Lecture 7: Human-like Robotic Movement (Hammering)

Tadej Petrič

Email: tadej.petric@ijs.si
WWW: http://abr.ijs.si


vancouver
7.2

1. Petrič, Tadej, et al. "Navigation methods for the skiing robot." International Journal of Humanoid Robotics (2013).

How to bridge the gap?

- Robots should learn more from humans
  - Learning by demonstration
  - Human in the loop learning
  - Learning task relevant information, e.g. impedance

- Robots should learn more like humans
  - Learning internal dynamic models
  - Learning task specific dynamics

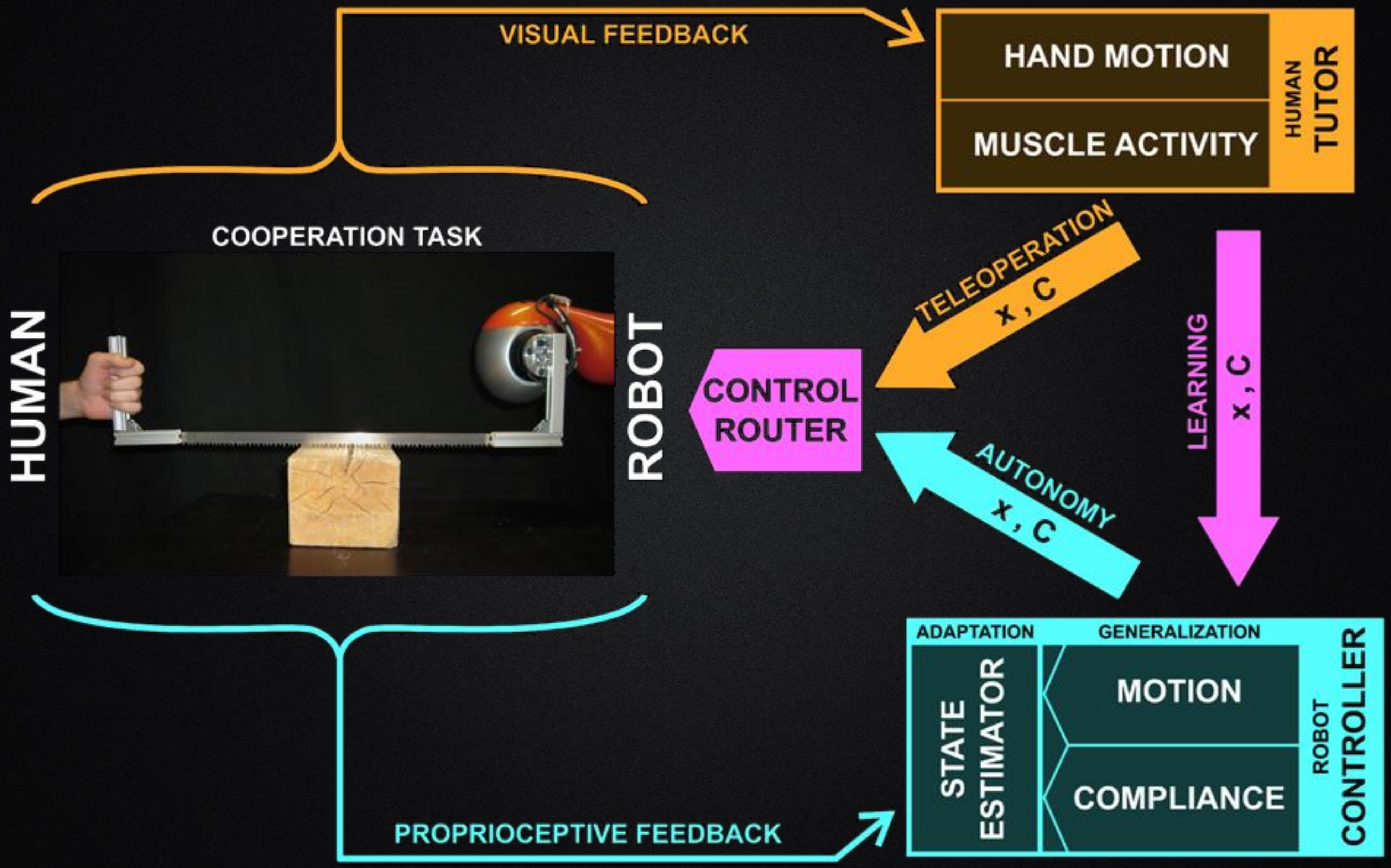
Robots should do both to work better with humans

ROBOTS SHOULD LEARN FROM HUMANS

Teaching robots by using them as tools

- L. Peternel, T. Petrič, E. Oztop and J. Babič. "Teaching robots to cooperate with humans in dynamic manipulation tasks based on multi-modal human-in-the-loop approach“ *Autonomous robots*, 2014
- L. Peternel, T. Petrič and J. Babič, ”Robotic assembly solution by human-in-the-loop teaching method based on real-time stiffness modulation” *Autonomous Robots*, 2017

Learning concept



Peternel, Luka, et al. "Teaching robots to cooperate with humans in dynamic manipulation tasks based on multi-modal human-in-the-loop approach." Autonomous robots (2014).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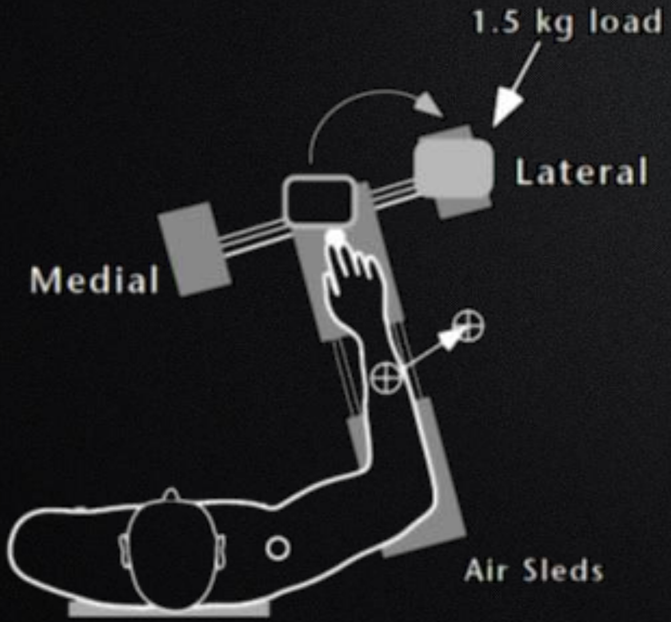
ROBOTS SHOULD LEARN LIKE HUMANS

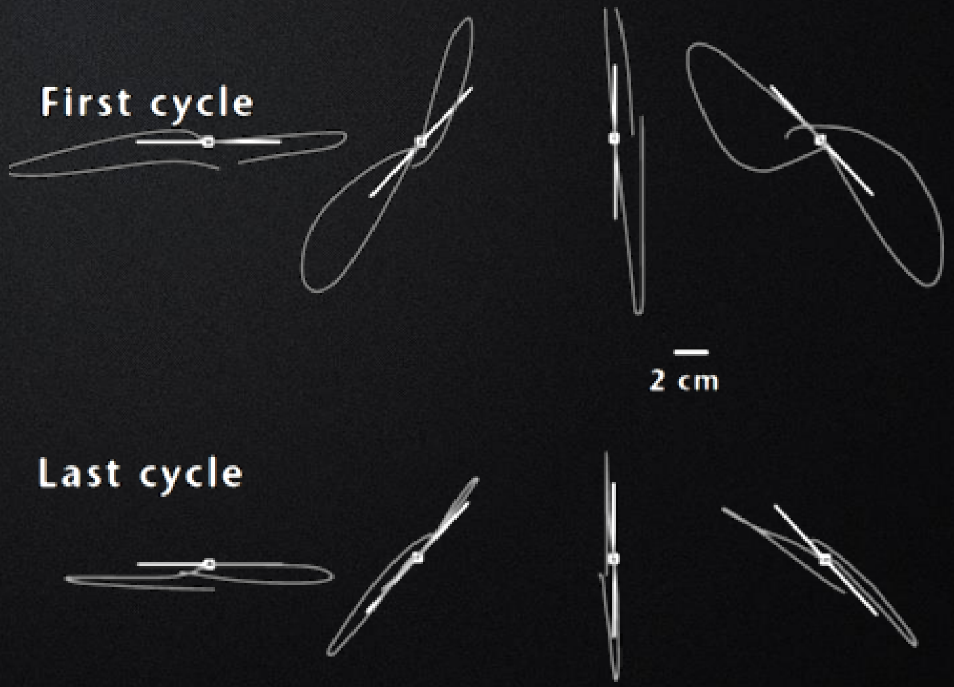
Applying neuromechanical insights to robots

