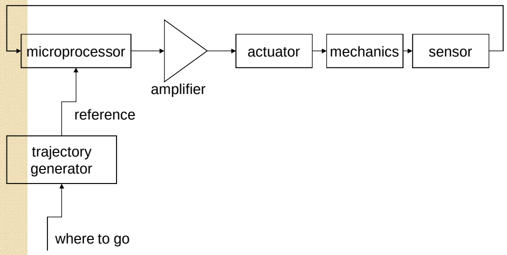
Robotica Antropomorfa

Lezione 4

Back to the global view



Now we take a slightly tangential route

- Computational motor control
- Control in biological systems
- There's something more than the control of the single joint
- Study how control is done in biology ↔ study how control has to be done in robotics

Computational motor control

- Motor control has to do with sensori-motor transformations
- Sensory info is clearly in different format of motor data

Also, something we haven't discussed yet

- The study of the motor system is also the study of dynamics

$$F = ma \text{ instead of } x = f(x, v)$$

Theory

- Optimization principles
- Internal models
- Motor learning

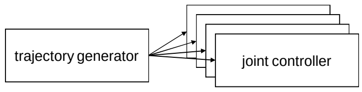
- Techniques developed in control theory and/or robotics applied to the study of the motor system

Optimization principles

- Don't describe the kinematics directly, rather the movement is described abstractly
- Global measure (cost):
  - Total efficiency
  - Smoothness
  - Accuracy
  - Duration

Trajectory generation

- This fits in "front" of the "single joint" controller we've seen so far
- Q: how do we generate a sequence of reference points for the controller?

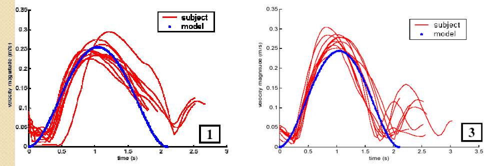


On the trajectory generation

- Note that the feedback controller by itself doesn't necessarily generate suitable trajectories especially for a complex kinematic structure (e.g. arm)

Most studied behavior: reaching

- Despite variation of movement direction, starting point, etc. there are some kinematic invariants; most notably:
  - Straight trajectory
  - Bell shaped velocity profiles



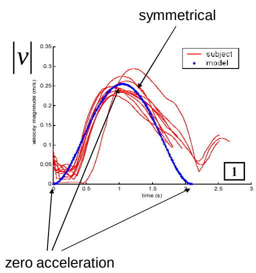
Further…

- There are variation from straightness especially at the periphery of the workspace
- Why is it so surprising that trajectories are straight:
  - Joints are rotational → easier to get curved trajectories

In addition

- There might be differences (from the bell-shaped profile) when feedback plays a role
  - See a moving object and try to intercept it
- Intuition: when "open-loop" trajectories are stereotyped otherwise they get distorted by feedback

Abstraction



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Optimization

- Q: what criterion might generate a similar trajectory profile?

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In formulas

$$x(t) \quad t \in [0,T]$$
$$\text{cost } \forall x(t) \rightarrow c \in \Re$$
$$g(x(t),t) \ \text{istantaneous cost}$$
$$J = \int_0^T g(x(t),t)dt$$

- g represents what is costly for us

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Minimize *J*

- In general – 2 techniques:
  - Dynamic programming
    - Computing all possible state transitions and cumulating the cost, then searching trajectories that minimize the cost → need to discretize the state space (curse of dimensionality)
    - Variation calculus: finding *x(t)* such that *J* is minimized → analytical

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Examples

- Minimum Jerk (proposed by Hogan):

$$J = \int_0^T \left[\frac{d^3x}{dt^3}\right]^2 dt$$

- By calculus of variation it was shown that:

$$x(t) = x_0 + (x_f - x_0)[10(t/T)^3 - 15(t/T)^4 + 6(t/T)^5]$$

- x is straight: obvious from the equation

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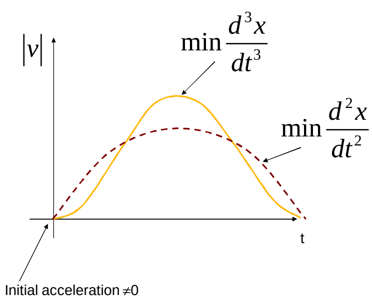
Note



