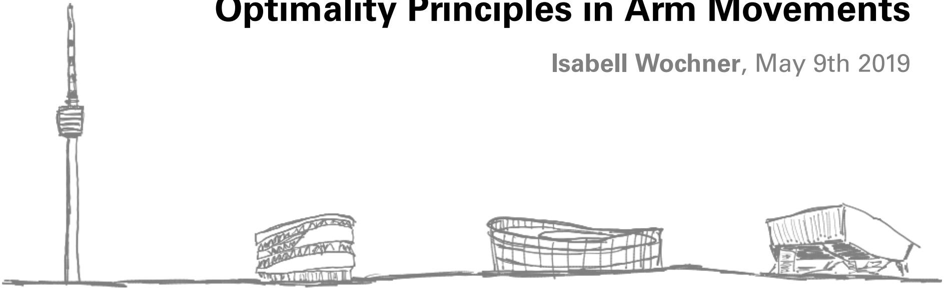
University of Stuttgart
Germany

Institute for Modelling and Simulation of
Biomechanical Systems (IMSB)

Optimality Principles in Arm Movements

Isabell Wochner, May 9th 2019



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SimTech

Motivation

Point-To-Point
[Abend, Bizzi, and Morasso 1982]

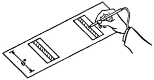
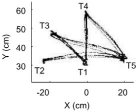
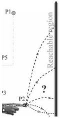


Plate-To-Plate
[Fitts 1954]

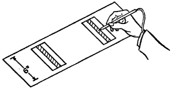


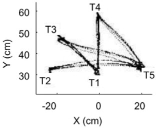
Multiple points
[Harris and Wolpert 1998]

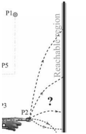


Point-To-Bar
[Berret et al. 2011]

Motivation







- arm movements are stereotypical for pointing tasks
- musculoskeletal system is redundant
- evolution: development of optimal control strategies

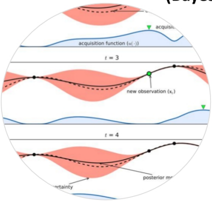
Overview

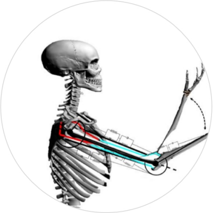
Input u

Neural policy
(Bayesian optimization)

Biological arm model

Cost function





Which cost function shall be used (optimality criteria)?

Arm Model

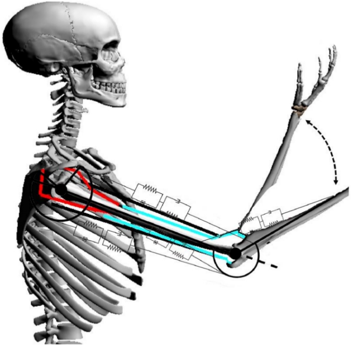
Six lumped Hill-type muscles

- **Monoarticular shoulder muscles** (anteversion and retroversion)
- **Biarticular muscles** (anteversion and retroversion)
- **Monoarticular elbow muscles** (flexor and extensor)

Two joint angles

Open loop control

Hatze activation dynamics



Cost Functions

Kinematic models

Angle acceleration: $J_{\mathrm{ACC}} = \int_0^T \left(\ddot{\varphi}^2 + \ddot{\psi}^2\right) dt$

Hand jerk: $J_{\mathrm{HJ}} = \int_0^T \left(\dddot{x}^2 + \dddot{z}^2\right) dt$

Angle jerk: $J_{\mathrm{AJ}} = \int_0^T \left(\dddot{\varphi}^2 + \dddot{\psi}^2\right) dt$

Dynamic models

Torque: $J_{\mathrm{T}} = \int_0^T \left(\tau_1^2 + \tau_2^2\right) dt$

Torque change: $J_{\mathrm{TC}} = \int_0^T \left(\dot{\tau}_1^2 + \dot{\tau}_2^2\right) dt$

Energetic models

Energy: $J_{\mathrm{EN}} = \int_0^T \left(|\dot{\varphi} \cdot \tau_1| + |\dot{\psi} \cdot \tau_2|\right) dt$