- T. Petric, A. Gams, L. Colasanto, A. J. Ijspeert, and A. Ude, “Accelerated Sensorimotor Learning of Compliant Movement Primitives” *IEEE Transactions on Robotics*, 2018
- Denisa, A. Gams, A. Ude, and T. Petric, “Learning Compliant Movement Primitives Through Demonstration and Statistical Generalization” *IEEE/ASME Trans. Mechatronics*, 2016.

Humans

- Krakauer, et al. (1999), Nature Neuroscience:
  - … hand kinematics are learned from errors in extent and direction in an extrinsic coordinate system, whereas dynamics are learned from proprioceptive errors in an intrinsic coordinate system…

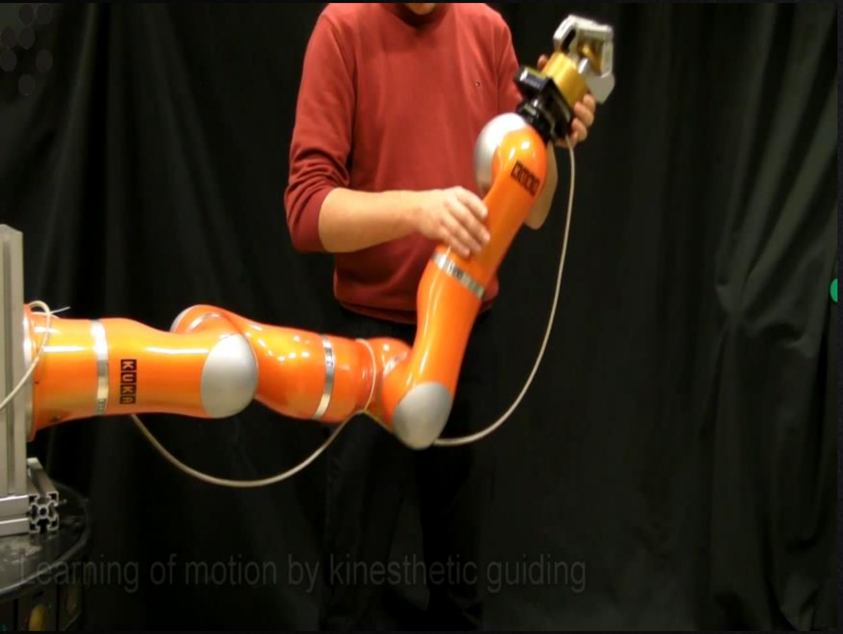




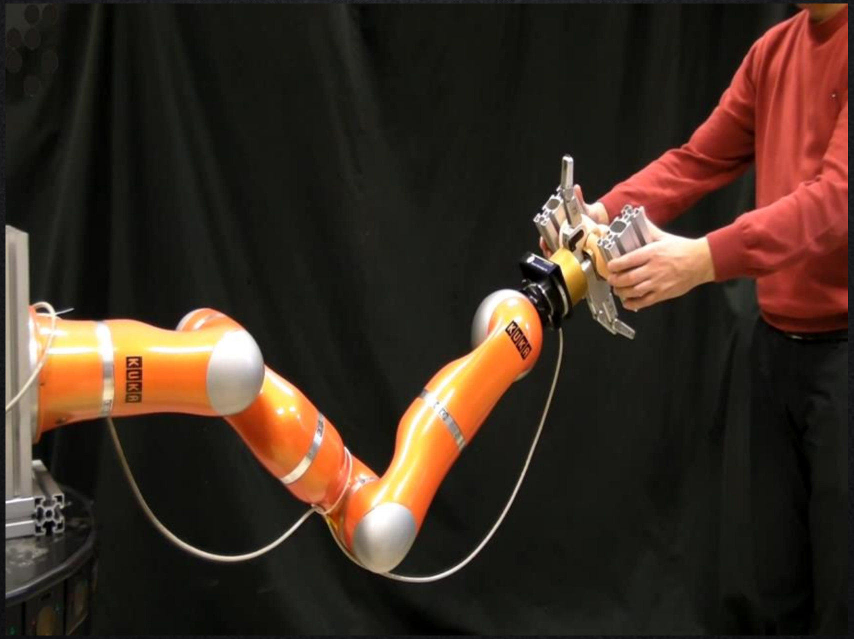
Compliant movement primitives

- CMP defines a task as a pair of signals: $\boldsymbol{h}(\boldsymbol{t}) = [\boldsymbol{q}_d(\boldsymbol{t}), \boldsymbol{\tau}_f(\boldsymbol{t})]$
- Three step process

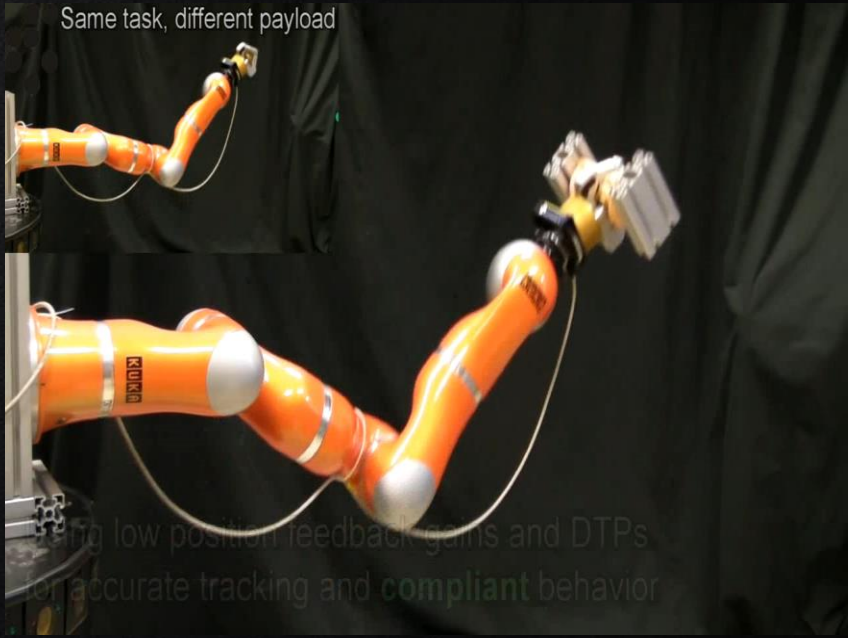
1. Motion trajectory $\boldsymbol{q}_d(\boldsymbol{t})$ is learned by human demonstration

