

Lecture 14

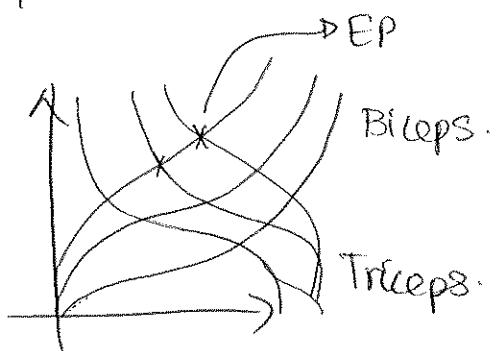
Last time: Started on higher-level motor control.

Talked about Equilibrium Point Theory.

EP - The position to which the neuromuscular sys. is driving the limb.

Elbow w/ 2 muscles.

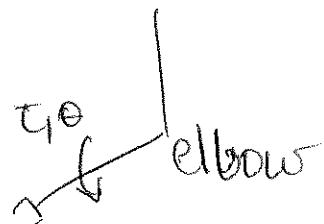
(Bizzzi, 1982)



Virtual Trajectory Theory (Hogan, 1984)

- the CNS specifies a series of EPs and the limb impedance takes care of the details of the movement production.
dynamic

Quantitatively: $\tau_{\text{joint}} = I \ddot{\theta}$



@ EP by definition $\tau_j = 0$

$$\dot{\theta} = 0$$

$$\ddot{\theta} = 0$$

$$\theta = \theta_0$$

or the set of α
 $\{\alpha\}$

does not have to be $\alpha_s \neq 0$

(p2)

One interpretation: Muscle activations α always define a virtual E.P. of the joint.

($\{\alpha\}$ encodes a lot more than that, but this is one interpretation)

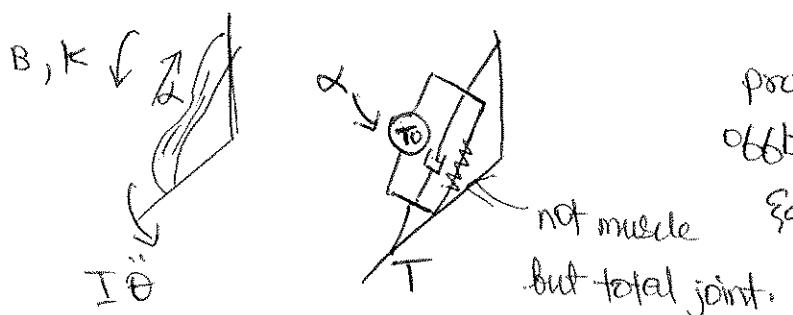
So V.T. hypothesis - a time history of virtual E.P.s is generated w/ varying α 's $\{\alpha\}$

\hookrightarrow position specified by $T_{\text{E.P.}}(t)$

$\hookrightarrow \Theta_0 T_{\text{E.P.}}(t)$

The actual V.T. hypothesis does not assume linearity btwn $T_{\text{muscle}}, x_m, \dot{x}_m$, but we will assume x_m & \dot{x}_m are uncoupled and linear wrt. T_m

Then $T_j = I^{\Theta} = T_{\text{E.P.}}(t) - b\dot{\Theta} - k\Theta$



↑
produced by
offbalance in
 $\{\alpha\}$

- total impedance @ joint caused by co-contraction that does not affect T
- these could vary w/ time, but we ignore it.

Assume $\xi \in \mathbb{S}$ defines EPs & $T_{\xi \in \mathbb{S}}(t)$ specifies EPs

$$\Theta_0 \xi \in \mathbb{S}(t)$$

Then @ EP $\tau = 0 = \ddot{\theta} = \dot{\theta} = 0$

$$\theta = \theta_0$$

$$\tau(t) = I\ddot{\theta} = T_{\xi \in \mathbb{S}}(t) - b\dot{\theta} - k\theta(t)$$

$$\Theta_0 \xi \in \mathbb{S}$$

$$\Rightarrow T_{\xi \in \mathbb{S}}(t) = k\Theta_0 \xi \in \mathbb{S}$$

If $\nu(t)$ is a series of $\Theta_0 \xi \in \mathbb{S}$ over time,

$$\text{then } T_{\xi \in \mathbb{S}}(t) = k\Theta_0 \xi \in \mathbb{S}(t)$$

$$I\ddot{\theta} = k\Theta_0 \xi \in \mathbb{S}(t) - b\dot{\theta}(t) - k\theta(t)$$