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Elaborations

- Don't want to specify the duration of the movement

$$J = \int_0^T [\gamma \left[\frac{d^3 x}{dt^3}\right]^2 + \underbrace{1}_{\text{time}}] dt$$

- This model predicts durations correctly

Further elaborations

- Minimize torque change → similar to jerk minimization but in dynamical conditions

$$J = \int_0^T \sum_i \left[\frac{d^3 \tau_i}{dt^3}\right]^2 dt \quad i \in [1..N]$$

- This model is due to Kawato

Considerations

- This description doesn't imply that the CNS is actually optimizing anything

Other issues

- Hp: use *P5(t)* as a movement primitive (computed on-line)
- Superimpose primitives (which primitives?)
- Incrementally update (x_f, x_0) in feedback so that the system responds to perturbations
- Neural net solution → in practice the neural net does the minimization
- VITE model: feedback + variable gain might obtain results similar to the optimization techniques

Internal models

- A system that mimics the behavior of a natural process
- Does the brain rely on internal models? (see Miall & Wolper paper)

- Types of models:
  - Forward models
  - Inverse models

Forward models

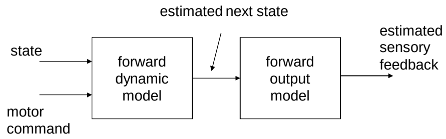
- Given the current state and input predict the next state of the system

- In physiology need to also estimate the state (measured, sensed) from the raw sensory input (it might be a complex computational problem – e.g. 3D from 2D information, etc.)

Prediction of the causal flow

- The forward model can be seen as a prediction (anticipation) of the causal flow
- Being "internal" it can be faster than reality
- Example: the prediction of the state of the motor system due to the outgoing motor commands

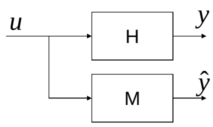
Example



Forward models again

- They're always well defined
- They could be one to one or one to many
- Another example:
  - Kinematics: computing the position in space of the end-effector as a function of the joint angles

Formally

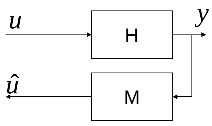


$$\|\hat{y} - y\| < \varepsilon$$

$$\min_{w} \|\hat{y} - y\|$$

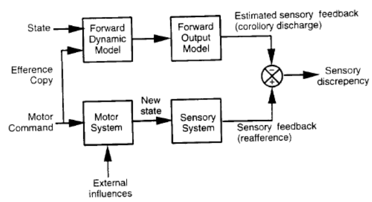
Inverse model

- More difficult: the underlying forward model can be a one to many, thus not invertible unless additional constraints are provided



$$\|\hat{u} - u\| < \varepsilon$$

Use of models: canceling sensory re-afferences



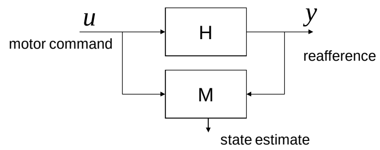
- Important for distinguishing our own motion from the environmental motion

In biology

- Ego-motion cancellation in pursuing a target
- Efference copy: a copy of the command
- Corollary discharge: the prediction of a signal computed by the CNS

State estimation

- How can we (the CNS in fact) integrate motor and sensory information in estimate the state of the arm (for example)?
- Observer:



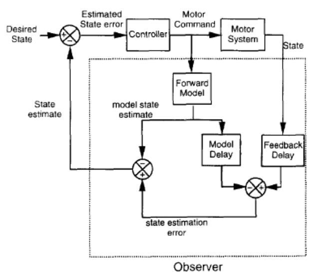
Internal feedback to overcome delays

- Feedback:
  - Robust, doesn't require a precise model of the system to be controlled
  - Issue: it suffers from delays
- Feedforward:
  - Requires a precise model
  - Doesn't care of delays since the control is computed in advance

Delays in the CNS

- We live delayed of 30-300ms!
- A fast arm movement can last around 200ms
- Feedforward controllers are required!