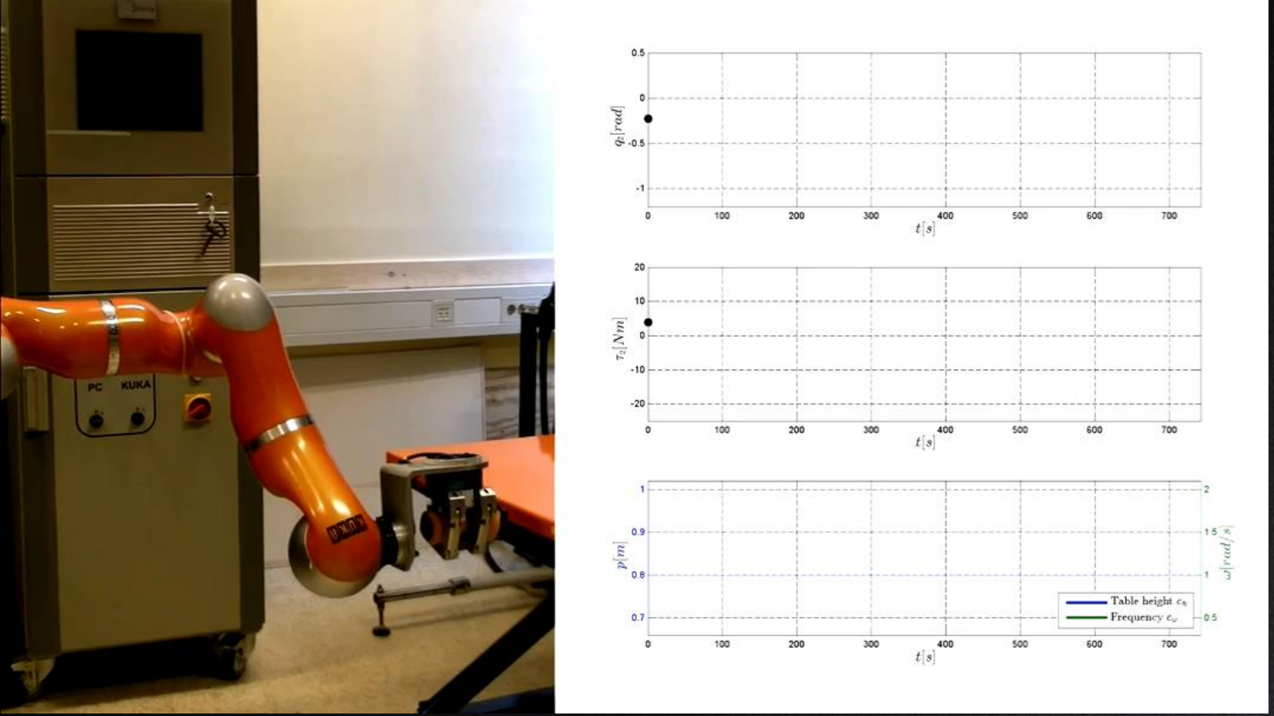


2. Iterative leaning of torque primitives $\boldsymbol{\tau}_f(\boldsymbol{t})$ is updated based on kinematics



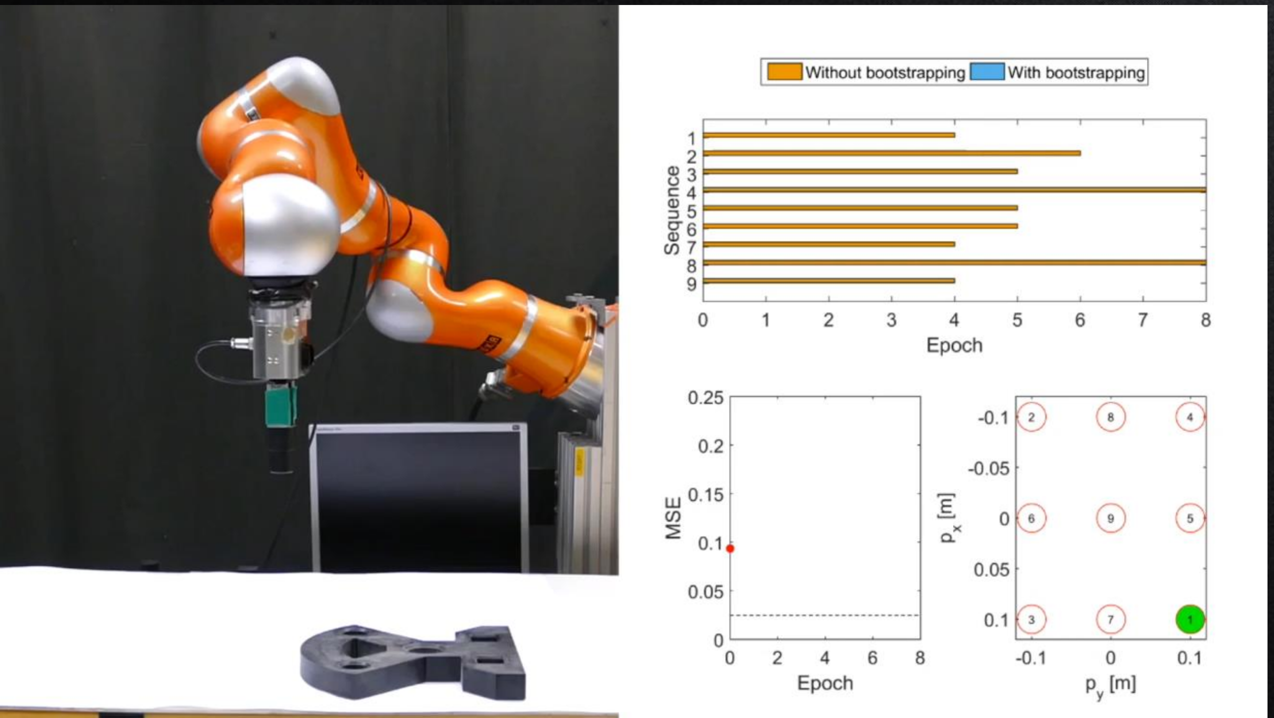
3. Movement and torque primitives are learned, stored and executed

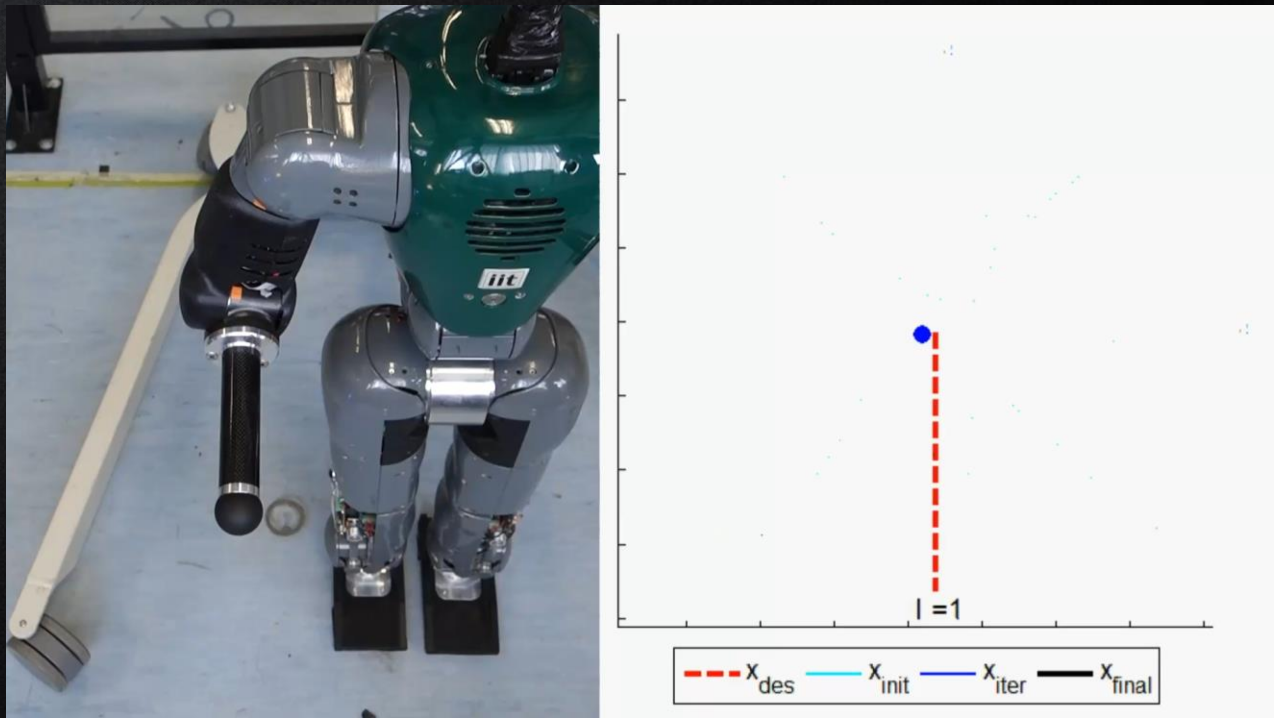




Part 2:

