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Evidence for a cost of time in the invigoration of isometric reaching movements

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Abstract

How the brain determines the vigor of goal-directed movements is a fundamental question in neuroscience. Recent evidence has suggested that vigor results from a trade-off between a cost related to movement production (cost of movement) and a cost related to our brain's tendency to temporally discount the value of future reward (cost of time). However, whether it is critical to hypothesize a cost of time to explain the vigor of basic reaching movements with intrinsic reward is unclear because the cost of movement may be theoretically sufficient for this purpose. Here we directly address this issue by designing an isometric reaching task in which target-directed movements can be performed accurately and effortlessly in prefixed durations. The cost of time hypothesis predicts that participants should be prone to spend energy to save time even if the task can be accomplished at no movement cost. Accordingly, we found that all participants generated substantial amounts of force to invigorate task accomplishment, especially when the prefixed duration was long enough. Remarkably, the time saved by each participant was linked to their original vigor in the task and predicted by an optimal control model balancing out movement and time costs. Taken together, our results supports the existence of an idiosyncratic, cognitive cost of time that underlies the invigoration of basic isometric reaching movements.

Introduction

Understanding the principles underlying movement invigoration is an important topic in neuroscience given its potential implications for disorders such as Parkinson's disease (Mazzoni et al., 2007). Parkinsonian patients typically suffer from bradykinesia (Berardelli et al., 2001), an overall movement slowness which is related to a dysfunction of the basal ganglia (Turner and Desmurget, 2010; Dudman and Krakauer, 2016; Robbe and Dudman, 2020). Vigor generally characterizes the preferred speed of movement, which has been experimentally quantified through the –idiosyncratic– increase of velocity and duration as a function of distance in simple point-to-point movements. Large differences in vigor were reported across individuals but, remarkably, these differences were consistent between/within sessions or between movement modalities (e.g. head vs hand movements, dominant vs non-dominant reaching or vs walking Reppert et al., 2018; Berret et al., 2018; Labaune et al., 2020). While biomechanical factors may of course play a role, inter-individual differences of vigor were primarily attributed to psycho-economical processes that reflect a trait-like feature of individuality (Shadmehr et al., 2016; Berret et al., 2018; Shadmehr et al., 2019; Carland et al., 2019; Shadmehr and Ahmed, 2020a). The main results point to a cost of time related to the brain's tendency to discount the value of delayed rewards (Shadmehr et al., 2010; Haith et al., 2012; Rigoux and Guigon, 2012; Choi et al., 2014; Berret and Jean, 2016). Assuming that the goal of any movement is to put the system in a more rewarding state (Shadmehr, 2010), moving slowly would decrease the subjective value of reward and would thus be avoided in the control of

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goal-directed actions. This principle has been formalized in optimal control theory by using a cost of time that explicitly penalizes the passage of time in sensorimotor control (Hoff, 1994; Berret and Jean, 2016), thereby compensating for the inability of classical trajectory-formation models to account for the duration of self-paced movement (e.g. Flash and Hogan, 1985; Uno et al., 1989; Berret et al., 2011).

However, people may also be reluctant to move slowly for alternative reasons (van der Wel et al., 2010; Park et al., 2017; Guigon et al., 2019). Producing a slow movement may be physiologically costly, so a cost of movement alone may be theoretically sufficient to explain our preferred speed. By implication, the cost of time assumed or identified in previous studies could be partly artifactual or only critical to explain the change of vigor in response to modulation of reward or urgency (Takikawa et al., 2002; Reppert et al., 2015; Manohar et al., 2015; Thura, 2020). Objective measures of the cost of movement have shown that metabolic energy expenditure increases at both low and fast speeds, which is a well-known result for walking that seems to be valid for arm reaching as well (Ralston, 1958; Huang and Ahmed, 2012; Shadmehr et al., 2016). Endpoint variance also tends to increase at both fast and slow speeds due to the effects of signal-dependent and constant motor noise unless efficient feedback corrections are triggered by the system (Wang et al., 2016). Effort and variance are two fundamental features of sensorimotor control that are thought to compose the cost of movement (Todorov and Jordan, 2002; Liu and Todorov, 2007; Gaveau et al., 2014, 2021; Berret and Jean, 2020). Interestingly, using a cost of movement was sufficient to explain the speed/accuracy trade-off –Fitts’ law– (Harris and Wolpert, 1998; Qian et al., 2013) and why our spontaneous movements are neither too fast nor too slow from mechanistic reasons only (van Beers, 2008; Berret et al., 2021). In this case, existing inter-individual differences of vigor could result from discrepancies in the cost of movement represented by people and biomechanical factors. Recently, it has been suggested that the cost of movement could be itself discounted over time (Shadmehr et al., 2016; Summerside et al., 2018) such that movement vigor would essentially reveals “how much we value the things we are moving toward” (Shadmehr and Ahmed, 2020a,b). Obviously, the cost of movement represented by the brain is not yet known exactly (Berret et al., 2011; Summerside and Ahmed, 2021) and this uncertainty is necessarily reflected in the cost of time, the role of which is then particularly unclear for daily actions with intangible rewards. Hence, does the cost of time mainly serve to modulate vigor around some nominal value or does it broadly set movement invigoration?

The goal of the present study was to clarify this issue by neutralizing the cost of movement experimentally. To this aim, we designed an isometric pointing task that could be performed accurately and effortlessly in prefixed durations. This is like an airport treadmill that carries travelers to their destination in more or less time depending on whether they stand still or walk on it. Here participants had to control a cursor on a screen via a force applied onto an isometric joystick. A baseline condition was first tested to characterize the behavior of participants in such an isometric reaching task where the reward –if any– is intrinsic, and estimate their original vigor. In a second condition, the cursor had an internal drive such that the task could be accomplished successfully without any participant intervention. If time matters in the control of this isometric reaching task, we predicted that the participants should exert a substantial amount of force onto the joystick to save time, especially when the drive duration is long enough according to the cost of time hypothesis. Furthermore the time savings of each participant should be related to their original vigor in the task if it reflects how they implicitly value task accomplishment. In contrast, if time does not matter and vigor is essentially determined by a cost of movement in this task, participants should favor restful strategies regardless of the drive duration. Indeed, this would be the optimal behavior with respect to the minimization of any cost of movement, whether related to energy, inaccuracy or other factors.

Materials and Methods

Participants

The experiment included 15 participants (7 females, mean age \pm SD: 27 ± 7). All participants were contacted through a mailing list of persons who volunteer to do experiments at the Italian

89 Institute of Technology and were paid 10 euros for the participation. All participant were naive
 90 with respect to the goal of the experiment and signed an informed consent. The experimental
 91 protocol was approved by the local ethical committee (C.E.R. Liguria, P.R.063REG2016).

92 Experimental methods

93 **Experimental apparatus** The experimental setup comprised an isometric joystick that mea-
 94 sured the force applied by the participant on it with a 6-dof force/torque sensor (Mini 45, ATI)
 95 and a screen (dimension 19 inch) in front of the participant (distance 65 cm). The joystick was
 96 connected to a computer via a digital acquisition card (USB-6211, National Instrument). The force
 97 was sampled at 10 kHz and filtered on-line by fitting a linear regression line to the most recent
 98 160 samples. A custom C++ program simulated the cursor dynamics at 1 kHz and updated its
 99 position on the screen at 60 Hz. The force and system state (position, velocity and external drive)
 100 were saved at 60 Hz.

