Human motor control

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Movement generation in animals

- Movement generation adapted to and directed at a sensed environment is the core of animal experience... and a key evolutionary factor

- => Animal are amazing autonomous movement machines..

- => The brain is strongly organized around movement generation... (the basis of a tradition of thought called “embodied cognition”)


Human movement

- Humans are particularly skilled at movement directed at objects.
  - Manipulation, compliant acting on objects.
- Humans are particularly flexible, versatile in their movement generation.
  - While some other animals excel at particular specialized motor acts.
A landscape of human movement

- looking: eye and head movements (gaze)
- orienting the body in space, upright stance
- legged locomotion
- navigation
- steering
- reach, grasp, manipulate
- sequences of motor acts
- speech articulatory movement
Qualities of human movement

- involuntary (reflexive)
- automatic/habitual (requires little attention)
- voluntary/intentional
Qualities of human movement

- whole body movements in space
- movements of hand/arm or other extremities while anchored in space
Qualities of human movement

- rhythmic
- discrete (in time)
Textbooks


What is entailed in generating an object-oriented movement?

- scene and object perception
- movement preparation
- movement initiation and termination
- movement timing and coordination
- motor control
- degree of freedom problem

=> spans perception, cognition and control
What is entailed in generating an object-oriented movement?

- tightly interconnected processes
- which this is why movement is so hard to study
- critical to understand integration
A neural architecture of reaching

[adapted from: Martin, Scholz, Schöner. *Neural Computation* 21, 1371–1414 (2009)]
the perception and cognition on which object-oriented action is based…. topic of my course in the WS
Scene perception

neural fields... dynamic field theory

[Zibner, Faubel: In DFT Primer (2016)]
Movement preparation

- coordinate transform into initial position of hand

[Erhagen Schöner, Psych Rev 2002]
Sequence generation

- every action is represented as a stable activation state in an "intentional field"
- that predicts its "condition of satisfaction"
- instabilities drive the transition from one intention to another

[Sandamirskaya, Zibner, Schneegans, Schöner: New Ideas in Psychology (2013)]
timing and coordination: Lecture 7/Exercise 6
degree of freedom problem: Lecture 6/Exercise 5
human motor control: how forces are generated and regulated
Human motor control

- consider a single DoF, the elbow angle..
- in a fixed posture
Posture is controlled

- The elbow does not behave like a passive mechanical system with a free joint at the elbow: $\ddot{J} = 0$

- Where $J$ is inertial moment of forearm (if upper arm is held fixed)

- Instead, the elbow resists when pushed => there is active control = stabilization of the joint

$=>$ experiment
Posture is controlled

- human effectors are not very stiff…. unlike robotic actuators
- stiffness expressed in Eigenfrequency => time scale ~ of the same order of magnitude as movement time
- => human movement is highly compliant…
The problem of human motor control

leads to major problems in human motor control: how to make a soft spring move fast to precisely reach a target and softly stop there...
The “mass spring” model

- a simplified macroscopic description
  - of the mechanics of the muscles
  - and the reflex control of the muscles
- the invariant characteristic
The mass-spring model

- **Elastic component**: proportional to position

- **Viscous component**: resistance depends on joint velocity

\[
J \ddot{\theta} = -k(\theta - \lambda) - \mu \dot{\theta}
\]

Active torques generated by the muscle
Agonist-antagonist action

- muscles only pull, so the invariant characteristic comes from pairs of muscle groups
- one lambda per muscle
- co-contraction varies stiffness
Stiffness

- the stiffness, k, can be measured from perturbations
- the viscosity “mu” is more difficult to determine

\[
J\ddot{\theta} = -k(\theta - \lambda) - \mu \dot{\theta}
\]
Muscle dynamics

Figure 6. Normalized force-length relationship for muscle. Thick dark lines indicate maximum activation, whereas the light thin lines are lower levels of activation. Note that the optimal fiber length is longer as the activation decreases. In the figure, $\beta = 0.15$, which means the optimal fiber length is 15% longer at zero activation.