Generalization of Discrete CMPs





IF ROBOTS COULD DO BOTH COLLABORATION WILL IMPROVE

Utilizing neuromehanical models with robots that learn from and like humans.

Robot control for enhanced collaboration

- Robots and humans collaborate in such a way as to enhance and emphasize the qualities of each other

- Humans will:
  - Improve speed-accuracy trade-off (Fitts' law)
  - Extend the efficient workspace (Manipulability)
  - Reduce the variability of motion

- Robots gain:
  - Workload
  - Proprioception
  - Cognition

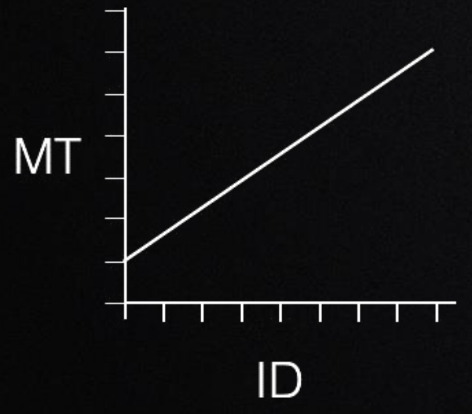
HOW FITTS' LAW IMPROVES HUMAN-ROBOT COLLABORATION ?

By predicting how much it takes to reach the target.

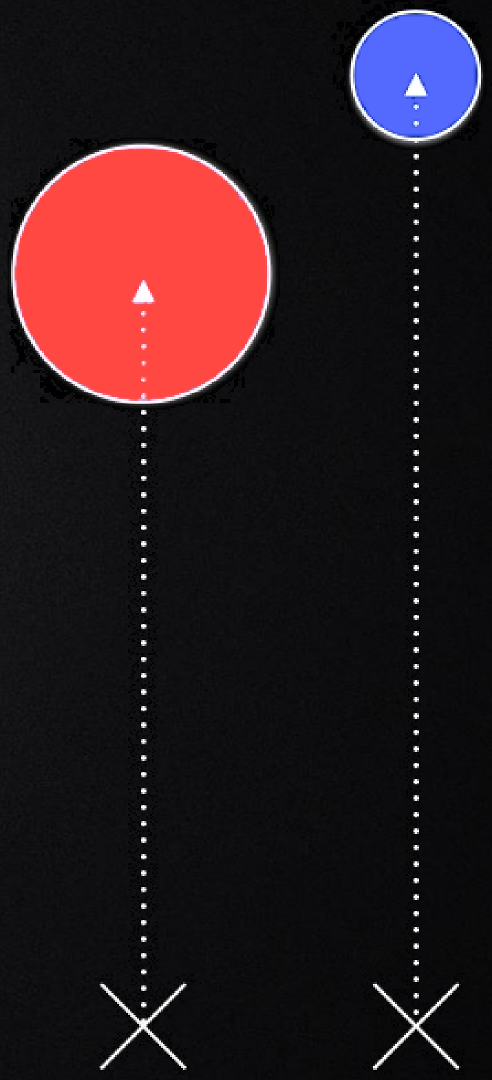
- T. Petrič, M. Cevzar, and J. Babič. "Utilizing speed-accuracy trade-off models for human-robot coadaptation during cooperative groove fitting task.“ *IEEE Humanoids 2017*
- T. Petrič, and J. Babič. "Cooperative human-robot control based on Fitts' law." *IEEE Humanoids 2016*

Fitts' law

- Fitts' law tells us how log it will take to move form a specific position to reach different targets.
- Targets that are larger and closer are easier to hit than ones that are smaller and further away.
- Fitts' law can be used to predict how long it takes to reach a target.
- There is a linear relationship between MT (Movement time) and the ID (Index of difficulty)



$$MT = a + b * ID$$



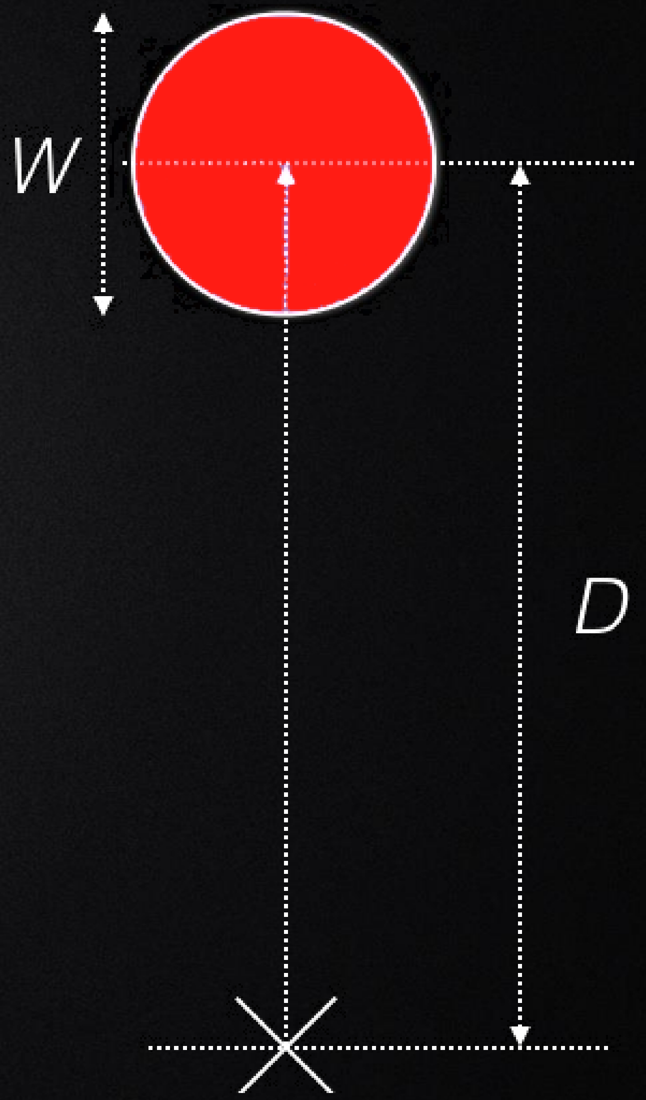
Index of difficulty

- The ID can be expressed in different ways.

- The following is an ISO standard expression for the ID. It is also known as the ‘Shannon formulation’:

$$ID = \log_2(\frac{D}{W} + 1)$$

It follows: The bigger and closer the target, the easier is to reach.