101 **Task** The participant sat in front of the table with the experimental setup and grasped the
 102 joystick with the right hand and the elbow bent at 90 degree angle. The participant was instructed
 103 to move a cursor toward the target at their preferred velocity. For simplicity the cursor was
 104 restricted to move only along the y -axis (bottom-up axis on the screen). The trial was self-started
 105 by pushing the space bar on the keyboard. The participant was told to avoid pushing the isometric
 106 joystick before the beginning of the trial and the level of force was checked to ensure the participant
 107 did not apply a force when starting the trial.

108 The experiment was divided into two sessions that were executed one after the other on the same
 109 day.

110 The first experimental session (Session 1) served as a baseline condition from which the vigor and
 111 the cost of time of each participant was inferred. It included four movement distances and no
 112 assistance was provided (amplitude 0.1, 0.2, 0.3 and 0.4 of screen size [height: 25.5 cm]). The
 113 goal of this session was to find out the movement time corresponding to each amplitude, compute
 114 nominal vigor scores for each participant and identify the cost of time that would predict these
 115 movement times, given a cost of movement based on effort and error (Berret and Jean, 2016).

116 The second session (Session 2) included two different movement distances (0.2 and 0.4). Impor-
 117 tantly in this session, an external drive that corresponded to biological movements of different
 118 durations ($T_d = 1, 2, 4$ or 6 s) was added to the cursor dynamics.

119 There were 20 repetitions for each condition, thus yielding 80 trials in the first session and 160
 120 trials in the second session. The order of presentation of movement amplitudes were randomized in
 121 the first session. The conditions in the second session were executed from the slowest to the fastest
 122 drive with the amplitude randomized within each condition. In session 2, we used a block-wise
 123 design to minimize surprise effects and evaluate behavior when the participant is aware of the
 124 current drive applied to the cursor dynamics. Accordingly, each condition in the second session
 125 started with two trials that showed the external drive and where the participants was instructed
 126 not to touch the isometric joystick.

127 **Cursor Dynamics** The cursor dynamics along the y -axis was as follows:

$$m\ddot{y} = f_s - v\dot{y} \quad (1)$$

128 where $m = 25$ kg and $v = 10$ kg/s are the simulated mass and damping of the virtual system.
 129 These values were chosen during preliminary experiments to induce comfortable behaviors and
 130 force levels.

131 The force f_s (measured by the force sensor) was the external force applied by the participant on
 132 the cursor. Hence, the force applied by the participant directly affected the cursor acceleration.
 133 The goal of the task in Session 1 was to move the cursor to a target (1.275 cm width), y_f , from a
 134 given home position, y_0 , at the participant's preferred speed.

135 **Choice of external drive** When an external drive was added, the cursor’s dynamics was mod-
 136 ified as:

$$m\ddot{y} = f_d + f_s - v\dot{y} \quad (2)$$

137 where f_d is the external action implemented by an external controller.

138 We noted in preliminary data that participants normally executed this isometric reaching task
 139 using bell-shaped velocity profiles. Therefore, we implemented an external drive as an optimal
 140 feedback control law that allowed to reach the target in a desired duration, T_d , with bell-shaped
 141 velocity profiles.

142 To this aim, we considered a minimum torque change model as it predicts smooth, bell-shaped
 143 velocity profiles (Uno et al., 1989). We noted this optimal control u_d which was the solution of the
 144 optimal control problem described hereafter. We denote by $\mathbf{x} = (y, \dot{y}, f_d)$ the column state vector
 145 and consider the dynamics:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}_d u_d \quad (3)$$

146 where

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & -v/m & 1/m \\ 0 & 0 & 0 \end{pmatrix} \quad \text{and} \quad \mathbf{B}_d = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}.$$

147 The optimal drive was chosen to move the system from an initial state $\mathbf{x}_0 = (y_f - y_0, 0, 0)$ to a
 148 final state $\mathbf{x}_f = (0, 0, 0)$ in desired time T_d while minimizing the cost:

$$C(u_d) = \mathbf{x}(T_d)^\top Q_f \mathbf{x}(T_d) + \int_0^{T_d} u_d^2(t) dt \quad (4)$$

149 where Q_f is the terminal cost matrix chosen as $Q_f = \text{diag}(6.297 \cdot 10^6, 6.301 \cdot 10^6, 10)$. These
 150 parameters were also determined from preliminary simulations and tests to design an optimal
 151 drive that achieves the task reliably for all durations.

152 Solving this optimal control problem (linear-quadratic in finite horizon) yielded an optimal feedback
 153 control of the form (e.g. Stengel, 1986):

$$u_d(t, \mathbf{x}) = K(t)\mathbf{x} \quad (5)$$

154 where $K(t)$ is the optimal feedback gain defined from $t = 0$ to $t = T_d$. For $t \geq T_d$, we defined
 155 $K(t) = K(T_d)$. Note however that this situation was assumed not to occur in practice as we did
 156 not expect participants to move slower than the duration given by the external drive (it would
 157 be non-optimal with respect to both the cost of movement and the cost of time). We computed
 158 optimal control for drives with duration of T_d equal to 1 s, 2 s, 4 s and 6 s and for distances equal
 159 to $y_f - y_0 = 0.2$ m and 0.4 m. Note that for simplicity we mapped the distances relative to screen
 160 size (see above) to S.I. units in the model for simulations (i.e. using the same numbers).

161 **Coupled cursor dynamics** Once the external drive is defined, we can consider the coupled
 162 dynamics used in the experiment of Session 2. Here the state-space dynamics was as follows:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}_d u_d + \mathbf{B}_s f_s \quad (6)$$

163 where $\mathbf{B}_s = (0, 1/m, 0)^\top$. The force input of the human participant thus affected directly the
 164 cursor acceleration.

165 Data processing and parameters

166 **Kinematics** The force was the only user input and was filtered on-line (see Experimental Ap-
 167 paratus). Position and velocity being integrated by the dynamic system (Eq. 6) were not filtered
 168 further. For each trial, we identified the beginning of the movement (velocity threshold 0.005 m/s).
 169 The trial and recording finished when the cursor position was inside the target with a velocity below
 170 0.02 m/s. For each trial, we computed the movement duration and the movement amplitude. We

also identified if a sub-movement was present (negative velocity) and counted the number of peaks in the force profile (each force peak corresponds to a period when the absolute of the force is above 1 N for at least 0.1 s). We excluded from the analyses about 13% of the trials because there was movement reversal, more than five peaks in the force profile or the movement time differed from the condition average by more than three standard deviation. To compute average trajectories, single trial trajectories were resampled to have the same number of samples and average duration.