[Buchanan et al. 2014]
Muscle dynamics

- Force generated depends on speed of lengthening / shortening
- Less force for shortening
- More for stretching

Figure 3.4: Muscle-tendon unit model. The MTUs model is shown on the left (A). The plots on the right show the force properties of the CE and passive elastic elements (B).
Muscle dynamics

- Hill type models

$$l_{opt}$$ $$l_{slack}$$

$$l_{ce}$$

$$l_{mtu}$$

$${CE}$$

$${SE}$$

$${BE}$$

$${PE}$$

Table 3.2: Common MTU parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$$w_{CE}$$</td>
<td>Force-length curve width</td>
<td>0.56</td>
</tr>
<tr>
<td>$$l_{opt}$$</td>
<td>Passive elastic elements</td>
<td></td>
</tr>
<tr>
<td>$$p_{PE}$$</td>
<td>Reference strain</td>
<td></td>
</tr>
<tr>
<td>$$w_{SE}$$</td>
<td>Reference strain</td>
<td>0.04</td>
</tr>
<tr>
<td>$$l_{slack}$$</td>
<td>Passive elastic elements</td>
<td></td>
</tr>
<tr>
<td>$$b_{BE}$$</td>
<td>Reference compression</td>
<td></td>
</tr>
<tr>
<td>$$w_{ce}$$</td>
<td>Force-velocity enhancement</td>
<td>1.5</td>
</tr>
<tr>
<td>$$K_{CE}$$</td>
<td>Force-velocity curvature</td>
<td>5</td>
</tr>
</tbody>
</table>
| $$f_{l}(l_{ce})$$ | Piecewise quadratic force-length relationship of the passive elements | $f_{l}(l_{ce}) = \exp\left(\ln(0.05) \cdot l_{ce} - \frac{3}{2}\right)$, (3.4)
| $$f_{v}(v_{ce}$$) | Force-velocity relationship  | $f_{v}(v_{ce}) = \begin{cases} \frac{v_{max} - N}{k_{v} v_{ce}} & \text{if } v_{ce} < 0 \\ \frac{v_{max} - N + v_{ce}}{k_{v} v_{ce}} & \text{o.w.} \end{cases}$, (3.5)
Neural basis of invariant characteristic: stretch reflex

- alpha-gamma reflex loop generates the stretch reflex

[Kandel, Schartz, Jessell, Fig. 37-11]
spinal cord: reflex loops

- the stretch reflex acts as a negative feedback loop

[Figure 31-12 from Kandel, Schwartz, Jessell]
spinal cord: coordination

- Ia inhibitory interneuron mediates reciprocal innervation in stretch reflex, leading to automatic relaxation of antagonist on activation of agonist

[Kandel, Schartz, Jessell, Fig. 38-2]
Reflex model

- monotonic relationship force-length
- reflex threshold can be varied by descending activation signals

[Latash, Zatsiorsky, 2016]
Movement entails change of posture

- the threshold lengths of the muscles must be shifted during movement so that after the movement, the postural state exists around a new combination of muscle lengths (\(\Leftrightarrow\) joint configuration)
Movement entails change of posture

- many models account for movement in terms of muscle activation/desired torques….

- => the shift of the EP is the single most overlooked fact in control models of movement generation.
Does the “motor command” specify force/torque?

- Not necessarily..
- because the same descendent neural command generates different levels of force depending on the initial length of the muscle
Virtual trajectory

Shifting the threshold lengths is necessary, but is it also sufficient?

first answer: yes... simple ramp-like trajectories of the combined threshold lengths of the antagonistic muscles ("r" command ~ virtual trajectory) may model movement
first answer: yes… simple ramp-like trajectories of the “r” command (“virtual trajectories”) shift the equilibrium point smoothly in time…

e.g. Pilon, Feldman, 2006

they are applied before the onset (Fig. 6a, b) or after the offset of fast movement (c, d). In all simulations shown in Figs. 4, 5 and 6, EMD=0 was used. Figure 7 shows the effect of EMD that initially was 40 ms but gradually (with time constant of 100 ms) decreased to 10 ms after the onset of muscle activation. Thus, the electromechanical delay influences the latency, rather than stability of posture and movement.

Discussion

Threshold control is a multifaceted phenomenon that seems to play a major role in the control of posture and movement, expediently solves the problem of the relationship between these two components of motor actions, and is essential in the organization and modification of spatial frames of reference in which threshold control is accomplished in the presence of intrinsic muscle elasticity ($j > 0$) the system remains stable for delays as high as 100 ms.