Human-robot motion prediction based on Fitts' law

- Fitts' law:

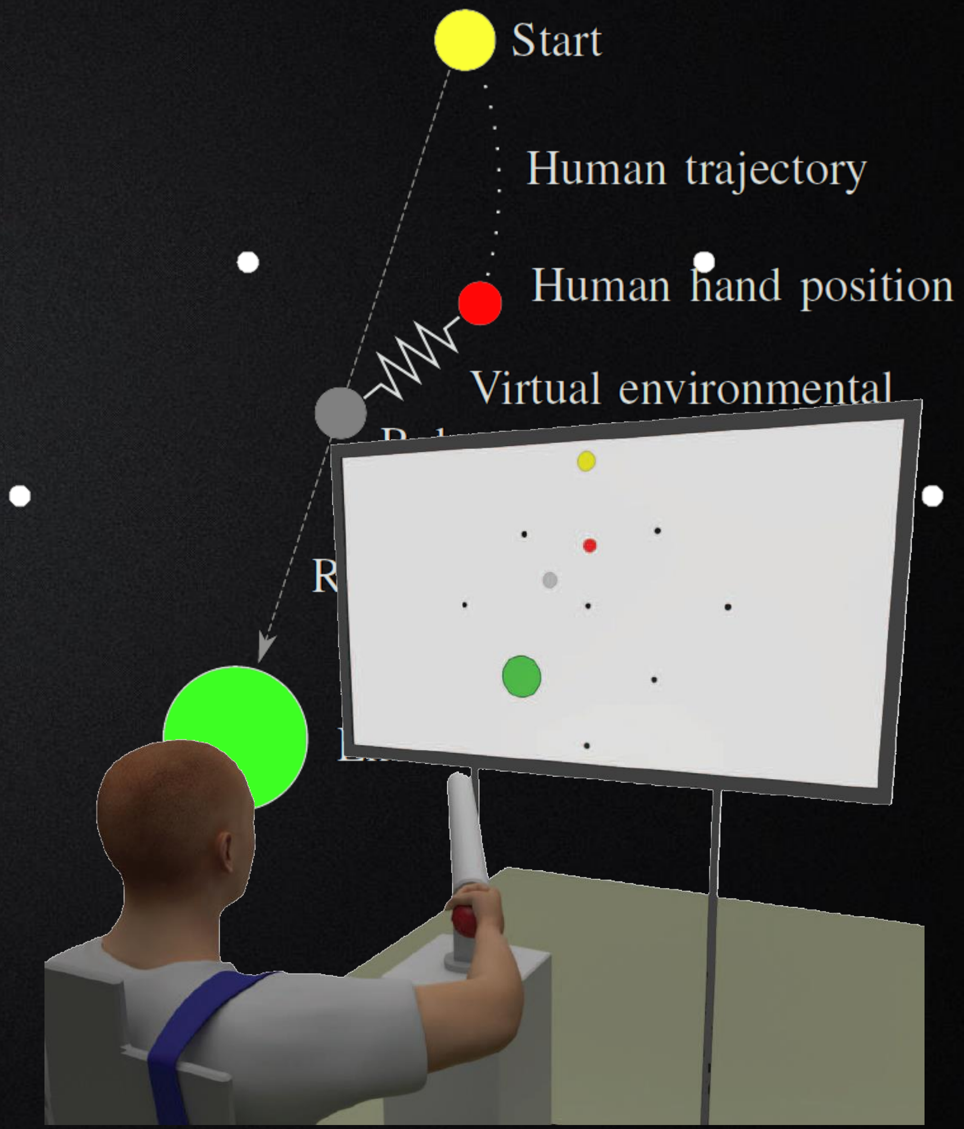
$$T = \zeta_1 + \zeta_2\, ID = [1\ ID]\zeta = \Upsilon'\zeta$$

$$ID = log_2\left(\frac{2D}{W}\right)$$

- The recursive least squares updates for the Fitts' law are given by

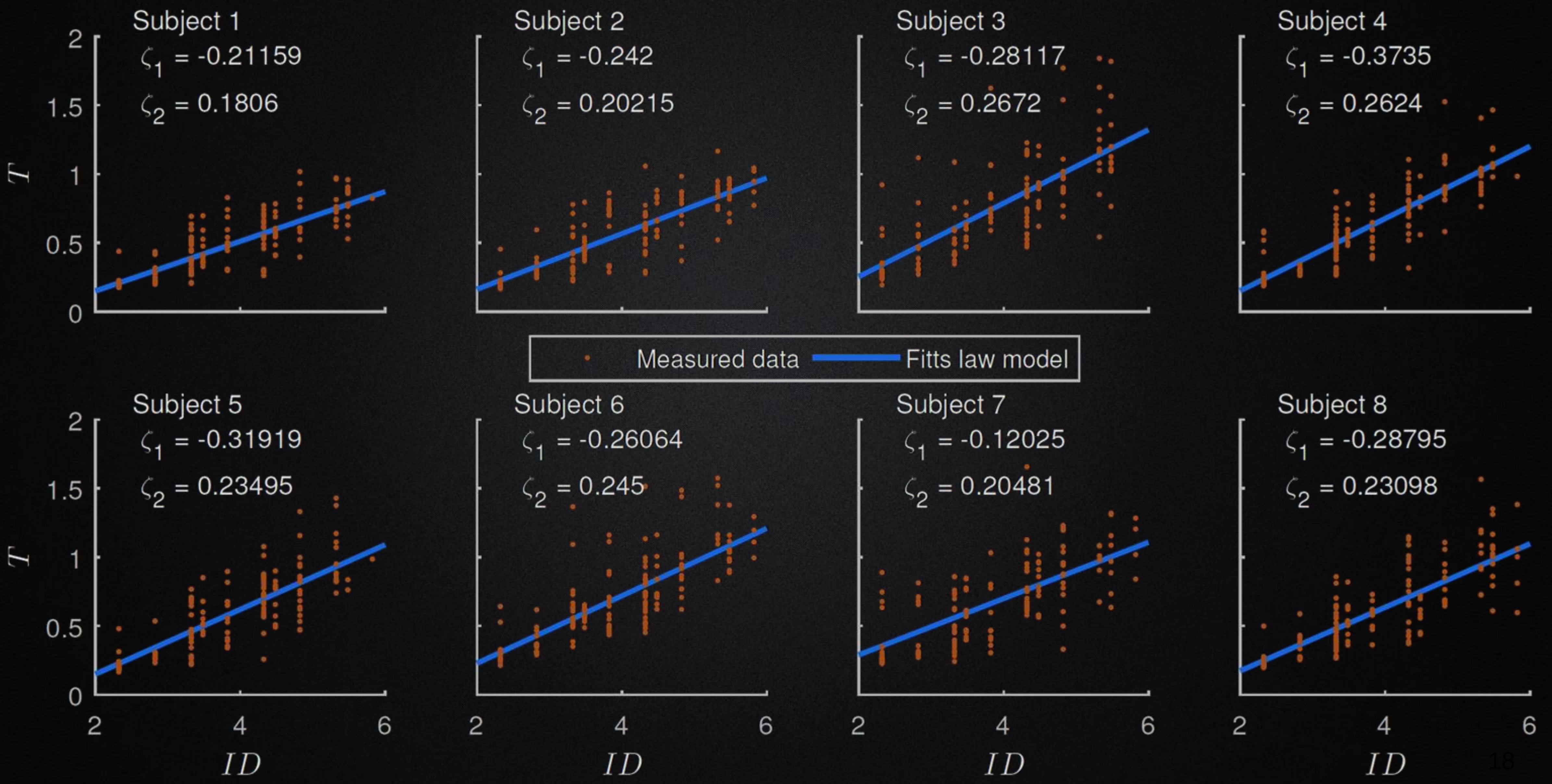
$$\mathbf{P}_{n+1} = \frac{1}{\lambda}\left(\mathbf{P}_n - \frac{\mathbf{P}_n\Upsilon\Upsilon'\mathbf{P}_n}{\lambda + \Upsilon'\mathbf{P}_n\Upsilon}\right),$$

$$\zeta_{n+1} = \zeta_n + \mathbf{P}_{n+1}\Upsilon\left(T_{n+1} - \zeta_n'\Upsilon\right)',$$