Amount of force In order to estimate the effort produced by the participant using an objective measure, we considered the *amount of force* applied during the trial, defined as (Shadmehr et al., 2016):

$$\int_0^{T_s} |f_s(t)| dt.$$

Vigor scores In this paper we computed vigor scores using the maximum likelihood approach described by Reppert et al. (2018) but we used the duration of movements instead of peak velocities. To this end, we first computed the grand mean duration of movements of each amplitude $A_i \in \{0.1, 0.2, 0.3, 0.4\}$ (data of all participants pooled together). These movement durations were then used to fit the function

$$T_i = g(A_i) = \alpha + \beta A_i, \quad \alpha, \beta \in \mathbb{R}$$

The vigor score of each participant $j = 1, \dots, 15$, denoted by vg_j , was finally computed as:

$$vg_j = \frac{\sum_{i=1}^4 g(A_i)^2}{\sum_{i=1}^4 T_{i,j} g(A_i)}$$

where A_i is the movement amplitude and $T_{i,j}$ the individual mean movement time for that amplitude. A score of vigor greater than 1 thus indicates a participant that is more vigorous than the average of the participants.

Statistical analyses

We used repeated-measure ANOVAs to analyze movement duration and average force as a function of movement amplitude and, in Session 2, drive duration. Both factors were coded with polynomial contrasts to conduct a trend analysis. All statistical analyses were conducted in R (R Core Team, 2019) with afex (Singmann et al., 2019) and emmeans (Lenth, 2019) packages.

Optimal control modelling

Here we model the behavior of participants in the second session. We extended the system state $\mathbf{x} = (y, \dot{y}, f_d)$ to include the human contribution, as $\tilde{\mathbf{x}} = (\mathbf{x}, f_s)$, and considered the following augmented dynamics:

$$\dot{\tilde{\mathbf{x}}} = \tilde{A}\tilde{\mathbf{x}} + \tilde{B}_d u_d + \tilde{B}_s u_s \quad (7)$$

with $\tilde{B}_d = (0, 0, 1, 0)^\top$ and $\tilde{B}_s = (0, 0, 0, 1)^\top$ and

$$\tilde{A} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & -v/m & 1/m & 1/m \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}. \quad (8)$$

where u_d is the optimal drive and u_s is the human motor command. In this model, the motor command u_s is at the level of force change, which reflects the fact that human force varies smoothly due to the low-pass filtering property of muscle contraction. The motor optimal drive u_d is also at the level of torque change and affects the cursor dynamics via f_d . In absence of participant intervention (i.e., $u_s \equiv 0$), the system is equivalent to Eq. 3 and the cursor moves according to the previously defined optimal drive.

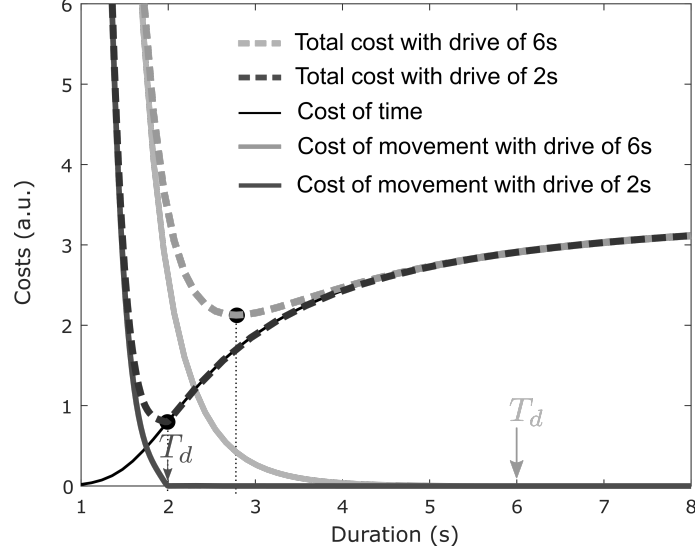


Figure 1: Optimal costs for the task with different drives corresponding to $T_d = 6$ s and $T_d = 2$ s, and a distance of 0.4 m. Cost of movement is zero for times $t \geq T_d$ because u_d already drives the system to the desired target (no effort and no error strategies). Moving faster than duration T_d will require some energy expenditure but allows saving time, which can be a relevant strategy if there is a cost of time. The optimal trade-off between the cost of time and the cost of movement, yielding an optimal movement duration, is indicated by filled circles. When the drive is fast (2 s), the optimal duration remains close to 2 s. However, when the drive is slow (6 s), the optimal duration from the trade-off is around 2.8 s. If there was no drive, the optimal duration would have been 3.1 s in this example.

205 We moreover considered the following cost function:

$$C(u_s) = \mathbf{x}(T_s)^\top Q_f \mathbf{x}(T_s) + \int_0^{T_s} (u_s^2(t) + h(t)) dt. \quad (9)$$

206 where $h(t)$ is the cost of time, T_s is the movement duration, and effort/error terms are modeled as
207 before.

208 The use of the optimal control model involved two steps: (1) an identification step with the data
209 of Session 1; and (2) a prediction step to compare with the data of Session 2.

210 In the identification step, we followed the methodology documented in Berret and Jean (2016) and
211 Berret et al. (2018) to identify the term $h(t)$ for each participant using the data of Session 1 where
212 movement duration T_s is known and external drive is absent ($u_d \equiv 0$ in the above equations).
213 In the prediction step, we solved an optimal control problem in free time to predict movement
214 duration T_s and effort f_s . In this step, external drive u_d is as defined experimentally and the cost
215 of time $h(t)$ is as identified in Session 1, and we assume that the participant minimizes force change
216 (u_s^2) and error (term in Q).

217 The procedure was repeated for each distance of Session 2 (0.2 m and 0.4 m), each T_d (1 s, 2 s, 4 s
218 and 6 s) and each participant (since each participant will have a different cost of time given that
219 their behaviors in Session 1 will differ).

220 This model predicts that participants who behave optimally should trade some physical effort for
221 a gain in time. In other words, if there is a cost of time, they should spend some energy even when
222 there is an external drive that achieves the task by itself. An illustration of the balance between
223 effort and time is provided in Fig. 1. If there is no cost of time, participants should not intervene
224 as it would be the optimal strategy with respect to any cost of movement (for instance effort or
225 accuracy here).