Simulated (solid lines) and experimental fast movements (dotted lines) practically match each other, as estimated by correlation coefficient ($R^2$). The movement extent is practically the same but peak velocity is greater in (b) than in (a) and a small overshoot is present in (b). With delay of 100 ms, the simulated kinematic patterns are still in the range of those characteristic of natural elbow movements. Delays higher than 100 ms produce atypical movement patterns characterized by long-lasting terminal oscillations.

Even strong pulse perturbations (arrows, 50 Nm during 10 ms) do not destabilize the system at the initial (a, b) or final position (c, d) in the presence of delays 60 (a, c) or 100 ms (b, d).
Shifting the equilibrium point is necessary, but is it also sufficient?

- Such simple ramp-like trajectories of the “r” command ("virtual trajectories") may be sufficient when movements are sufficiently slow
- Interaction torques/mechanical conditions unchallenging

- But is this generally true?

- (Answer: no)
Limit case: velocity dependent force field

After adapting to a velocity dependent force field the hand reproduces the “natural” path, but must generate compensatory forces on the way.

[Shadmehr, Mussa-Ivaldi, 1994]

center-out movements before force-field adaptation

velocity dependent force-field = zero at rest

center-out movements at four stages during force-field adaptation
Shifting the equilibrium point is necessary, but is it also sufficient?

- r-command must still shift from initial to final posture, but must also generate the forces to compensate for the force field during the movement

- that probably takes the form of non-monotonic, “complex” time courses…

- are such temporally complex (e.g., non-monotonic) r-commands necessary during unperturbed movement
Estimating the descending signal (~virtual trajectory)

- descending activation
- muscle activation
- length
- joint angle
- sensor activation
- joint angle
- muscle activation
- descending activation of agonist
- time
(1) Estimate the descending activation by inverting a neuro-muscular model

- simplified version Hill type mode: [Gribble, Ostry et al., 98] .. 4 muscles

[Hummert, Zhang, Schöner]
two joint limb with 4 muscles

- 2 pairs of mono-articulatory muscles

neglect: bi-articulatory muscles

muscle length link to joint angles

\[ l_i = c_i + c_{i,s} \theta_s + c_{i,e} \theta_e \]
muscle activation from descending command

\[ A_i = [u_i + l_i + \mu \dot{l}_i]^+ \quad [x]^+ = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases} \]

forces from muscle activation

\[ F_i = M_i[(f_1 + f_2 \cdot \arctan(f_3 + f_4 \cdot \dot{l}_i)) + k(l_i - c_i)]. \]

\[ \tau^2 \ddot{M} + 2\tau \dot{M} + M = \tilde{M} \quad \tilde{M}_i = \rho_i \cdot (e^{sA_i} - 1). \]

torques from forces

\[ T_i = -H_i \ast F_i \]

motion from torques

\[ \ddot{\theta} = I^{-1}(T - T_{ext} - C\dot{\theta}) \]

[Hummert, Zhang, Schöner]
Comparing data to movements predicted from estimated descending activation

data: red/magenta (for the two directions)
model: green/cyan

Figure 2: The End-effector path (red, magenta backwards movements) for one participant and the simulated End-effector path (green, cyan backwards) for a C-commands of 1.1 rad

To obtain experimental data for the estimation of descending commands, we performed a standard movement experiment in the manner of [Hollerbach & Flash, 1982]. We aimed at naturalistic movements, restraining movement to planar, two-joint action by instruction rather than constraining the arm mechanically by an manipulum. Twelve participants performed the eight movements illustrated in Figure 1. (A thirteenth participant was excluded due to failure to complete enough valid trials, see below.) All participants (8 female, 4 male, mean age = 25.67 years, SD = 3.80, age range: 22–35) were right-handed and had given informed and written consent. The participants were compensated with 10 Euro for the one hour experimental session.

Figure 1: Top view of the experimental set-up. The participant is seated in front of a horizontal monitor with the center of his shoulder at a distance of 0.2m to the monitor. Participants moved their right arm between targets displayed on the monitor. Infrared markers (red asterisks) were attached to the shoulder and elbow joints and to the hand. Shoulder (✓) and elbow (✓) joint angles are marked.

Comparing data to movements predicted from estimated descending activation
We developed an inverse dynamic approach to estimate the descending commands for reaching movements. The estimated virtual attractor trajectory differs for movements of different speeds so that R is relatively monotonic in the N-shape in the fast. For slow movements the virtual attractor trajectory changes gradually with an increasing complexity of virtual trajectories compensates for changes in cocontraction or to joint space like the virtual attractor trajectory R.