← plug this back in

$$I\ddot{\theta} + b\dot{\theta} + k\theta = k\Theta_0 \xi \in \mathbb{S}(t)$$

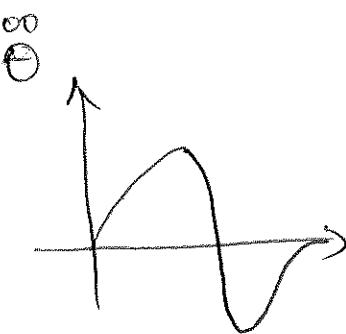
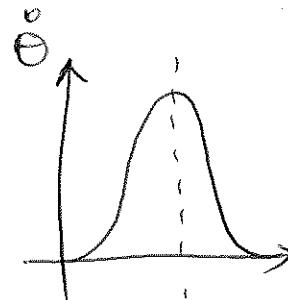
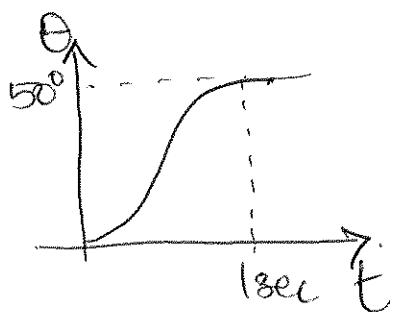
actual joint coord

virtual joint coord.

You will play w/ virtual vs real joint mvs in fs 4

Ex. Human / Monkey / Animals / Biological Sys. have typical mnts @ medium speeds (most commonly used)

Simple mnts



Bell-shaped vel.

profile

More on this in a lecture or 2.