226

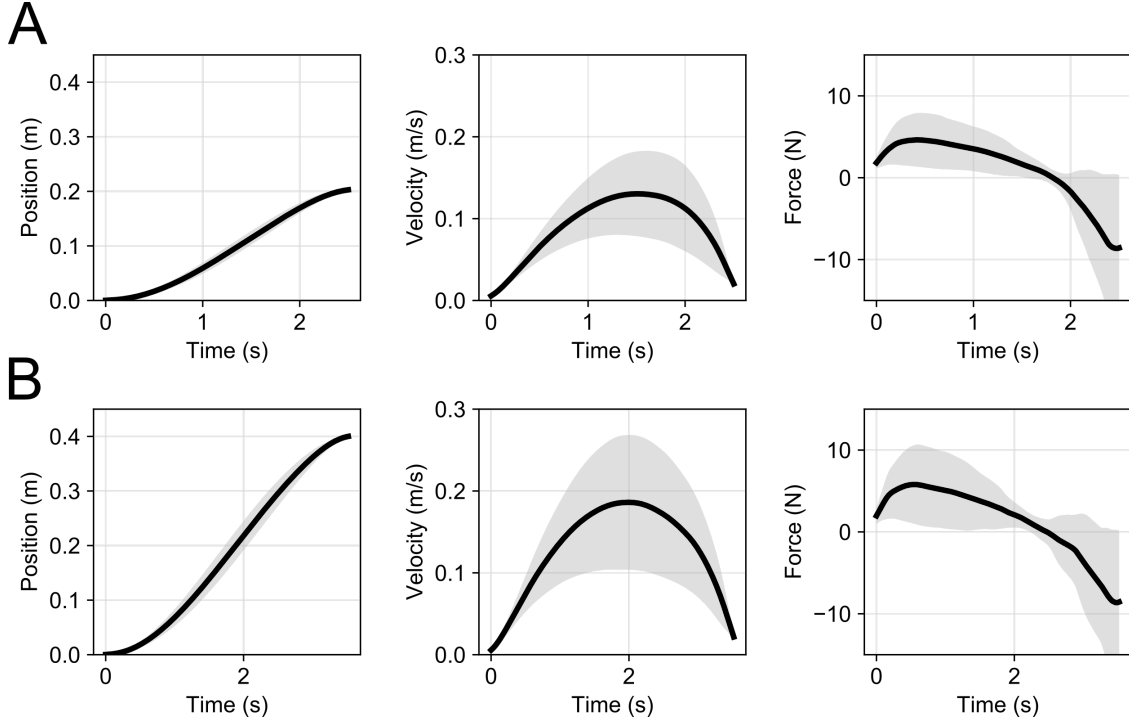


Figure 2: Grand mean trajectories in Session 1. A. Mean displacement, velocity and force for the distance 0.2m. Thick black lines are means across participants and shaded areas are standard deviations. Trajectories were normalized temporally before computing means and deviations. B. Same information for the distance 0.4 m.

Results

Experimental results of Session 1 (without drive)

Mean trajectories Here we describe the average self-paced behavior of the participants in absence of an external drive. The grand mean trajectories are reported in Figure 2 for the distances 0.2m (Fig. 2A) and 0.4 m (Fig. 2B) respectively. Velocity profiles are approximately bell-shaped even though the experimental protocol stopped motion according to some threshold that is visible at the end of the velocity profiles. Force profiles resemble acceleration profiles and mainly consist of a positive phase (to accelerate the cursor) and a negative phase to decelerate it. The force profiles do not return to zero because of the criterion used to detect the end of a trial (see Methods). Substantial inter-individual differences can be noted for instance on velocity peaks or on the force used to perform the task. Repeated-measures ANOVA confirmed that movement duration ($F_{3,42}=85.33$, $\eta_G^2=.39$, $p<.001$) and force ($F_{3,42}=93.93$, $\eta_G^2=.36$, $p<.001$) varied across amplitudes. A trend analysis revealed that movement time and average force increased linearly with movement amplitude for the range of values included in the study.

Amplitude-duration and amplitude-force relationships The overall behavior of participants in terms of movement duration and amount of force are shown in Figure 3 (black filled circles). As in real point-to-point arm reaching experiments, the duration of movement was found to increase with amplitude almost linearly, as confirmed by trend analysis (linear: $t_{42}=15.88$, $p<.001$; quadratic: $t_{42}=-1.95$, $p=.06$). Movements of distance corresponding to 0.2m and 0.4 m were performed in about 2.5s and 3.5s respectively. The amount of force also increased with amplitude in a similar way (linear: $t_{42}=16.76$, $p<.001$; quadratic: $t_{42}=-0.92$, $p=0.36$). The grand mean amount of force was about 7 N for the distance 0.2 m and 11 N for the distance 0.4 m. Again, a relatively large inter-individual variability was visible here and we thus focus on some individual

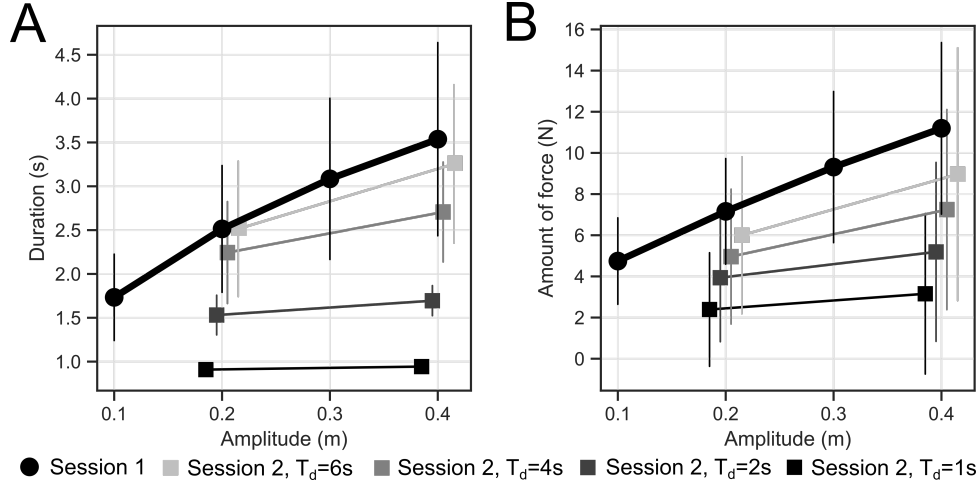


Figure 3: Mean behavior across participants as a function of distance. A. Amplitude-duration relationships in Sessions 1 and 2. Filled circles are data from Session 1 for the 4 tested amplitudes. Grey-colored filled squares are data from Session 2 for the 4 drives and the 2 amplitudes tested. Vertical bars represent standard deviations in all cases. B. Same information for the amplitude-amount of force relationships.

performance scores in the following.

Individual movement vigor scores and costs of time The relationship between amplitude and duration for each individual is reported in Figure 4A. A color code is used to track each individual throughout the study. Linear regressions confirmed that duration increased with movement amplitude in an approximately affine way for every participant ($R^2 = 0.97 \pm 0.03$ across participants). From these relationships, it was possible to compute vigor scores and sort individuals according to these scores (Fig. 4B) (see Methods).

Furthermore, the same relationships allowed us to identify the cost of time for each participant (see also Methods). The resultant costs of time are depicted in Figure 4C. As expected since both measures are derived from the same data, there is a strong correlation between the vigor of participants and the magnitude of their cost of time (Fig. 4D). Typically, the faster participants in Session 1 (i.e. with larger vigor scores) penalized time more steeply (i.e. increased more quickly, and to a higher asymptotic value, their time costs).

