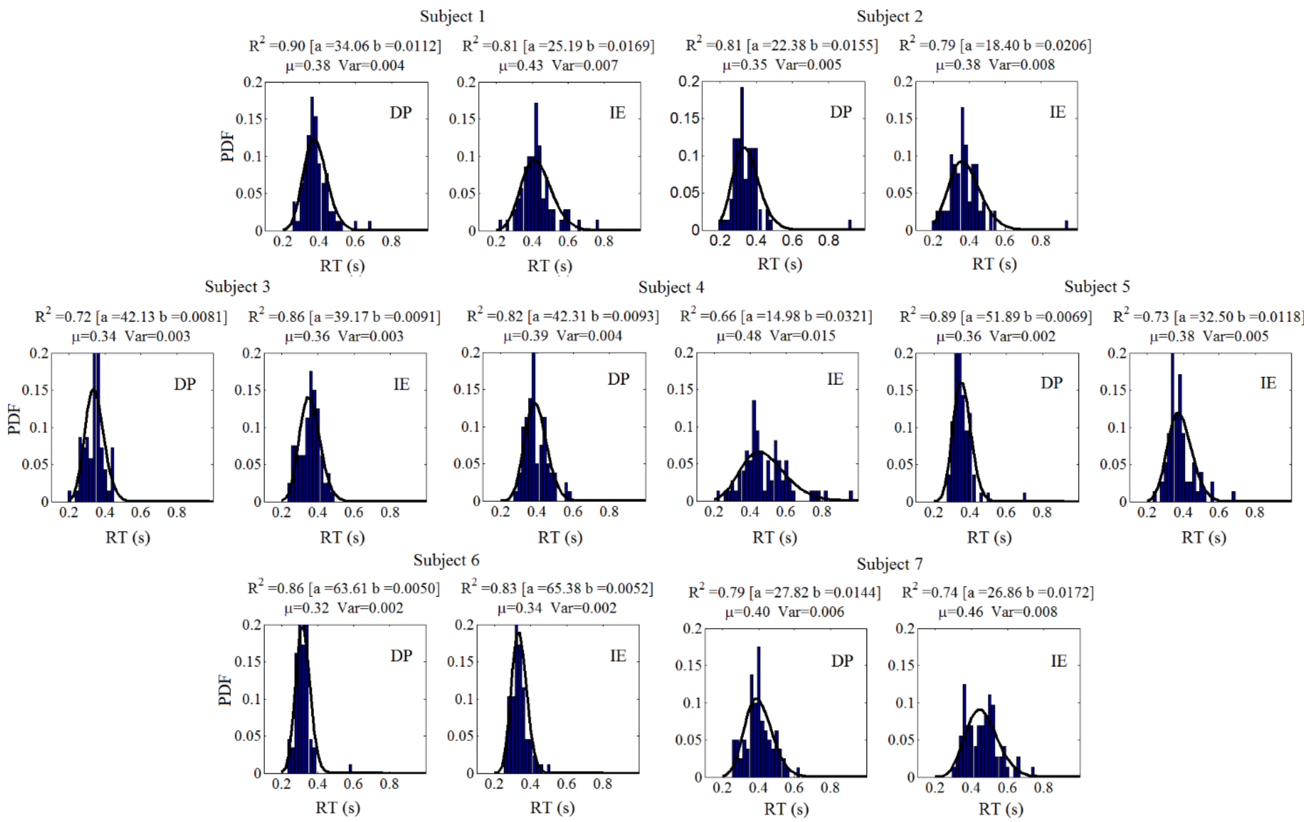

Fig. 2. Best fit γ-distributions (black lines) of the probability density function (PDF) of the RT, for DP (left) and IE (right) movement per subject, with the R^2 value and the estimated shape, a, and scale, b, parameters (1st title line) as well as the mean, μ, and variance, Var (2nd title line).