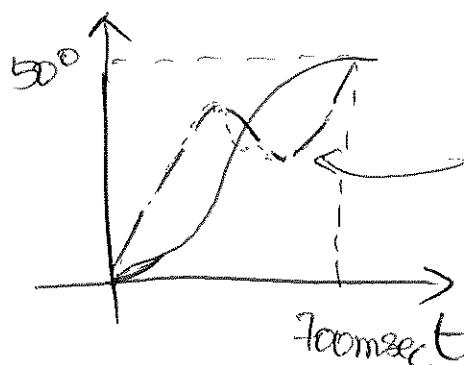
For typical values of I, B, K

$$I = 0.014 \text{ kg/m}^2$$

$$B = 0.173 \text{ Nms/rad.}$$

$$K = 1.48 \text{ N/deg}$$

Moving 50° in n 700 msec

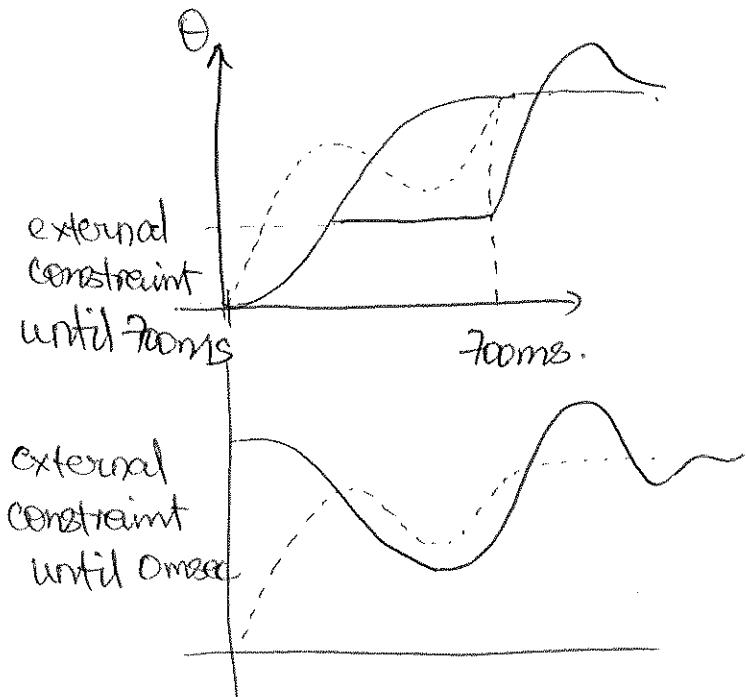


calculated $\theta_{0.2dS}$

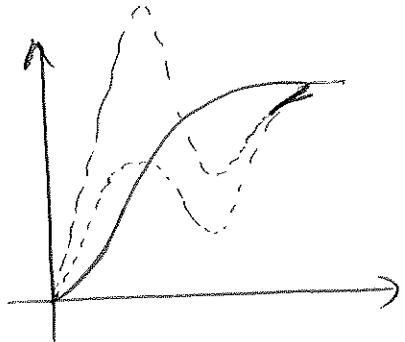
It so turned out
if $\theta_{0.2dS}$ is recorded,
it has similar
profile to this!

(p5)

Using computer, you can simulate limb dynamics under the same V_{OT} but w/ constraints



Now what happens for really fast mts?



For the same I, B, K, large fluctuation
in $\dot{\theta}_0(d)(t)$ and has abrupt change

However when $\dot{\theta}_0$ is recorded, they do not fluctuate as much
& don't have the abrupt change (as if V.T were scaled)

So what changed? B & K!

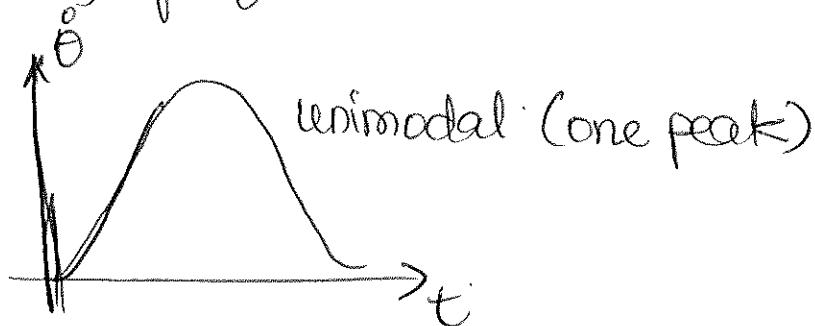
Remember K is controllable w/ co-contraction
(& B changes w/ K)

Increasing $B + K$ allows smoother VoTo

↳ Intuitively, we increase K when we make fast m/s

— — —
Going back to the bell-shaped velocity profile mentioned earlier.

↳ For a variety of joints (fingers, arm, hip, jaw, etc.) + a variety of species, one thing that is common is the shape of the velocity profile.



Relate to dynamic optimization:

What does optimization here mean?

- Out of so many options to make a mvt. from one place to another, somehow one strategy is used by all of us.

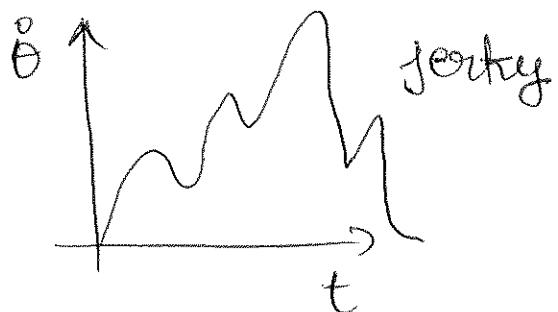
- What is so good about this strategy?

- How is this strategy exactly?

- What parameters are minimized/optimized?

(PPT)

Another interesting thing \rightarrow babies' mvt's do not have unimodal bell-shaped vel. profile



So we "learn" to ~~not~~ optimize something over time

Main characteristics of learned mvt's : smoothness.

Smoothness \rightarrow quantitatively characterized by

$$\int_0^d \frac{1}{2} \frac{d^3\theta}{dt^3} dt \quad d = \text{moving duration}$$

$\theta = \text{joint angle}$.

3rd derivative of position \rightarrow jerk

Optimizing smoothness \Rightarrow minimizing jerk.

$$\min \int_0^d \frac{1}{2} \frac{d^3\theta}{dt^3} dt$$

"Minimum jerk theory" Flash & Hogan (1982-85)

More on this next time.