Experimental and simulation results of Session 2 (with drive)

We now consider the experimental data of Session 2 where the external drive allows, in theory, the participant to complete the task without any muscular force. Figure 5 depicts the grand mean behavior across participants for two different drives (2s and 6s) and the two distances tested in this Session (0.2 m in panels A-C and 0.4 m in panels D-F). These two distances were illustrated for Session 1 in Fig. 2 for comparison. Black/grey traces show the experimental data and red/purple traces show the simulated data. The simulations relied on the costs of time identified from the data of Session 1 (one cost of time per participant) and the free-time optimal control simulations minimizing a trade-off between the cost of movement and the individual-based cost of time (which explains why simulated data also vary across participants). Velocity profiles are bell-shaped as in the first Session. Force profiles appear more irregular but they still present a positive and negative peaks that corresponds to an acceleration and deceleration of the cursor, even though the presence of the drive may both accelerate and decelerate the cursor on its own. The figure shows that participants used some force to save time, thus achieving the task in less than 3.5s when the drive

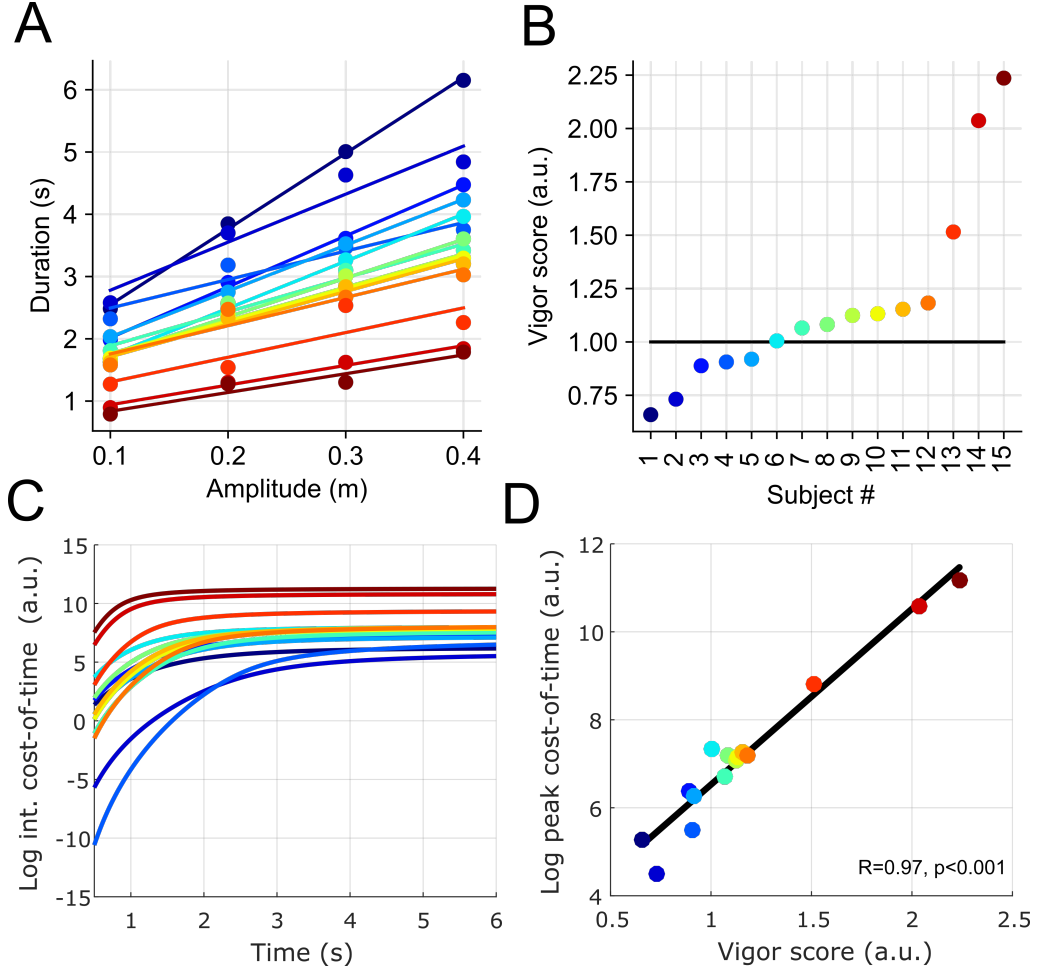


Figure 4: Individual vigor scores. A. Amplitude-duration relationships in Session 1. Each color is the data of one participant. Linear regression lines are displayed. The cost of time was inferred from these individual-level relationships. B. Corresponding vigor scores allowing to sort individuals from the slowest to the fastest in the isometric reaching task of Session 1. The horizontal black line corresponds to a reference vigor score of 1. C. Logarithm of the costs of time identified for each participant, i.e. $\log(\int_0^T h(t)dt)$. D. Correlation between the vigor scores and the logarithm of the peak derivative of the costs of time (i.e. the maximal value of $h(t)$).

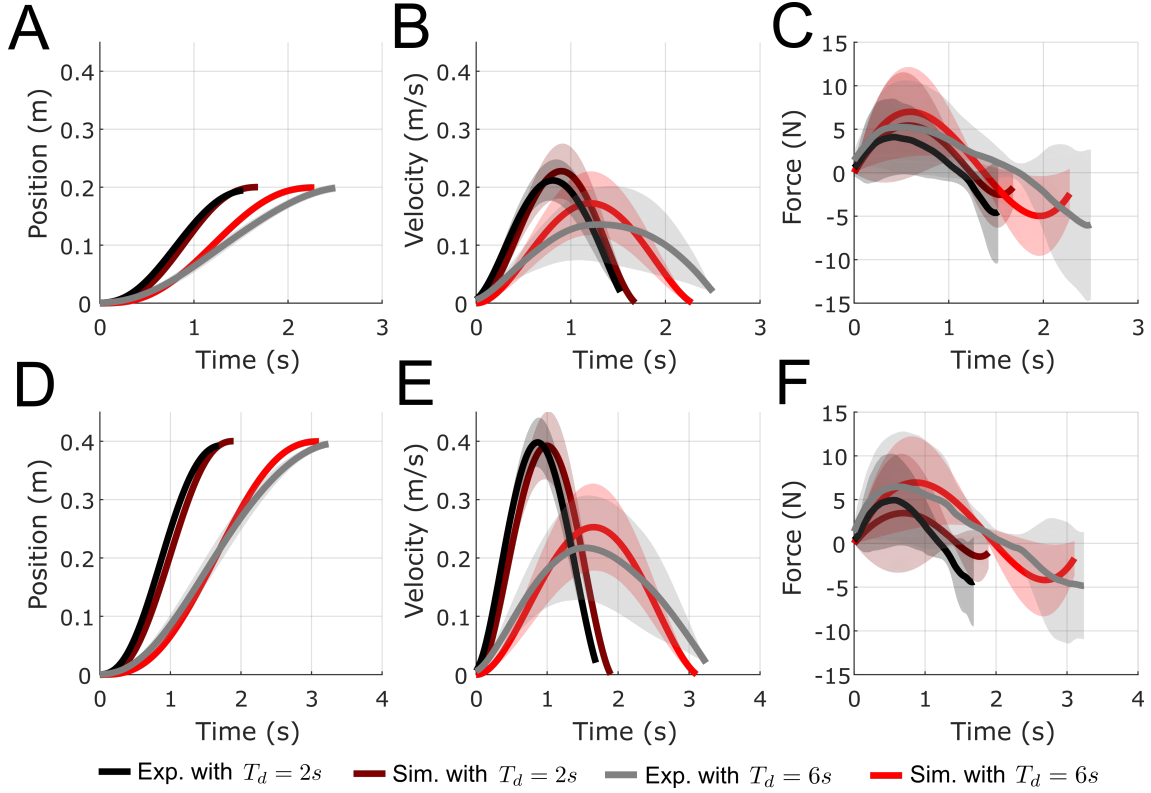


Figure 5: Experimental and simulated trajectories in presence of the drive. A. Cursor displacements in the experiments (black/grey) and simulations (purple/red), for two different drive durations (2 s and 6 s), for the distance 0.2 m. Mean trajectories across participants are reported with standard deviations as shaded areas. B-C. Same information for the velocity and force respectively. D-F. Same information but for the distance 0.4 m.

corresponded to a 6 s movement duration for example. Noticeably, participants still used some force on average even when the drive was stronger and would lead to a 2 s long movement on its own.