III. RESULTS

For each subject, we estimated the probability density function (PDF) for the RT measured in DP and IE movements, separately. We then fit a γ- distribution on the empirical PDF and calculated the fit statistics (Fig. 2). Interestingly, the mean RT for DP was found to be consistently lower than the mean RT for IE. As all subjects had similar (and very low) error percentages, we used the estimated mean and variance of the best fit γ-distribution to cluster the subjects into groups of similar performance (Fig. 3). Subjects 2, 3, 5 and 6 exhibited similar RT distributions and were grouped to form a SS with the remaining subjects forming a second group of participants. The formed SS had mean correct RT: 385 ms and 450 ms, probability correct: 0.96 and 0.93, for DP and IE, respectively.

We fit the RD models to the SS data for the two movement directions and combined the information from BIC and AICc to select our best fit models (Table I). Since BIC is known to penalize model complexity more heavily than the AIC_C and AIC_C is better in situations when a false negative finding would be considered more misleading than a false positive, we combined the two statistical criteria to narrow the number of possible models that best fit the data. Specifically, the BIC and AIC_C estimates were used to define the low and the upper end of the best-fit range of models, respectively. Hence, for the SS, the best fit model included the {v, Ter} (proposed by the BIC) and the $\{a, v, T_{er}\}$ models (proposed by the AIC_C), suggesting that at least two cognitive components of RT vary between DP and IE ankle movements. Importantly, the free parameters of the best-fit models varied consistently across conditions: comparing DP to IE movements, v decreased and T_{er} increased. The boundary parameter, a, did not change significantly across movement directions, as depicted by the $\{a, v, T_{er}\}$ model, for this SS.

In Fig. 4, the quality of the fits and the parameter estimates for the $\{a, v, T_{er}\}$ model are shown. In the first row, quintile probability plots comparing actual data to theoretical fits of the RDM are shown for DP and IE. The probabilities of correct and erroneous responses and the shapes of the RT distributions for both real and simulated responses are shown in the second row. These fits show that the RD model captured the changes in RT and accuracy as a function of ankle movement direction for both correct and erroneous responses. Thus, the parameter values were very likely to

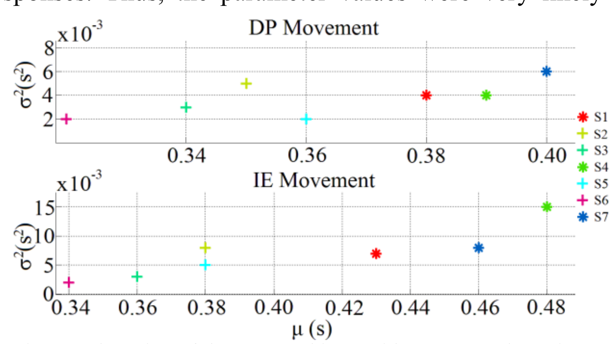

Fig. 3. Clustering of the seven subjects with respect to the estimated mean, μ, and variance, σ^2, of the best fit γ distribution, shown in Fig. 2. Subjects marked with a cross (+) and an asterisk (*) denote two different clusters of responses.

TABLE I

AIC$_C$ AND BIC VALUES FOR EACH OF THE MODELS FIT TO THE SS RT

Model Constraints	AIC$_C$	BIC
none	2090.5259	2121.7671
a	1993.6657	2029.3450
v	1974.5844	2015.2636
Ter	2021.1498	2056.8291
a, v	1978.7211	2019.8320
a, T_{er}	2367.0712	2407.1821
v, T_{er}	1972.2951	2012.4061
a, v, T_{er}	1971.1800	2013.7163

represent the behavior of the components of processing in the experiment. The last row of Fig. 4 shows the estimated parameter values as a function of movement direction and their corresponding error bars as estimates of the standard error of estimation of the parameters calculated with the delta method [50].