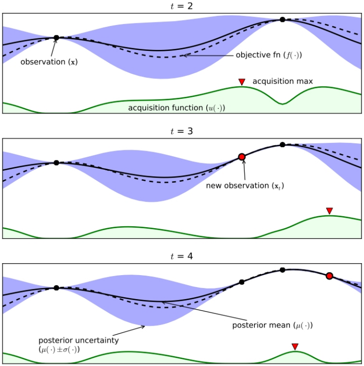
Neural models

Effort: $J_{\mathrm{EFF}} = \sum_{i=1}^{6} u_i^2$

Hybrid models

Hybrid jerk and energy: $J_{\mathrm{JE}} = \int_0^T \left(|\dot{\varphi} \cdot \tau_1| + |\dot{\psi} \cdot \tau_2|\right) dt + 10^{-3} \cdot \int_0^T \left(\dddot{\varphi}^2 + \dddot{\psi}^2\right) dt$

Bayesian Optimization



[Brochu, Cora, and De Freitas 2010]

Bayesian Optimization

Algorithm Bayesian optimization algorithm

for n = 1,2,... **do**

select muscle stimulation $u_n \in \mathbb{R}^6$ by optimizing the acquisition function a_{UCB}

$u_n = \arg\max_{u \in \mathscr{U}} a_{\mathrm{UCB}}(u; \mathscr{D}_{n-1})$

Run dynamic simulation of musculoskeletal system to obtain $\xi(u_n)$

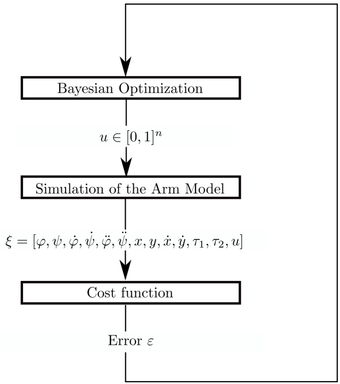
Evaluate the cost function $J(\xi(u_n))$

Augment the data $\mathscr{D}_n = \mathscr{D}_{n-1} \cup \{(u_n, J(\xi(u_n)))\}$

Update Gaussian process model of the cost function

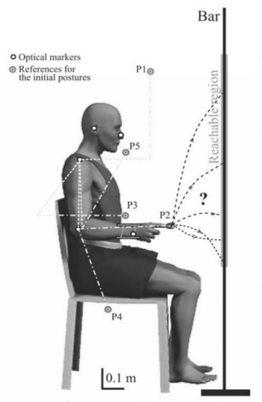
end for

Workflow


Bayesian Optimization
$u \in [0,1]^n$
Simulation of the Arm Model
$\xi = [\varphi, \psi, \dot{\varphi}, \dot{\psi}, \ddot{\varphi}, \ddot{\psi}, x, y, \dot{x}, \dot{y}, \tau_1, \tau_2, u]$
Cost function
Error ε

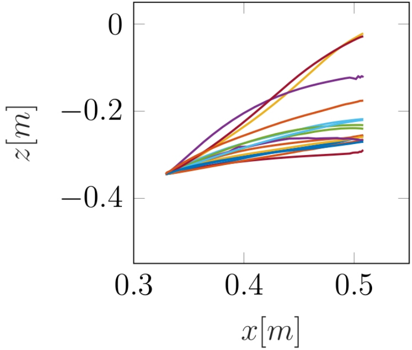
Experimental Results

Experimental Setup



[Berret et al. 2011]

Recorded Trajectories



Numerical Setup

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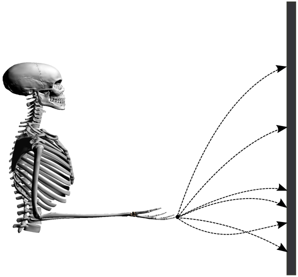


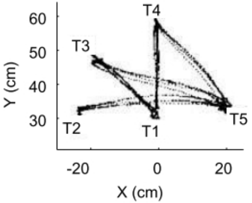
External Task Constraint

$$J_{\text{total}} = ||x_T - x^{\star}||^2 + 0.01 \cdot J_{\text{opt}} \quad (1)$$

x_T : reached x-position of the hand
$x^{\star}$: desired horizontal end position
(location of the bar) [Li and Todorov 2007]

Take Home Message

- **evidence that human movement is optimal**
- evidence for composite cost functions
- potential of point-to-manifold experiments to show optimality
- Bayesian optimization as representation of natural learning
- it is necessary to use muscle systems for optimality investigations rather than torque-driven systems



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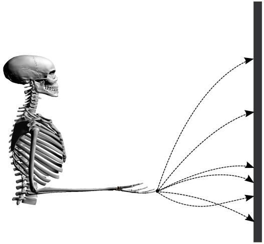

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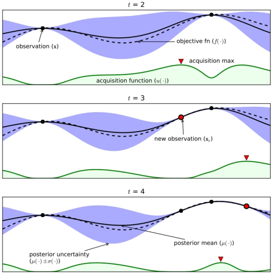

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References

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Questions?