Mean movement duration and amounts of force across participants are reported in Figure 3 (filled squares). As expected, the performance became closer to that of Session 1 as the drive duration increased. Average movement duration increased with drive duration ($F_{3,42}=69.25$, $\eta_G^2=.68$, $p<.001$) and amplitude ($F_{1,14}=393.36$, $\eta_G^2=.10$, $p<.001$). The statistically significant interaction ($F_{3,42}=63.47$, $\eta_G^2=.065$, $p<.001$) reflected a steeper increase of the movement duration with drive duration for large movement than for small movements (contrast between linear trends: $t_{42}=16.62$, $p<.001$). A similar analysis of average force revealed the same trends. Average amount of force also increased with drive duration ($F_{3,42}=17.27$, $\eta_G^2=0.15$, $p<.001$) and amplitude ($F_{1,14}=19.56$, $p<.001$). The statistically significant interaction ($F_{3,42}=21.33$, $\eta_G^2=0.01$, $p<.001$) reflected a steeper increase of the average force with drive duration for large movement than for small movements (contrast between linear trends: $t_{42}=6.02$, $p<.001$).

In Figure 6, we depict mean movement durations chosen by participants in Session 2 and compare them to drive durations (black identity line –indicating the optimal duration if only a cost of movement is minimized–) and model predictions (red trace and shaded area). The overall behavior was as follows: movement duration increased with the duration of the drive and tended to plateau near the movement duration obtained in Session 1 for slow drives. Indeed, the movement duration of participants for a drive of 6 s was closed to the duration obtained in Session 1 (dotted line in Fig. 6). Noticeably, the model replicated quite well this average behavior. An optimal trade-off

between movement and time costs thus leads to this evolution of movement duration with respect to drive duration for each distance.

Next, we analyzed the force that participants were prone to exert to save a given amount of time. We thus focused on the relationship between the gain of time and the amount of force used by the participants to complete the task, the gain of time being defined as the drive duration minus the actual duration. We found that all the participants tended to increase the amount of force to save more time across conditions (Fig. 7). The model replicated this trend quite well although it generally tended to overestimate the amount of force necessary to save a given amount of time. Important inter-individual differences could also be noted. For instance, to save one second, participants could use quite different amounts of force (e.g. less than 5 N for the participant with the lowest vigor to more than 10 N for the participant with the higher vigor).

Finally, we investigated if there was any relationship between the vigor of participants in Session 1 and their behavior in Session 2 (Fig. 4). Remarkably, we found that the more vigorous participants in Session 1 were indeed the ones saving more time in Session 2 (high correlations with $r > 0.90$ for both tested distances, $N=15$ participants). These participants were also the ones using a greater amount of force (correlation coefficients between vigor and average amount of force $r > 0.90$ –not depicted–). In summary, vigorous participants spent more energy to save more time.

Discussion

Recent studies have suggested that the vigor of movement results from a trade-off between a cost related to movement production and a cost related to the passage of time. However, whether a cost of time underlies the vigor of simple reaching movements remains unclear as a cost of movement could be theoretically sufficient to explain our preferred speed on average. This cost of time could mainly serve to modulate our speed around a reference value according to the urgency or reward of the task. To disambiguate this question, we designed an isometric pointing task that makes distinct predictions depending on whether a cost of movement or a cost of time is prevalent. In some conditions, a drive moved the cursor to the target with a certain duration such that the task could be accomplished accurately and effortlessly with no participant intervention. Despite this self-completion of the task, the participants exerted all the more force the slower the movement of the cursor was and the higher their original vigor in the task was, in agreement with optimal control simulations assuming a trade-off between time and effort. These findings are compatible with the existence of an idiosyncratic, cognitive cost of time underlying the invigoration of basic isometric reaching movements.

Producing a movement inevitably entails a motor cost that can be translated into tangible variables such as metabolic energy, effort, smoothness, error or variance. The identification of the cost that best reproduces human trajectories has attracted a lot of attention in optimal control theory (see Engelbrecht, 2001; Todorov, 2004; Berret et al., 2019 for reviews) but it has proven difficult to unequivocally identify the cost of movement because of its potential compositeness and subjectivity (Berret et al., 2011; Summerside and Ahmed, 2021). The design of our task circumvents this issue by creating a condition in which the task accomplishes by itself, thereby neutralizing the cost of movement for specific motion durations. Despite this opportunity to perform the task accurately and effortlessly, our participants systematically exerted some force onto the joystick to achieve the task more quickly. They clearly favored saving time over saving energy in this task. Yet, when the drive was present, it was always optimal to remain inactive with respect to any cost of movement. This suggests that slow movements are generally avoided, not specifically because they may incur a large cost related to movement execution but mostly because they last long (van der Wel et al., 2010). This predominance of movement duration over energy expenditure was also found in a perceptual decision-making task at movement initiation (Lunazzi et al., 2021). Morel

