

Why don't we move slower?

On the cost of time in the neural control of movement

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Warning

- This is not a non-holonomic talk. . . not even a mathematical one.
- Application of optimal control to the modelling of human motor control.

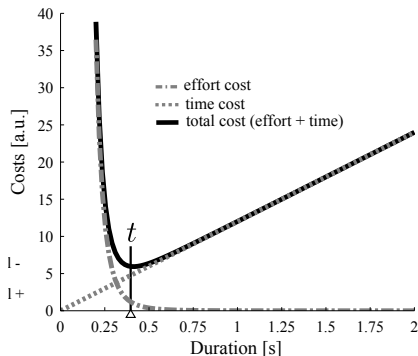
Outline

- 1 Cost of time in human motions
- 2 Recovering g
- 3 Inverse optimal control
- 4 Experimental results
- 5 From self paced to slow/fast motions

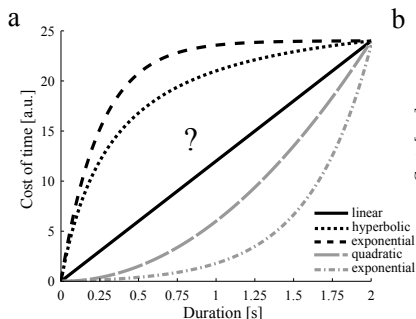
What is the duration of a natural movement?

(Natural = realize one task, without constraint of time, precision,...)

Usual theory: duration results from the minimization of a compromise between the cost of the time and the cost of the motion.



- Cost of the motion (in fixed time):
solution of an inverse optimal control problem,
large literature in the case of the arm [Flash, Shadmehr, Berret, ...]
- Cost of the time: lot of different modelling,
 - psychologists → hyperbolic costs (concave functions)
 - economists, behaviourists → exponential costs (convex functions)
 Only interpretations/explanations, no quantitative results.



Modelling

Dynamics of the motion: $\dot{x} = f(x, u)$

Paradigm

Any registered trajectory $x(\cdot)$ from x^0 to x^f is an optimal solution of

$$\min_u \int_0^{t_u} (g(t) + L(x_u(t), u(t))) dt,$$

among all $u(\cdot)$ defined on $[0, t_u]$ s.t. $x_u(0) = x^0$, $x_u(t_u) = x^f$.

- $\int_0^T g(t) dt$: cost of the time T
- $\int_0^T L(x_u, u)$: cost of the motion in **fixed time** T

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- $\int_0^T g(t) dt$: cost of the time T ← what we are looking for!
- $\int_0^T L(x_u, u)$: cost of the motion in **fixed time** T

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Necessary condition

Fix x^f . Value function of the problem in **fixed time**:

$$V(t, x) = \inf \left\{ \int_0^t L(x_u, u) : \text{for } x_u \text{ joining } x \text{ to } x^f \text{ in time } t \right\}$$

Set $T =$ movement time from x^0 to x^f . Then

$$T \in \operatorname{argmin}_{t \in [0, +\infty)} \left(\int_0^t g(s) ds + V(t, x^0) \right),$$

and so $g(T) = -\frac{\partial V}{\partial t}(T, x^0)$.

More precisely, $g(T) = -H_0(x^*(T), p^*(T), u^*(T))$ where:

- $H_0(x, p, u) = \langle p, f(x, u) \rangle + L(x, u)$ normal Hamiltonian in fixed time,
- $(x^*(\cdot), u^*(\cdot))$ optimal solution in time T with adjoint vector $p^*(\cdot)$.

Remark: requires two technical assumptions on the fixed time problem:

- existence of minimizers
- no abnormal minimizers (property of the dynamics)

Recovering g from experimental data:

- Fix x^f and choose initial conditions $x^0(a)$, $a \in [a_1, a_2]$.
- Experiments $\longrightarrow T(a) =$ time of motion from $x^0(a)$ to x^f .
- Assume $a \mapsto T(a)$ is invertible and set $a^*(t) = T^{-1}(t)$

[Ex: a amplitude $\Rightarrow T \nearrow$]

$$\text{Then} \quad g(t) = -\frac{\partial V}{\partial t}(t, x^0(a^*(t))).$$

Conclusion

Given the cost of motion $L(x, u)$,
the cost of time g can be deduced from simple experiments.