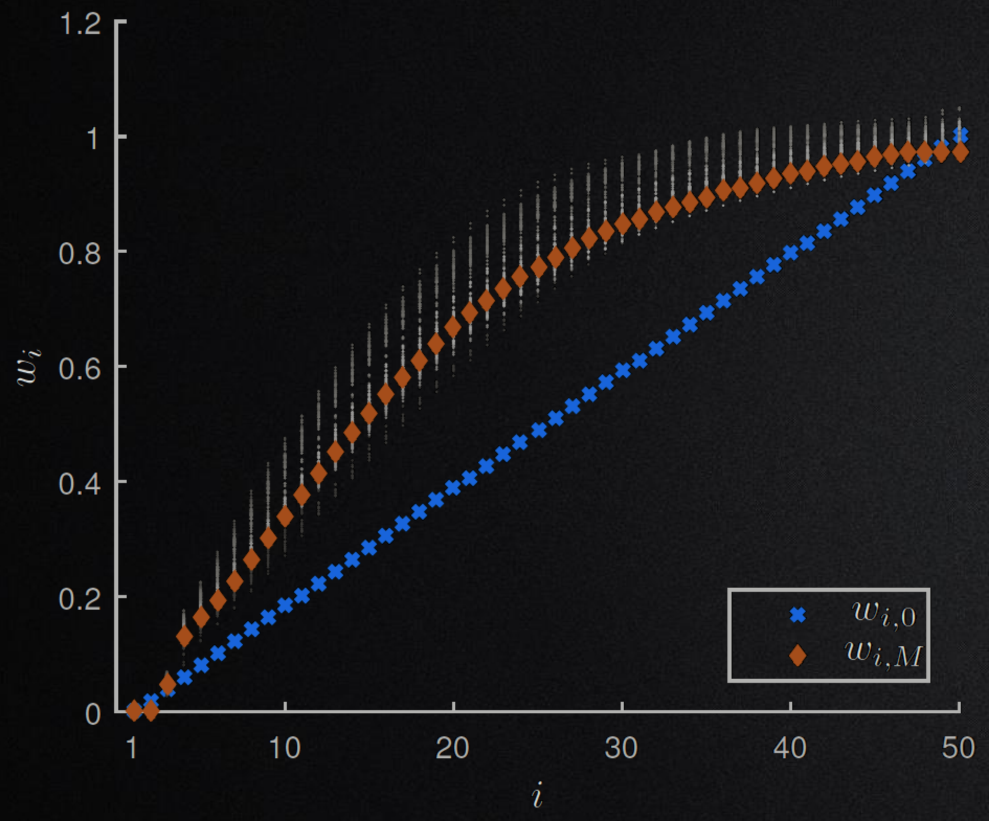


Fitts‘ law adaptation

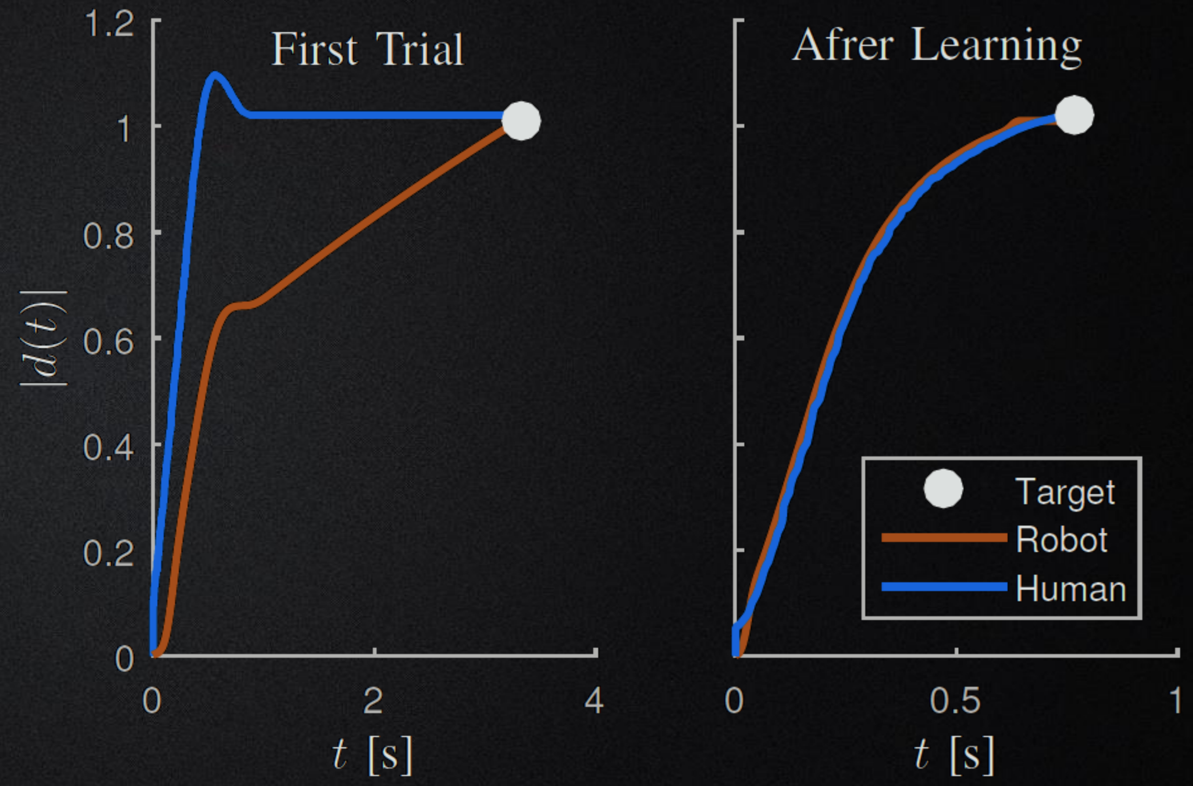
Fitts’ law models for all participated subjects.



Movement adaptation



Adaptation of DMP weights for one subject during one session. The initial weights are in orange and the final weights are in blue. The intermediate steps are indicated with shades of gray.



Comparison of human and robot trajectories for the initial trial (left plot) and trial after the finished adaptation of the movement profiles and Fitts' law parameters (right plot).