The descending commands are qualitatively different from muscle activations, in which the re ex loop does not enter. The virtual trajectory changes slowly for smaller C-commands. The estimated virtual trajectory changes with increased motorneuron, which in turn activated the muscle dependent on the descending command u. The time courses are increasingly complex for faster movements. Their estimated trajectories are in joint space an thus directly represented in joint space and an analytical solution to Gribbles model we simplified.

Achieved mean movement times: D slow = 779 ms D fast = 445 ms. We investigated eight multi-joint, planar movements at different speeds and tracked the joint angles with the motion capture system. The T-test of the RMSE for different C-commands was not significant for different speeds so that R is relatively monotonic in the N-shape in the fast.

<table>
<thead>
<tr>
<th>speed</th>
<th>activation</th>
</tr>
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<tbody>
<tr>
<td>slow</td>
<td>green: muscle activation</td>
</tr>
<tr>
<td>fast</td>
<td>blue: descending activation</td>
</tr>
<tr>
<td>slow</td>
<td>solid: fast</td>
</tr>
<tr>
<td>fast</td>
<td>dashed: slow</td>
</tr>
</tbody>
</table>
time course of descending activation

... as a virtual trajectory

![Graph showing time course of descending activation](image)

- **Elbow**
  - Slow: $N_E = 0.0953$ rad
  - Fast: $N_E = 0.165$ rad

- **Shoulder**
  - Slow: $N_S = 0.0565$ rad
  - Fast: $N_S = 0.095$ rad

**Results**

The virtual trajectories are compared to experimental data, and the goodness of fit is measured using RMSE. The simulations show that the virtual trajectories can accurately predict the movements, with the RMSE for different C-commands being compared.

**References**

- The T-test of the RMSE for different C-commands was not significant for both elbow and shoulder on a 5% level and (Elbow: $N_E = 0.095$ rad, Shoulder: $N_S = 0.0565$ rad).
- The deviation of the N-shape (N = 0.0565 rad) was most pronounced for smaller C-commands.
- The virtual trajectory changes gradually with an increasing C-command, which compensates for changes in cocontraction (C = {0.2, 0.4, 0.6, 1.0}).

**Conclusion**

The simulation error is relatively invariant to changes in C-commands. For fast reaching movements, the descending command is shifted to a new value after the movement is completed. The descending command u is the input to the neuromuscular control (Gribble et al., 2002).
(2) Estimate minimal descending activation

“minimal” change of descending activation

$$\min_{\vec{u}} \Psi(\vec{u}) = \int_0^T \ddot{\vec{u}}(t)^2 dt$$

to bring about the movement

$$\vec{\theta}(t_0) - \vec{\theta}_{\text{start}} = 0, \quad \dot{\vec{\theta}}(t_0) = 0, \quad \ddot{\vec{\theta}}(t_0) = 0,$$

$$\vec{\theta}(t_f) - \vec{\theta}_{\text{final}} = 0. \quad \dot{\vec{\theta}}(t_f) = 0. \quad \ddot{\vec{\theta}}(t_f) = 0.$$

$$\vec{\theta}(t) < \vec{\theta}_{\text{max}}, \quad \lambda_{\text{min}} \leq \vec{\lambda}(t) \leq \lambda_{\text{max}} \quad t \in [t_0, t_f].$$

$$\dot{\vec{\theta}}(t) < \dot{\vec{\theta}}_{\text{max}}.$$

[Ramadan, Hummert, Jokeit, Schöner (under revision)]
Why “lambda” rather than “r”? 

Figure 3: For a symmetric pair of muscles (thin black lines), their threshold lengths, $\lambda_{\theta,1}$ and $\lambda_{\theta,2}$, uniquely determine the equilibrium posture of joint, $R_{\text{sym}}$, irrespective of co-contraction. (Note that threshold lengths are transformed from length space to joint space by $\lambda_{\theta,i} = (\lambda_{c,i})^{\frac{1}{c_0}}$ for $i = 1, 2$). At non-zero co-contraction, the equilibrium posture, $R_{\text{asym}}$, of an asymmetrical muscle pair (fat, red lines) depends on the level of force generated.