Problems: how to determine $L(x, u)$?

Robustness of the construction of g ?

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Inverse optimal control

(Direct) Optimal control problem

Given a dynamic $\dot{x} = f(x, u)$, a cost $C(x_u)$ and a pair of points x_0, x_1 , find a trajectory x_{u^*} solution of

$$\inf\{C(x_u) : x_u \text{ traj. s.t. } x_u(0) = x_0, x_u(T) = x_1\}.$$

Inverse optimal control problem

Given $\dot{x} = f(x, u)$ and a set Γ of trajectories, find a cost $C(x_u)$ such that every $\gamma \in \Gamma$ is solution of

$$\inf\{C(x_u) : x_u \text{ traj. s.t. } x_u(0) = \gamma(0), x_u(T) = \gamma(T)\}.$$

Applications to analysis/modelling of human motor control (physiology)

→ looking for optimality principles

Inverse problem: Choose a class \mathcal{C} of reasonable costs and let

$$\Phi : C \in \mathcal{C} \mapsto \Gamma \text{ optimal synthesis.}$$

Inverse optimal control problem = find an inverse Φ^{-1} .

Well-posed problem?

- Φ injective?
- Continuity (and stability) of Φ^{-1} ?

→ Very few general results:

- Calculus of Variations case [Krupkova, Prince, . . . 1990-2000's],
- Linear-Quadratic case [Kalmann 64, Nori-Frezza 04],
- numerical methods

[Mombaur-Laumond 2010, Pauwels-Henrion-Lasserre 2014]

Theoretical result

Dynamics = the one of the 1 doF arm motion (single-input linear system)

Let \mathcal{SC} = set of smooth functions $L(x, u)$ such that

- $\frac{\partial^2 L}{\partial u^2} > 0$ (strict convexity)
- $(0, 0)$ unique minimum, $L(0, 0) = 0$, and $\frac{\partial^2 L}{\partial u^2}(0, 0) = 1$ (normalization)

Theorem

There exists a dense subset Ω s.t. Φ injective on Ω .

(Proof based on Thom transversality)

Open questions:

- continuity of $(\Phi|_{\Omega})^{-1}$?
- $\Phi(\Omega)$ dense in $\Phi(\mathcal{SC})$?

Practical point of view

- Linear dynamics: $\dot{x} = Ax + Bu$, $x \in \mathbb{R}^n$.
- Class of admissible costs = class of quadratic costs,

$$\mathcal{C} = \{L(x, u) = u^T Qu + x^T Rx + 2x^T Su, \quad Q \succ 0, \quad L \text{ sym}, \quad \succeq 0\}.$$

→ optimal controls in time T of the form $u(t) = K_T(t)x(t)$.

Remark: $\{K_T(\cdot), T > 0\}$ uniquely determined by a pair (K_-, K_+) , optimal solutions in time T of the form:

$$x(t) = e^{(A+BK_+)t}y_+ + e^{(A+BK_-)(t-T)}y_-.$$

- Hyp: Single input case, i.e. $u \in \mathbb{R}$

Theorem (adapted from Nori-Frezza, 2004), single-input case

For any $L \in \mathcal{C}$, there exists a unique $k \in \mathbb{R}^n$ s.t.

$$\Phi(L) = \Phi((u - k^T x)^2).$$

Moreover, $(K_-, K_+) \mapsto k$ continuous ($k = -K_+^T$).

→ the inverse optimal control problem is well-posed.

Application to the computation of g

- Find (K_-, K_+) by identification from experimental data;
- set $k = -K_+^T$ and $L(x, u) = (u - k^T x)^2$;
- compute the function $\frac{\partial V}{\partial t}(t, x)$ using the Hamiltonian;
- set $g(t) = -\frac{\partial V}{\partial t}(t, x^0(a^*(t)))$.

→ Method robust w.r.t. perturbations of the data
and w.r.t. the choice of cost.