Human - robot collaboration results in
fast and accurate performance
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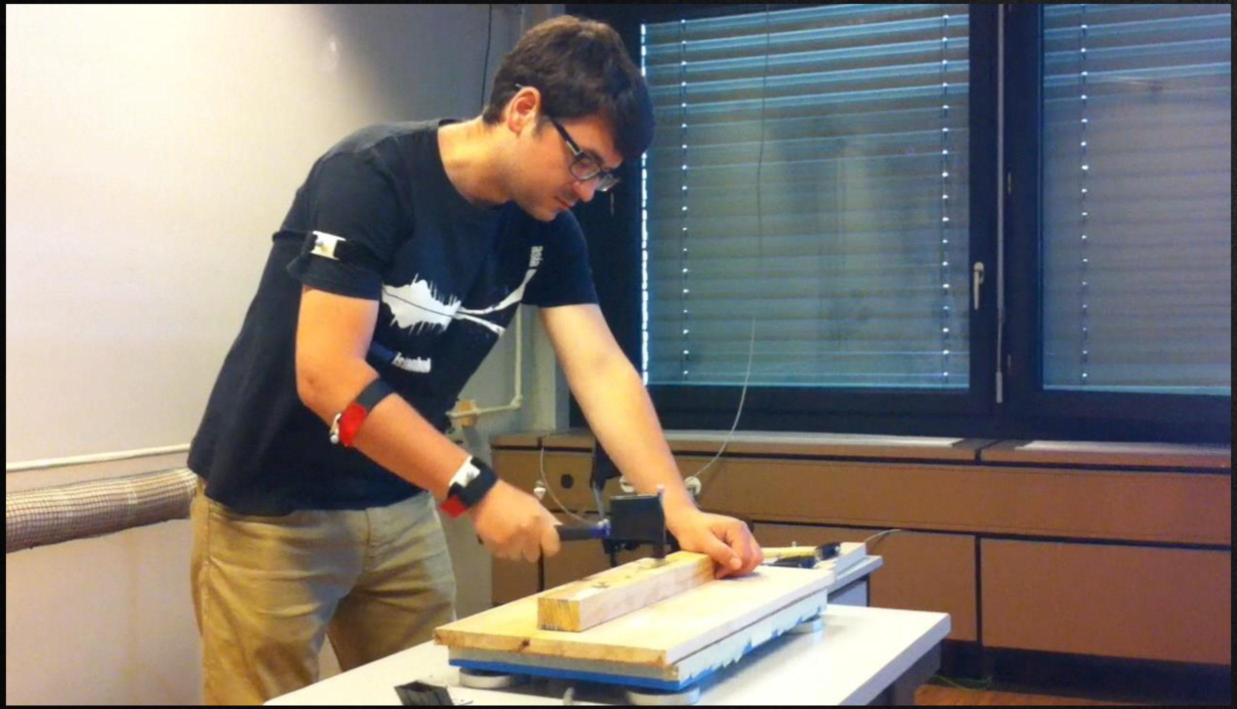
HOW DO HUMANS INTERACT WITH THE BOUNDARY OF A HARD CONSTRAINT?

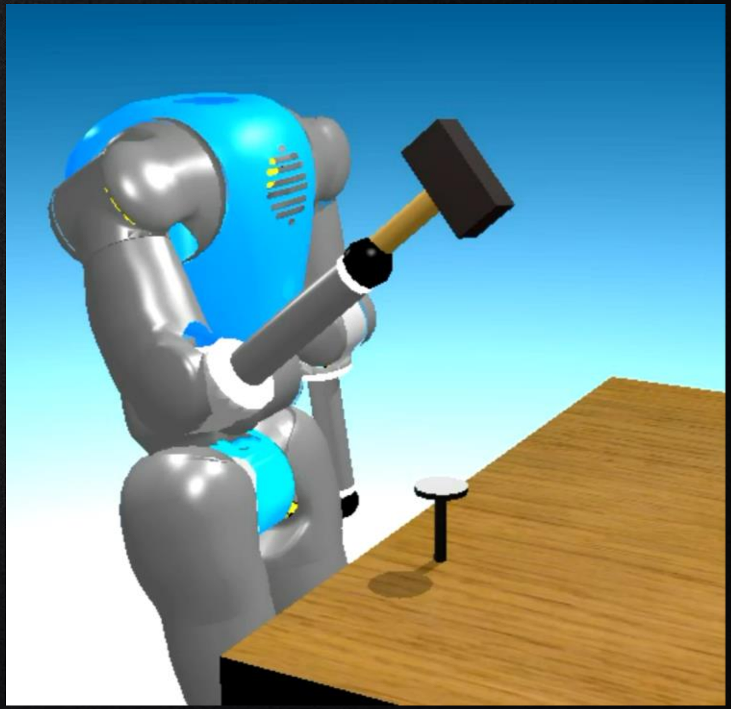
Most studies: How do humans control reaching movements far from constraint boundaries (Wang et al., 2001; Flanagan and Lolley, 2001; Todorov and Jordan, 1998) **or how do humans avoid obstacles?**

- T. Petrič, C.S. Simpson, A. Ude and A. J. Ijspeert, "Hammering Does Not Fit Fitts' Law." *Frontiers in computational neuroscience,* 2017

Hammering task

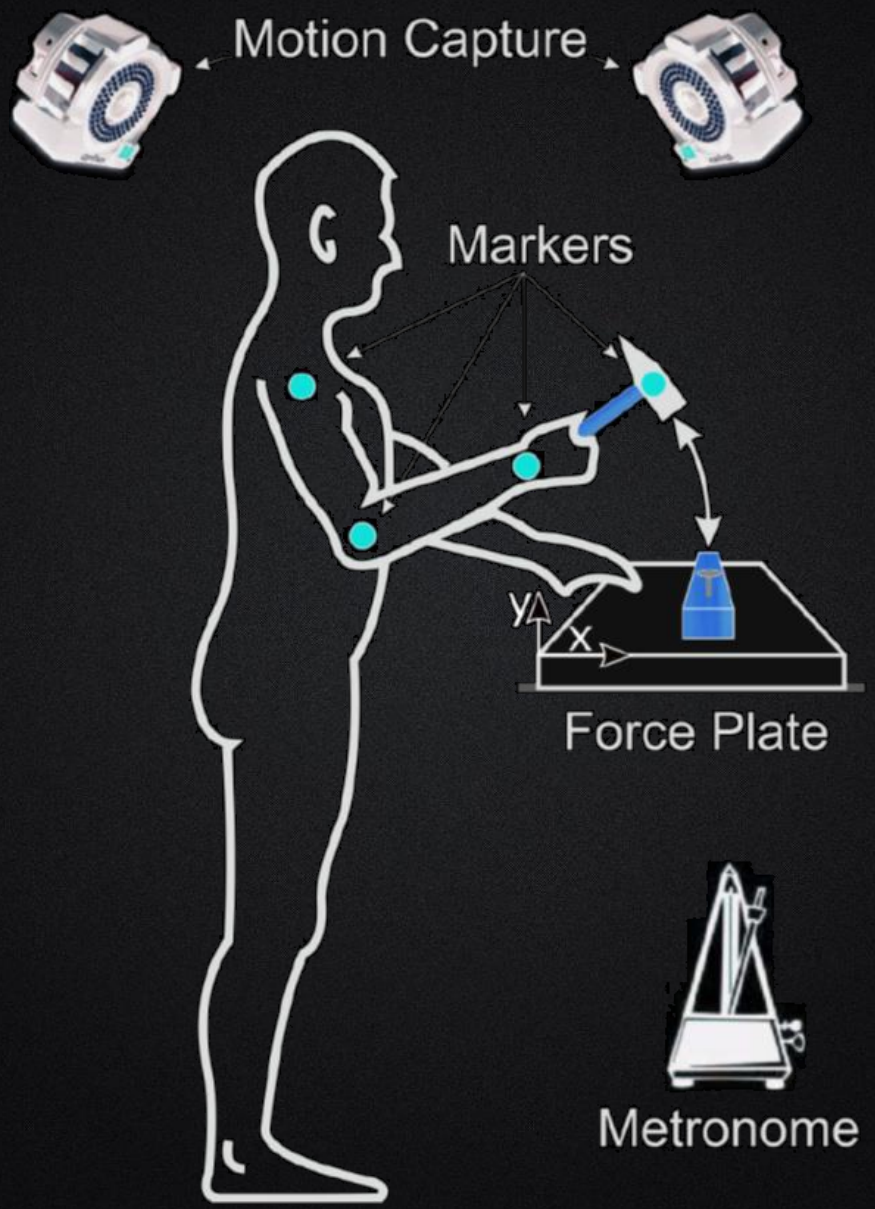
How does the existing models of motor control cope with a periodic targeted impact task extended from Bernstein's seminal work: hammering a nail into wood.





Experimental setup of the study.

- Can we use Fitts' law to predict timings ?



Different cases of hammering were tested

Hammering frequencies of 1, 2, 3, 4, and 5 Hz were used.

