

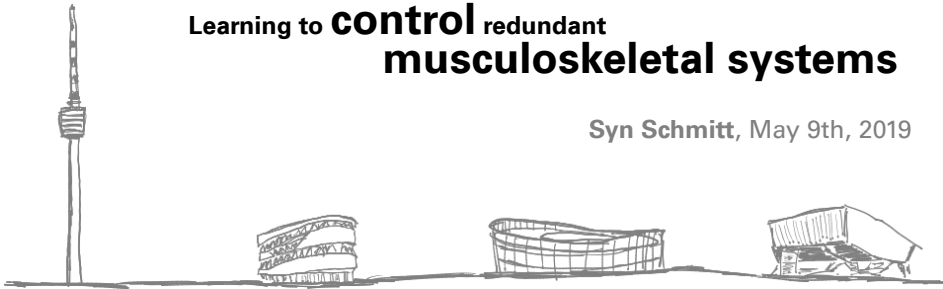


University of Stuttgart  
Institute for Modelling and Simulation  
of Biomechanical Systems

# Motion in Man and Machine

Learning to **control** redundant  
**musculoskeletal systems**

Syn Schmitt, May 9th, 2019



imprs-is

SimTech

A banner image featuring a hand holding a glowing blue and green 3D model of a human head, overlaid with a network of white nodes and lines. The text 'International Max Planck Research School for Intelligent Systems' is displayed in a blue box over the image.

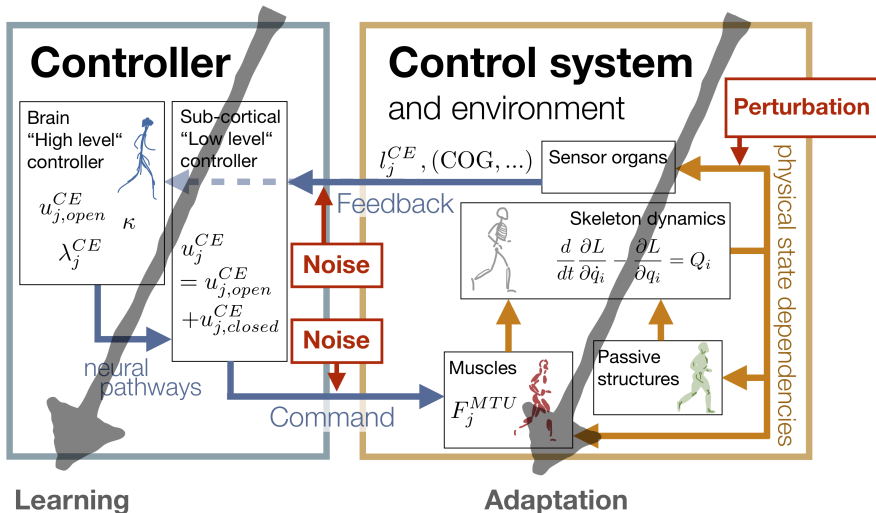
## International Max Planck Research School for Intelligent Systems

## Application

We seek students who want to earn a doctorate while contributing to world-leading research in areas such as:

- Computational Cognitive Science
- Computer Graphics
- Computer Vision
- Control Systems
- Haptics
- Machine Learning
- Micro- and Nano-Robotics
- Perceptual Inference
- Robotics

**Application will open soon**  
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## Model of high-level motor control

EP control  $\Lambda_i^{\text{move}} = \{\vec{\lambda}_1, \vec{\lambda}_2, \vec{\lambda}_3, \dots, \vec{\lambda}_n\}$

Joint space control

continuous vs. intermittent

**model-based control**

**learning-based control**



## Model of skeletal muscle

Hill-type model

$$F_j^{\text{MTU}} = f_f(l_j^{\text{MTU}}, i_j^{\text{MTU}}, l_j^{\text{CE}}, a_j)$$

$$i_j^{\text{CE}} = f_v(l_j^{\text{MTU}}, i_j^{\text{MTU}}, l_j^{\text{CE}}, a_j)$$

$$\dot{a}_j = f_a(a_j, l_j^{\text{CE}}, u_j)$$

## Model of low-level motor control

monosynaptic reflex

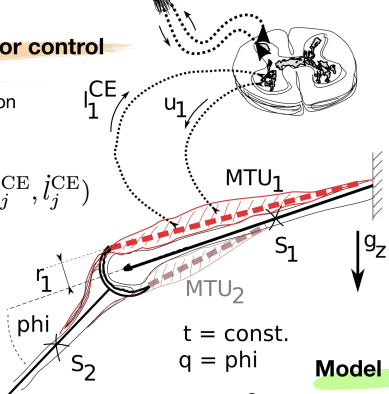
alpha-gamma co-activation

$$u_j = u_j^{\text{open}} + u_j^{\text{closed}}$$

$$u_j^{\text{closed}} = f_n(\kappa, \lambda_j^{\text{CE}}, l_j^{\text{CE}}, i_j^{\text{CE}})$$