Quantitative result:

Assume $x^f = 0$ and $x^0(a) = ax^0(1)$. Then:

- $\frac{\partial V}{\partial t}(T, x^0) = -u_a(T)^2$, where $u_a(\cdot) =$ optimal control from $x^0(a)$
to x^f in time T .

- $u_a(T) = a\nu(T)$, where

$$\nu(T) = (K_+ - K_-) \left(e^{-(A+BK_-)T} - e^{-(A+BK_+)T} \right)^{-1} x^0(1).$$

$$\Rightarrow \boxed{g(t) = \nu(t)^2 a^*(t)^2}$$

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Two kind of motions:

- Pointing motions of the arm in a horizontal plane (1 degree of freedom),
- Saccadic eye movements.

In both cases:

- the dynamic is of the form:

$$\theta^{(n)} + c_{n-1}\theta^{(n-1)} + \dots + c_0\theta = u,$$

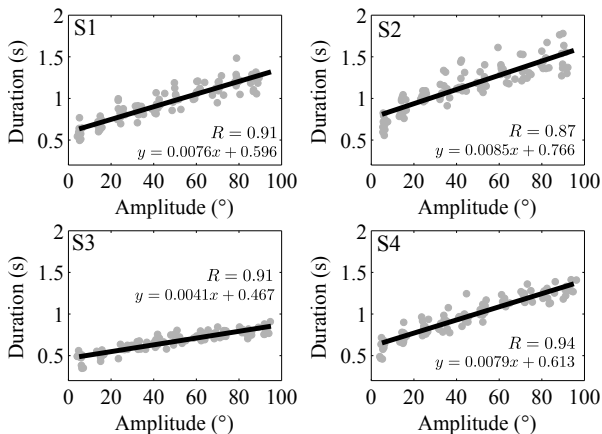
→ linear with a state $x = (\theta, \dot{\theta}, \dots, \theta^{(n-1)})$ ($n = 2$ or 3 in general)

- Initial and final states are equilibria, typically:

$$x^0(a) = (a, 0, \dots, 0) \quad \text{and} \quad x^f = 0.$$

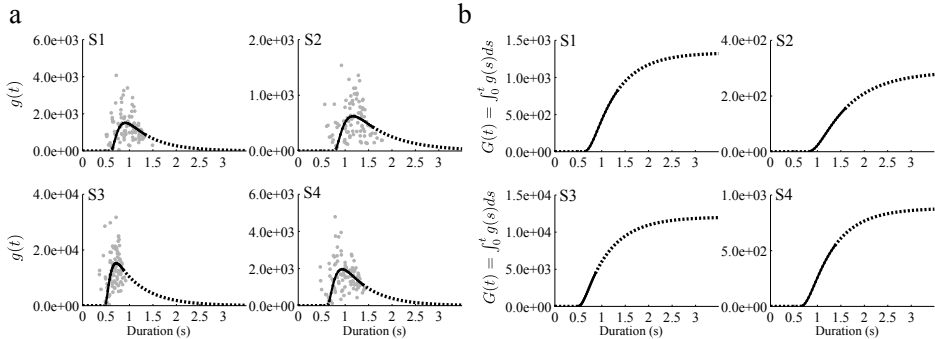
Observations: For arm pointing motions, $T(a)$ affine function

$$\Leftrightarrow a^*(t) = \alpha t - \beta.$$



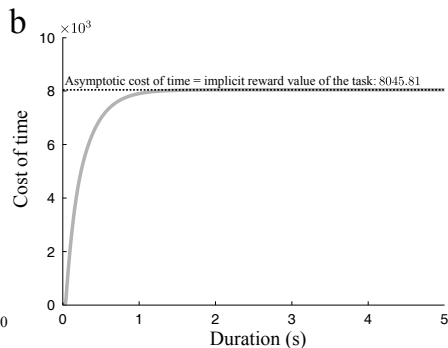
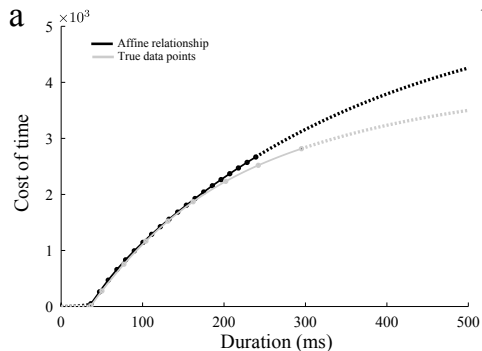
Computation of g

For arm pointing motions:
cost of time neither hyperbolic nor exponential...