The Smith predictor model



In practice

- A forward model + delay estimates the feedback signal
- This signal is compared with the delayed feedback and provides a correction due to feedback to the state estimation (slow, with some delay, low gain)
- State estimation proceeds open-loop otherwise directly from the model (fast, little delay)

Moreover…

- State estimation of course could be extended into prediction
- Humans can get to zero delay in tasks where the target follows a predictable trajectory

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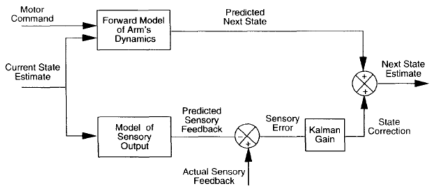
Kalman filter



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In essence

- Under certain conditions Kalman filter is optimal (linear system, quadratic cost, Gaussian noise)

$$x_{t+1} = f(x_t, u_t) + k(y_t - g(f(x_t, u_t)))$$

$$\begin{cases} x_{t+1} = f(x_t, u_t) + \xi_t & f \text{ is linear} \\ y_t = g(x_t) + \eta_t & g \text{ is linear} \end{cases}$$

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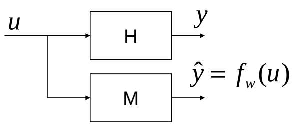
Learning the models

- What does it mean to learn the models?



$$\min_w \frac{1}{2}\|\hat{y} - y\|^2 = \min_w \frac{1}{2}\|f_w(x) - y\|^2 \Rightarrow w$$

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How do I get the samples?

- Direct-inverse modeling
- Feedback error learning
- Distal supervised learning
- Reinforcement learning
- …

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Direct-inverse

- Simply send "certain" inputs to the system and measure the output. Use the set of samples collected to find the min of the cost
  - If there are many solutions to the problem (e.g. redundancy) the direct-inverse approach is not well behaved
  - For linear or otherwise simple problems the approach can work

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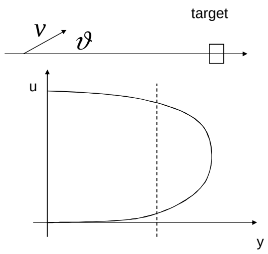
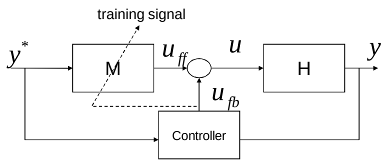
Example

- Archery problem: goal of the controller is to determine the angle

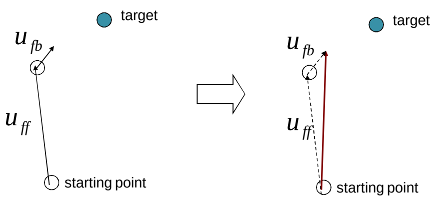


Feedback error learning

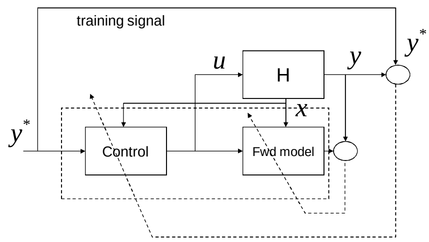
- Use something simpler to bootstrap learning of something more complicate



Example

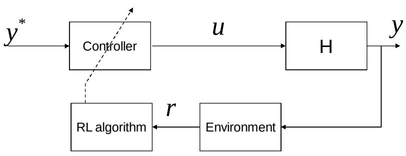


Distal supervised learning



Reinforcement learning

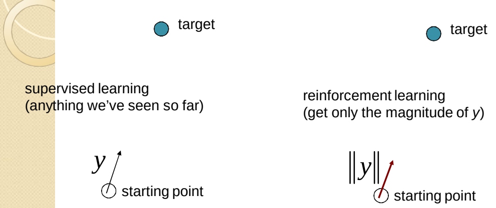
- Reduced feedback from the environment



RL (2)

- *r* is a scalar, much harder problem than anything we've seen so far
- Interaction with the environment is explicit
- Link of RL to dynamic programming, in practice RL is an approximation of DP
- It can solve difficult problems and it can generate controllers that perform better than the teacher

Why is it so hard?



- Need to reconstruct a gradient from a scalar information (at best), in many cases information is even poorer (imagine playing chess: you only get information at the end of the game)