Parameters

Initial conditions



Numerical solution

$$\vec{q}(t) = ?$$

$t = \text{const.}$

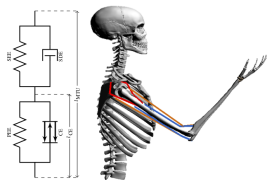
$q = \text{phi}$

## Model of skeletal structure

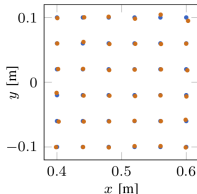
$$M(q)\ddot{q} = C(q)\dot{q}^2 + E(q, \dot{q}) + G(q) + R(q)F^{\text{MTU}}$$



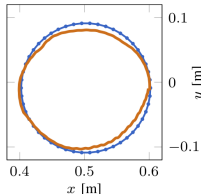
# Deep control using a biosimulator and a biorobot



Simulation model including 6 MTU  
16 states, hand position  $\mathbf{x} \in \mathbb{R}^2$



(a) Point reaching evaluation.



(b) Circle trajectory following.

Goal:  $\pi: \mathbf{x}_{ref} \in \mathbb{R}^d \rightarrow \mathbf{u} \in [0, 1]^m$ ,  $\pi(\mathbf{x}_{ref}) = \mathbf{u}_x$ , data  $\mathcal{D} = \{(\mathbf{u}_i, \mathbf{x}_i)\}_{i=1}^n$

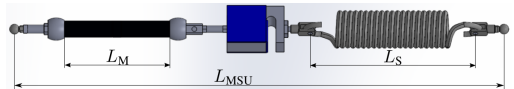
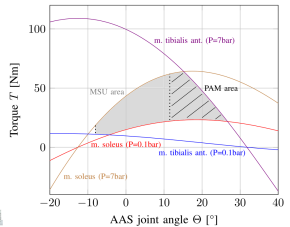
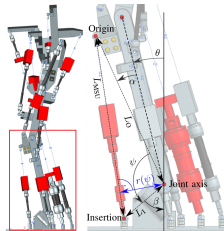
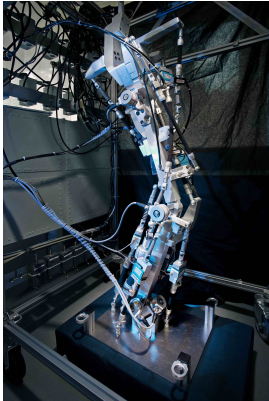
Forward model to learn:  $\phi: \mathbf{u} \in [0, 1]^m \rightarrow \mathbf{x}_{ref} \in \mathbb{R}^d$ , initial data:  $\mathcal{D} = \{(\mathbf{u}_0, \mathbf{x}_0)\}$

Control policy:  $\mathbf{u}_x^* = \underset{\mathbf{u} \in \mathbb{R}^m}{\operatorname{argmin}} \|\mathbf{u}\|_{\mathbf{W}}^2 + \lambda \|\mathbf{u} - \mathbf{u}_0\|_2^2$  s.t.  $\phi(\mathbf{u}) = \mathbf{x}_{ref}$

(Driess et al. 2018)



# Muscle-spring units as bio-inspired actuators



$$\mathbf{F}^{MSU} = f_F(\mathbf{p}, l^{MSU}) \quad (\text{Wolfen et al. 2018})$$



## References

- Driess, Danny et al. (2018). "Learning to Control Redundant Musculoskeletal Systems with Neural Networks and SQP: Exploiting Muscle Properties". In: *Proc. of the International Conference on Robotics and Automation*.
- Schmitt, Syn, Michael Günther, and Daniel FB. Haeufle (2019). "The dynamics of the skeletal muscle: a systems biophysics perspective". In: *Journal of Applied Mathematics and Mechanics (ZAMM)* accepted.
- Wolfen, S. et al. (2018). "Bioinspired pneumatic muscle spring units mimicking the human motion apparatus: benefits for passive motion range and joint stiffness variation in antagonistic setups". In: *25th International Conference on Mechatronics and Machine Vision in Practice (M2VIP)*, pp. 1–6. DOI: 10.1109/M2VIP.2018.8600913.