Computation of g

For eye saccadic movements:
cost of time hyperbolic, as expected



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Interpretation

Form of the infinitesimal cost (with $x^f = 0$):

$$g(t) + u^2 + x^T R x \quad [+ \text{eventually mixed terms } x^T S u]$$

- $g(t)$ = cost of the time
- u^2 = cost of the particular motion (objective cost)
- $x^T R x$ = cost related to the target (penalization)

⇒ change of the instructions (“faster/slower”) = change of R

Example: for 1 doF motions,

$$x^T R x = s_0 \theta^2 + s_1 \dot{\theta}^2 + \dots + s_{n-1} (\theta^{(k-1)})^2$$

- “Go quickly to the goal” = increase s_0
- “Go slowly” = increase s_1

Let $T_{s_0, \dots, s_{n-1}}(a) =$ duration of an optimal solution between $x^0(a)$ and x^f .

Lemma (Sensitivity analysis)

$$\begin{cases} s_0 \mapsto T_s(a) \searrow \\ s_1 \mapsto T_s(a) \nearrow \end{cases}$$

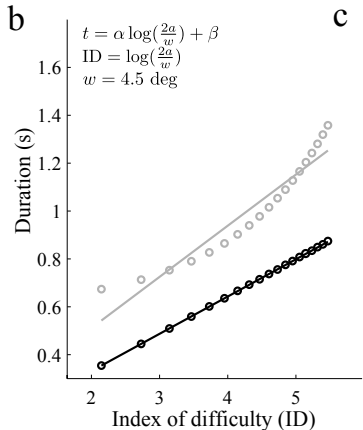
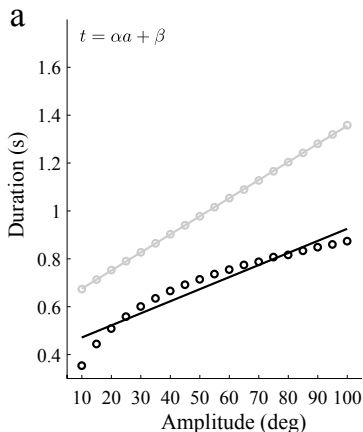
Moreover, when $s_0 \rightarrow \infty$, $\theta^*(t) \sim aCe^{-\lambda t}$ for $t \in [T_s(a)/2, T_s(a))$

Consequence: if the target centered at 0 has a width w , the motion stops at a time T s.t. $\theta(T) = w/2$

$$\Rightarrow T \sim \frac{1}{\lambda} \log\left(\frac{a}{w}\right) + \frac{\log 2C}{\lambda}.$$

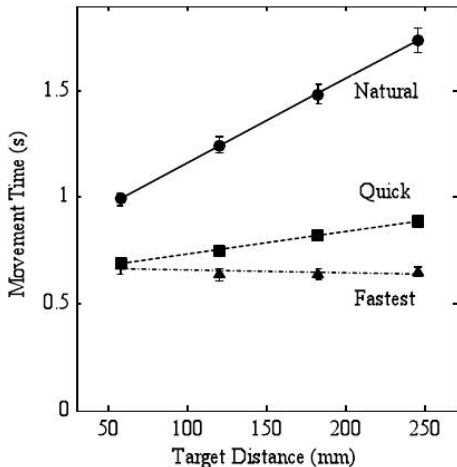
→ Fitts's law

Self-paced (gray) or maximal speed (black) movements:
 duration = affine w.r.t. amplitude a or $ID = a/w$



Aim

Show that the above interpretation may explain the picture below.



Data from [Young 2009]:

time vs amplitude
with constant $ID = a/w$