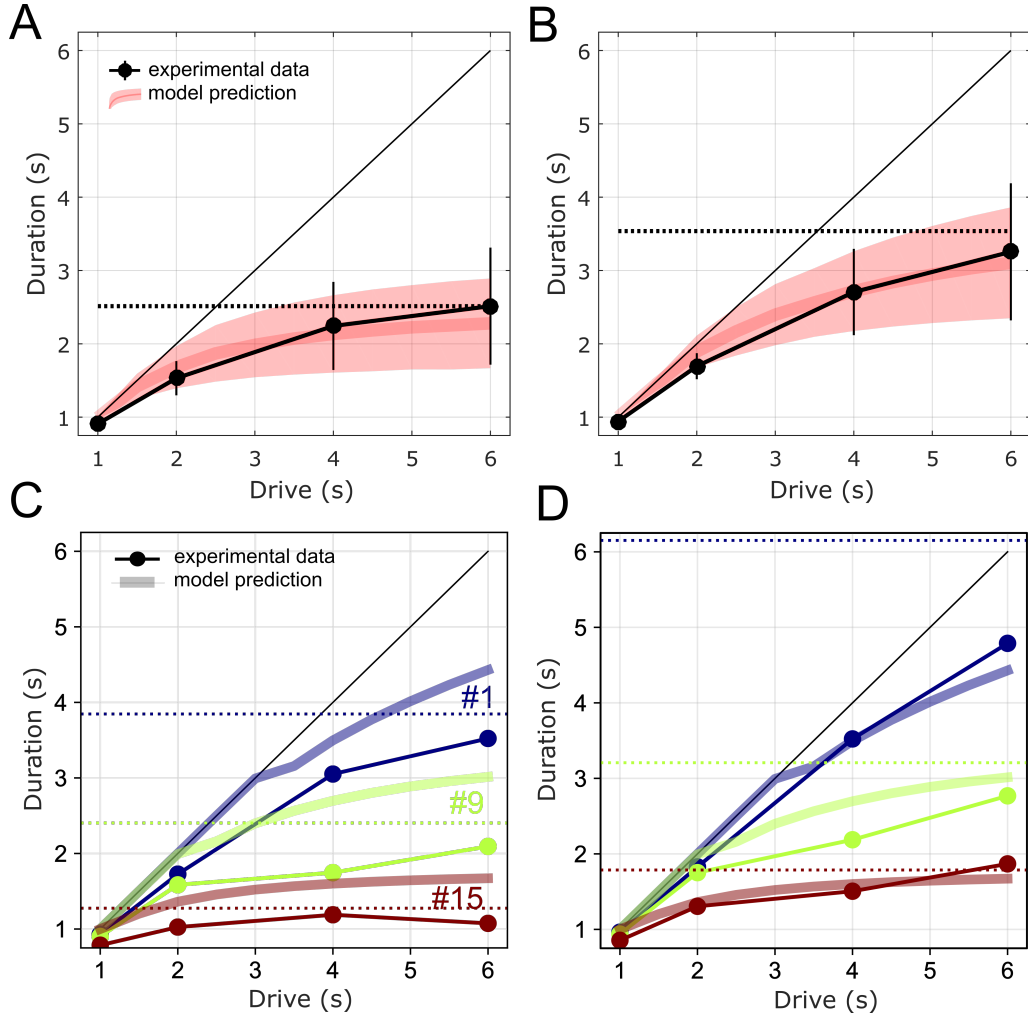


Figure 6: Movement duration with respect to drive duration in Session 2. A. Mean experimental and simulated data for distance 0.2m. Black markers and traces are experimental data. Mean and standard deviations across participants are reported. Red traces and shaded areas are model predictions (also mean and standard deviations across participants). The horizontal dotted line correspond to the mean duration measured in Session 1 for that distance. The identity line corresponds to the drive duration, which would be the optimal duration if only a cost of movement is minimized. B. Same information for distance 0.4m. C-D. Same information for three participants with high, medium and low vigor respectively.

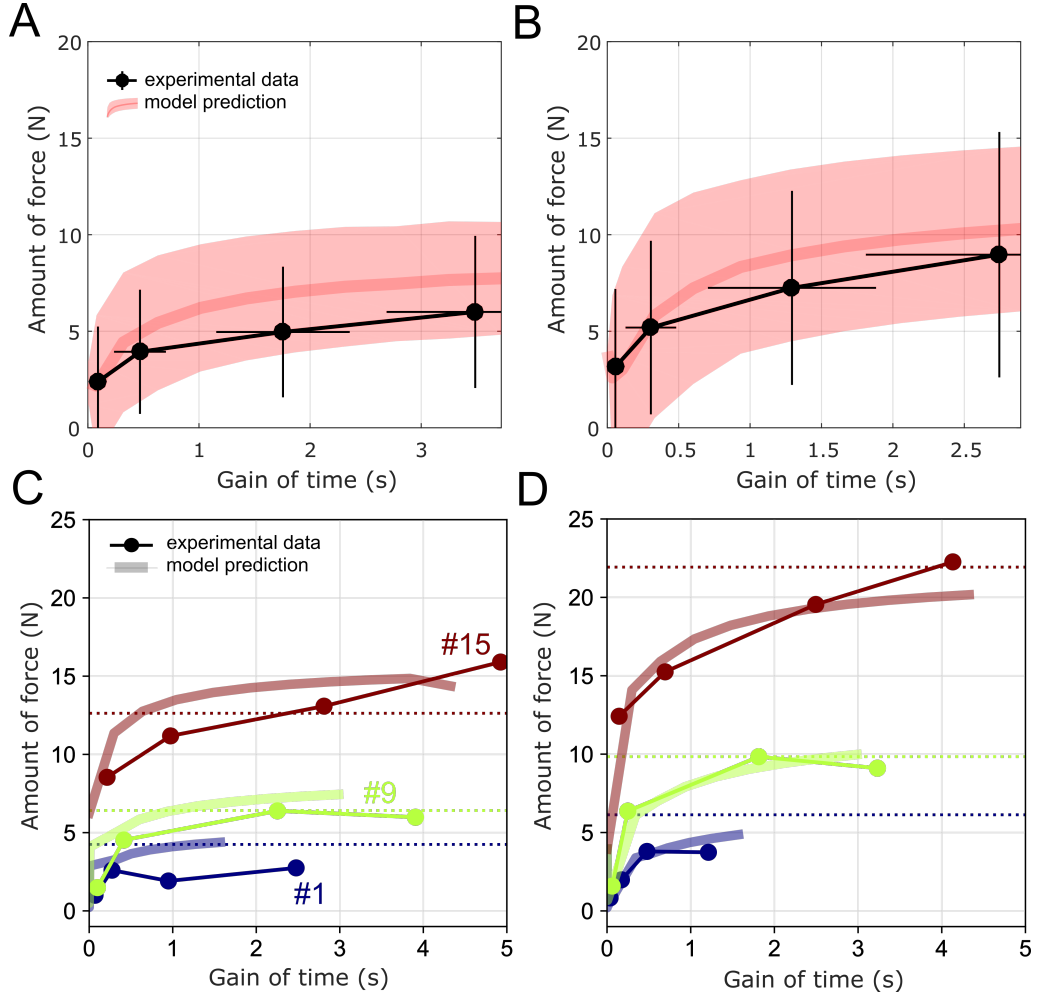


Figure 7: Relationship between gains of time and amount of forces used in Session 2. A. Mean experimental and simulated data for distance 0.2m. Black markers and traces are experimental data. The black filled circles correspond to the drives in the following order: 1 s, 2 s, 4 s and 6 s respectively. Mean and standard deviations were calculated across participants. Red traces and shaded areas are model predictions (also mean and standard deviations across participants). The horizontal dotted line correspond to the mean amount of force measured in Session 1 for that distance. B. Same information for distance 0.4 m. C-D. Same information for three participants with high, medium and low vigor respectively.

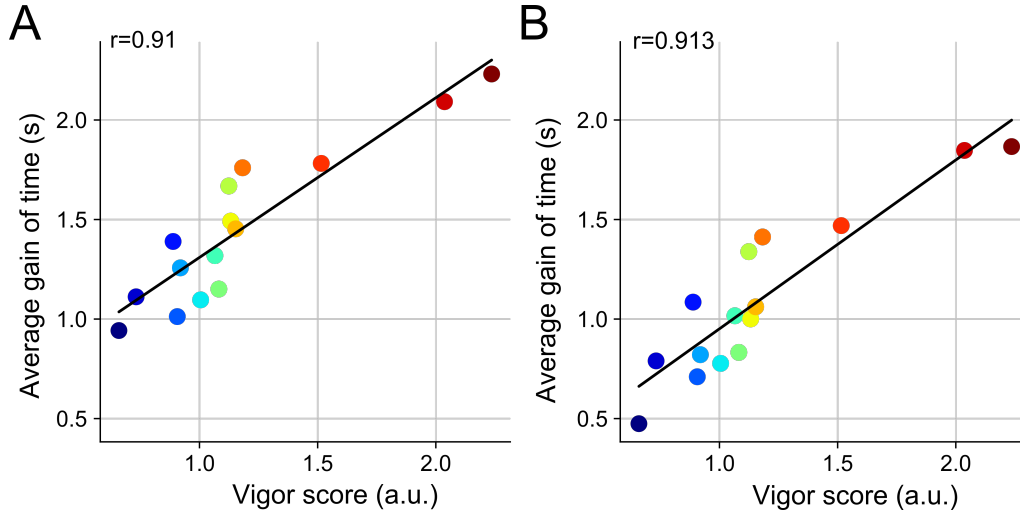


Figure 8: Relationship between vigor scores as measured in Session 1 and average gains of time in Session 2. Same color code than in Figure 4. Each dot is a participant. A. Distance 0.2 m. B. Distance 0.4 m.