3.4 Estimating the virtual attractor trajectory

At any moment in time, the reference command defines a stable state of the complete model. The time course of this stable state in terms of the physical variables, joint angles or hand position, represents the attractor trajectory (Hodgson & Hogan, 2000). The attractor state corresponds to an equilibrium posture, in which all muscle forces are balanced. When opposing muscles differ in strength, that equilibrium posture is not, in general, determined by the reference lengths of the opposing muscles alone. Unless co-contraction is exactly zero, the equilibrium posture also depends on muscle force as illustrated in Figure 3. This is why attractor trajectories may be physically more meaningful than the reference command itself. In the model, estimating the attractor trajectory is trivial. At every moment in time we compute the joint angles (and associated muscle lengths) at which the torques contributed by all muscles sum up to zero, given the current levels of the reference commands, $\tilde{\lambda}(t)$, and the current levels of the rates of change of muscle lengths, $d\tilde{\lambda}(t)/dt$. Attractor trajectories in joint space can be transformed to attractor trajectories in hand position space by the kinematic model.
two joint limb with 6 muscles

- = 2 pairs of mono-articulatory m.
- + 1 pair of bi-articulatory m.

muscle length link to joint angles

\[ l_i = c_i + c'_{i,s} \theta_s + c'_{i,e} \theta_e \]

[Ramadan, Hummert, Jokeit, Schöner, under revision]
4 Results

4.1 Experimental results

4.1.1 Movement time

The movement times of the eight different movements performed at two instructed durations are listed in Table 1. Mean movement time across all movements and participants was 0.779 s in the slow condition and 0.445 s in the fast condition with standard deviations of 0.032 s and 0.022 s, respectively.

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<tr>
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<tbody>
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<td>1</td>
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<td>0.025</td>
<td>0.455</td>
<td>0.025</td>
</tr>
<tr>
<td>2</td>
<td>0.791</td>
<td>0.018</td>
<td>0.448</td>
<td>0.018</td>
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<tr>
<td>3</td>
<td>0.809</td>
<td>0.030</td>
<td>0.460</td>
<td>0.030</td>
</tr>
<tr>
<td>4</td>
<td>0.755</td>
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<td>0.443</td>
<td>0.023</td>
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<td>6</td>
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<td>0.019</td>
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<tr>
<td>7</td>
<td>0.809</td>
<td>0.019</td>
<td>0.482</td>
<td>0.019</td>
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<tr>
<td>8</td>
<td>0.855</td>
<td>0.019</td>
<td>0.479</td>
<td>0.019</td>
</tr>
</tbody>
</table>

Table 1: Movement time (T) and its standard deviation (T SD) across participants for each of the eight movements in the two movement conditions, slow vs. fast.

4.1.2 Kinematics

There is nothing new or surprising about the kinematics of these standard movement data: Hand paths are relatively straight, hand velocity profiles (absolute value of velocity along the movement path as a function of time) are bell-shaped, joint trajectories and joint velocity profiles are smooth (Morasso, 1981). The hand paths (means across participants) are plotted in Figure 4 together with the paths from the simulations. Because participants have different segment lengths and were not all blue: experiment black: model
Minimal descending activation

![Graphs showing minimal descending activation for different muscles and movement times.](image)

- **Flexor**
  - Shoulder
  - Elbow
  - Biarticular

- **Extensor**
  - Shoulder
  - Elbow
  - Biarticular

**Legends**:
- **Slow**: dotted
- **Medium**: dashed
- **Fast**: solid

**Movement time**: [%]

**Graph Notes**:
- The graphs illustrate the minimal descending activation for different muscle groups and movement times.
- The x-axis represents movement time in percentage, ranging from 0 to 100.
- The y-axis represents the difference in muscle activation ($u - u_0$).

**References**:
- Gribble et al. (1998). Are complex (complex...) movements...
Minimal lambda trajectories

Shoulder lambda

Elbow lambda

Biarticular lambda

flexors

[m]

slow: dotted

medium: dashed

fast: solid

0 20 40 60 80 100

time [%]

0 20 40 60 80 100

time [%]