IV. DISCUSSION & CONCLUSION

In this article, we measured RT in the ankle using a robotic device. Our analysis of the perceptual decision making was done in an experimental paradigm in which subjects used their ankle to respond to equiprobable on-screen targets presentation. We found that RT follows a γ-distribution. We used the parameters of the γ-function that best fit on each subject's RT to quantitatively assess subjects that responded similarly in both DP and IE directions. We used our proposed clustering approach to group RT from similar subjects and formed a SS. Average (usually vincentized) data, often accounted for a non-accurate representation of the individual subjects, have been used in the RDM fitting quite successfully. Specifically, in more than a dozen large studies with 30 to 40 subjects per group, all parameter values obtained from fitting the model to data averaged over subjects were found close (within 1 or 2 SD of each other) to the parameter values obtained from averaging the parameters resulting from fits of the model to the data from individual subjects [51-53].

We applied the RDM to ankle RT and tested whether it could successfully simulate the 2-alternative forced choice tasks. We examined a range of architectural features that the RDM could take and tried to determine which would best fit the SS data. Statistical analyses of different models narrowed the range of a "best-fit" set of models for which the prediction quality could no longer be discerned visually. A combination of best-fit statistics proposed $\{v, T_{er}\}$ and $\{a, v, T_{er}\}$ as the best models of the SS data. Model parameter estimates from these models were then interpreted as meaningful components of cognitive processing to explain performance differences between DP and IE. In both models, v and T_{er} were found to differ significantly between movement directions. The RDM strongly suggested that there is an important difference at least in the motor response between the talocrural (upper ankle) joint, which permits DP movement, and the subtalar (lower ankle) joint, which permits IE movement. A detailed understanding of processing similarities and differences associated with disorders of the motor system across joints and modalities, could evaluate the response to a therapeutic intervention and

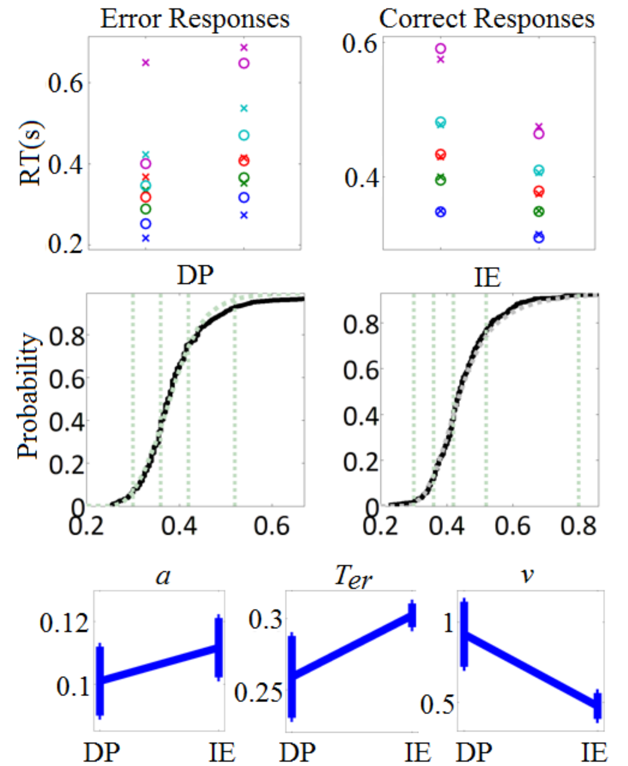

Fig. 4. Diffusion model fits to the RT distributions for a super-subject. The $\{a, v, T_{er}\}$ model is shown. Model allowed boundary separation (a), non-decision time (T_{er}) and drift rate, v, to vary across conditions (DP and IE). First row: Quintile probability functions; The x-crosses (x) in both plots represent the quintiles of the empirical RT distributions. The circles represent the fits of the diffusion model. Second row: The empirical (solid black) and predicted (dotted gray) CDF for correct responses, in DP and IE. Third row: The estimated parameter values as a function of condition and their corresponding error bars as estimates of the standard error of estimation of the parameters calculated with the delta method.

potentially lead to better assessment of neurological diseases that originate in the brain but affect the periphery. Our findings strongly support further exploration of RT in the ankle as a neuro-rehabilitation tool.

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