et al. (2017) have shown that duration is indeed a key factor that makes people judge a reaching movement as “effortful”, and that this judgement does not seem to be based on objective measures such as metabolic energy. Here, it was clear that our participants did not minimize isometric force production alone, which suggests that the passage of time may contribute to action selection *per se* and perhaps to a subjective representation of effort. It has been proposed that the cost of time mainly expresses a subjective temporal discounting of reward within the brain, which could explain why the participant achieved the task more quickly than what is prescribed by the drive. This cost of time has been reviewed in several recent articles (Shadmehr et al., 2019; Carland et al., 2019) and a monograph (Shadmehr and Ahmed, 2020a), and might even reflect general personality traits (Choi et al., 2014; Berret et al., 2018). Hence the most vigorous participants should be the steepest temporal discounters and/or the ones who attribute the greatest subjective value to task accomplishment (Reppert et al., 2015; Yoon et al., 2020; Shadmehr and Ahmed, 2020a). This prediction agreed well with our findings that the most vigorous participants (as sorted from a baseline experiment) were the ones spending more energy to save a given amount of time. In our case, the cost of time may also capture an attentional cost related to the fact that participants were observing the motion of the cursor on the screen even when exerting no force, or just that they were engaged in the task. Since these higher-level costs are not strictly related to movement production processes, they are excluded from our definition of the cost of movement but can be integrated into a cognitive cost of time.

Although we mainly interpreted our results within the cost of time theory, it could be argued that participants just preferred to be active in the task. In this case, participants would also have preferred to move the cursor by themselves rather than to passively look at it. Assessing passivity from an amount of force lower than 0.15 N, a total of 3, 2, 1 and 0 participants passively executed the task for the drive durations 1 s, 2 s, 4 s and 6 s respectively (for both distances). For instance, one participant (#6) remained passive for drive durations ≤ 4 s but suddenly became active when the drive lasted 6 s. However, participants were generally active even for the smaller drive durations. The critical observation is that participants did not exert forces onto the joystick arbitrarily or just by habituation (e.g. using a fixed amount of force or fixed gain of time in the task). In contrast, they saved time and exerted force in an idiosyncratic manner that was closely linked to their the original vigor in the task and that depended on the drive duration as predicted by an optimal control model based on their identified cost of time (which were obtained before the drive was introduced). Accordingly, highly vigorous participants were highly active in most conditions even for the 1 s or 2 s drives. These participants were clearly prone to spend a substantial effort to save a small amount of time. This may seem surprising but it fits well with

the theory of vigor (Shadmehr and Ahmed, 2020a) and a putative link with personality traits like impulsivity or boredom proneness (Choi et al., 2014; Berret et al., 2018). Weakly vigorous participants were also active in most conditions but produced much lower amounts of force in the task, that is, they were also inclined to save time but much less than participants with high vigor scores. These observations show that participants did not simply prefer to be active with arbitrary levels of force and durations, nor did they try to replicate their baseline behaviour regardless of the duration of the drive. Instead, they energize the movement according to both their own vigor (or implicit motivation, Mazzoni et al., 2007) and the characteristics of the drive in agreement with an optimality principle minimizing a trade-off between a cost of movement and a cost of time. Another argument may be that the passage of time is subjectively faster when one is actively moving. The literature indeed suggests that the perception of time could be itself modulated by our ongoing voluntary actions (Eagleman, 2008; Merchant and Yarrow, 2016). For instance, saccadic eye movements seem to produce a time compression (Morrone et al., 2005), an observation which has been generalized to hand reaching movement and isometric force production (Tomassini et al., 2014). In the latter study, participants had to judge the time interval between tactile taps and time intervals defined by tactile stimuli were perceived as shorter when hand movements were prepared and executed. This psychophysical phenomenon is not incompatible with the hypothesis of a cognitive cost of time. Indeed, to either save true time or its subjective perception, it would have been worthwhile for the participants to energize task’s achievement. Interestingly, the link between impulsivity and the sense of time have been reviewed in (Wittmann and Paulus, 2008) and it was suggested that “[impulsive] individuals are more likely to experience a slowing down of time during situations in which they are not able to act on their impulsive urges, for example when one has to wait for a delayed reward and is confronted with the passage of time”.

To draw the present conclusions we relied on an isometric reaching task. The advantage of this task is that it allows resolving a number of issues that would occur with real movements. First, it removes the problem of dealing with participant-dependent or poorly known biomechanical limb parameters for different participants (inertia, centers of mass etc.). This lack of knowledge is typically problematic when estimating an objective cost of movement using musculoskeletal models. Here every participant controlled the same virtual point mass. Therefore, only the endpoint force was used to move the cursor, which allowed for a simpler definition of the movement cost in this task even though different choices were still possible. Here we used the amount of force as in (Shadmehr et al., 2016) (i.e. force-time integral) to estimate energy expenditure as objectively as possible from our experimental data. One limitation could be that we did not consider the metabolic cost of sitting with the arm still on the handle. However, this constant cost is unlikely to explain the motor decisions of the participants in our task as it is not related to movement but posture (see also Summerside and Ahmed, 2021 for a similar conclusion in a study estimating metabolic cost using expired gas analysis). Differences between participants could still arise from differences in their force production capacities, although this would not disprove the evidence for a cost of time in this task because the cost of movement was neutralized in any case with the drive. Second, isometric reaching simplifies the implementation of the drive because there is no physical interaction between the moving cursor and the participant. It should be possible to create similar experimental tasks with real movements. For instance, generalization of this task could involve a long treadmill for walking or an exoskeleton/manipulandum for providing participants with assistive control laws at different speeds. Another limitation of our study is that an isometric reaching task may not be very ecological. Yet, isometric reaching tasks have been used successfully in the past to explore the neural control of movement, in particular trajectory planning, motor adaptation, muscle synergies and optimal control (Ghez et al., 1997; de Rugy et al., 2012, 2013; Berger et al., 2013; Rotella et al., 2013). Hence, it has proven to be an interesting paradigm that can provide relevant insights about the control of goal-directed actions. Choosing between time and effort is indeed a commonly encountered situation in daily life (e.g. the airport’s treadmill example) and it is possible that the principles of such in-lab experiments will generalize to more ecological tasks such as choosing between taking the car or go by foot, take an escalator or climb the stairs, use his/her slow neuro-prosthetic arm or healthy arm and so on. Future work will aim at using a motorized upper-limb exoskeleton to assist the movements of participants and test whether similar principles apply when muscles produce work and a real movement of the limb occurs.

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