0 20 40 60 80 100

time [%]
Minimal lambda trajectories

Shoulder lambda

Elbow lambda

Biarticular lambda

eextensors

\begin{align*}
\text{slow: dotted} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{medium: dashed} & \quad 0.2 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 \\
\text{fast: solid} & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24
\end{align*}

time [\%]

\begin{align*}
\text{extensors} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{slow: dotted} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{medium: dashed} & \quad 0.2 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 \\
\text{fast: solid} & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24
\end{align*}

\begin{align*}
\text{extensors} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{slow: dotted} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{medium: dashed} & \quad 0.2 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 \\
\text{fast: solid} & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24
\end{align*}

\begin{align*}
\text{extensors} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{slow: dotted} & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 & \quad 0.38 & \quad 0.34 \\
\text{medium: dashed} & \quad 0.2 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 & \quad 0.22 & \quad 0.18 \\
\text{fast: solid} & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24 & \quad 0.26 & \quad 0.24
\end{align*}
Hodgson-Hogan attractor trajectories

The orthogonal component is constant for slow speeds, reflecting approximately straight paths. At larger speeds, the orthogonal component becomes slightly "S-shaped" for some movements, which may reflect compensation for increasing interaction torques.

Figure 13: Attractor trajectories from the model for the 8 movement directions (rows, arrows on the left margin illustrate the movement direction). The component along the direction from the start to the target position is shown in the first column, its orthogonal complement in the second column. Slow (dotted), intermediate (dashed) and fast (solid) movements are shown.
attractor trajectory in hand-space

- at higher speeds (solid line), attractor trajectories are temporally structured “just right” for the hand to reach the target.
Do the time courses of lambda matter?

- making a slow lambda (ramp in hand space) fast => doesn’t make movement fast

The kinematic or quasi-postural conception of the reference command amounts to postulating such an invariant. The implied scaling law is a linear rescaling of time, in which fast movements can be obtained from slow reference commands by linear time compression, and slow movements can be obtained from fast reference commands by linear time dilation. Figures 14 and 16 illustrate that this scaling law fails for ramps and for the minimal reference commands.

First, we constructed a ramp with constant rate of change in end-effector space, which we simply gave a very short duration of 0.1 s, shorter than the fast ramps we found for the minimal reference commands. Does such a short ramp lead to a faster movement? Figure 14 shows that this is not the case: the movement that is produced is, in fact, slower than the fastest movements we modeled with the minimal reference command. In the simulation shown, co-contraction was set to 50 N. Increasing co-contraction further did not make the movement faster.

**Figure 14:** Results for a linear Ramp in end-effector space from [0.0m, 0.3m] to [0.0m, 0.55m] scaled to a ramp duration of 0.1 s. Left: Hand path. Middle: Elbow (solid red) and shoulder (solid blue) joint angle trajectories, whose target angles are shown as dashed lines. Right: Reference commands for bi-articular (black), shoulder (blue) and elbow (red) muscles.

Why does this scaling of the ramp to faster movements fail? This can be understood by looking at the attractor trajectory implied by a short (0.1 s) ramp (Figure 15). Notice how at the end of the short ramp, the attractor trajectory sharply reverses and as a result acts to decelerate the joint, slowing down the movement. This reversal is due to the contribution of the rate of change of muscle length both at the level of muscle activation (Eq. 9) and of muscle force (Eq. 7).
Do the time courses of lambda matter?

Making a fast lambda slow: doesn’t make a good slow movement.
(3) Estimate descending activation from EMG

- Unloading experiment to determine linear relationship between EMG and descending activation

(by estimating threshold length in unloading)

[Zhang, Feldman, Schöner]
(3) Estimate descending activation from EMG

- unloading experiment to determine linear relationship between EMG and descending activation
- (by estimating threshold length in unloading)

\[ EMG = p_1 \times (l - l_{Th}) + p_2 = p_1 \times (l - (u_{Th} - u)/k ) + p_2 \]

[Zhang, Feldman, Schöner]
\[ A = \left[ k(l + \mu l) - (u_{Th} - u) \right]^+ = k[l + \mu l - l_{Th}]^+ \]
Why is this important?

- quasi-postural picture
  - target is an attractor….

- optimal control picture
  - a precise time course of a motor command must be computed and generated to move to the target and reach zero velocity there

=> demands on the neural computations

=> demands on learning
Human movement uses “soft” muscles that have nonlinear muscle dynamics

Postures are stabilized by reflexes, whose thresholds must be shifted during movement

Those shifts by descending commands so solve the “optimal control” problem = the right time course so that the effector arrives at the target in the desired time with small velocity and a smooth temporal shape

Conclusion: Human motor control