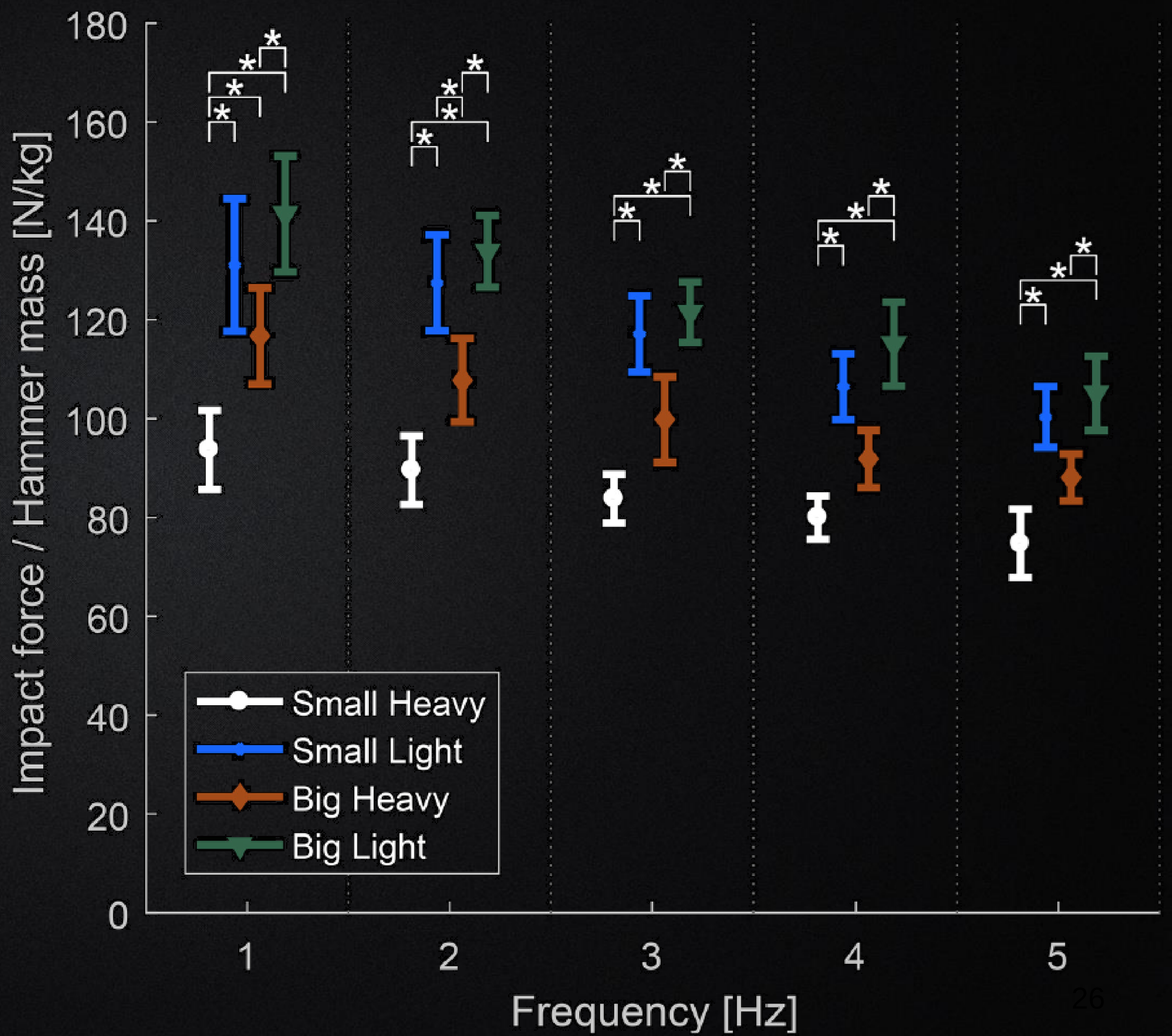
Different cases of hammering were tested

394 g

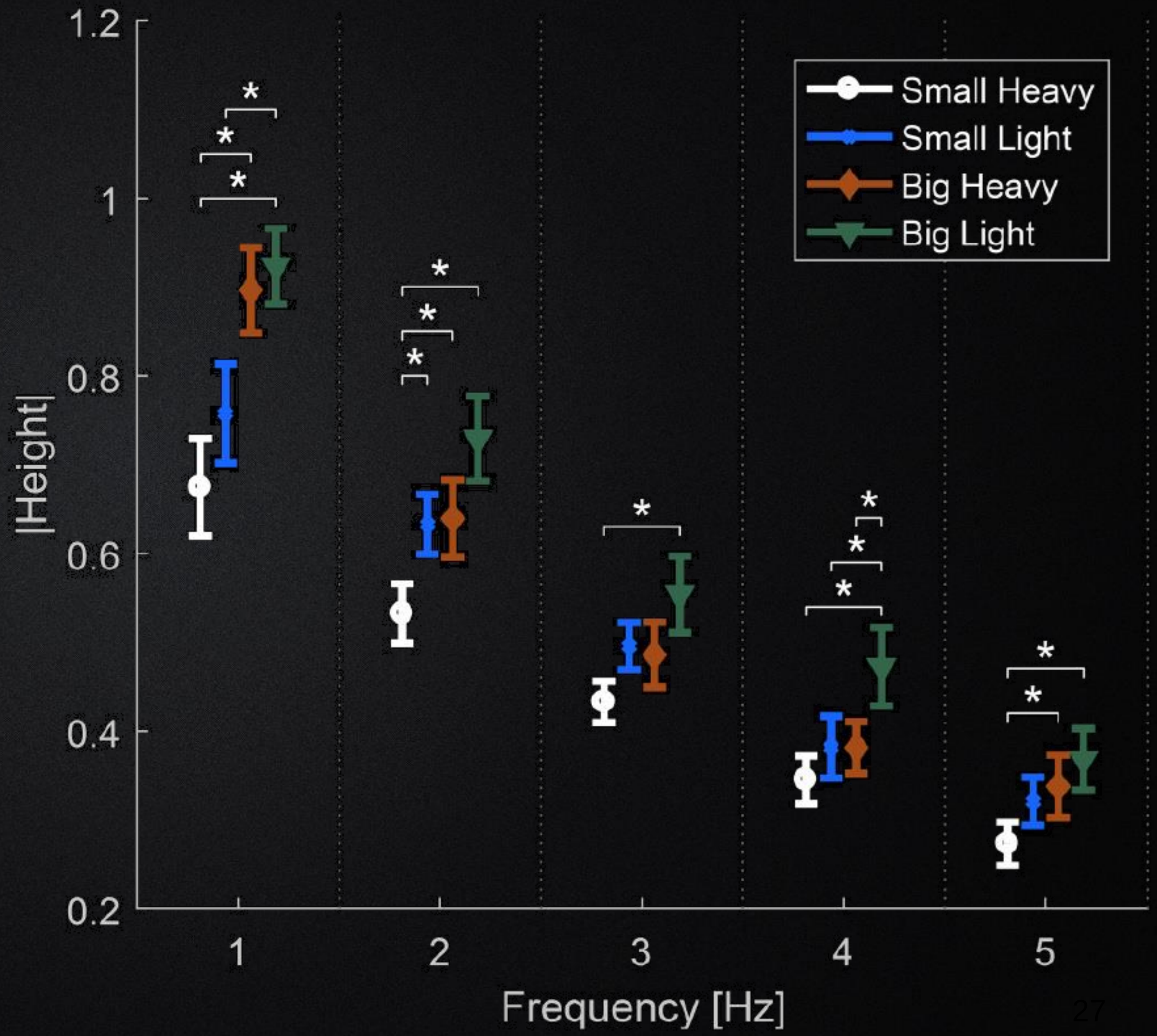
214 g

Maximal impact forces

The heavy hammers generally had lower impact forces per unit mass than the lighter hammers across hammering frequencies



Maximal height



Height of the hammer head decreases as hammering frequency increases

Fitts' law results for hammering

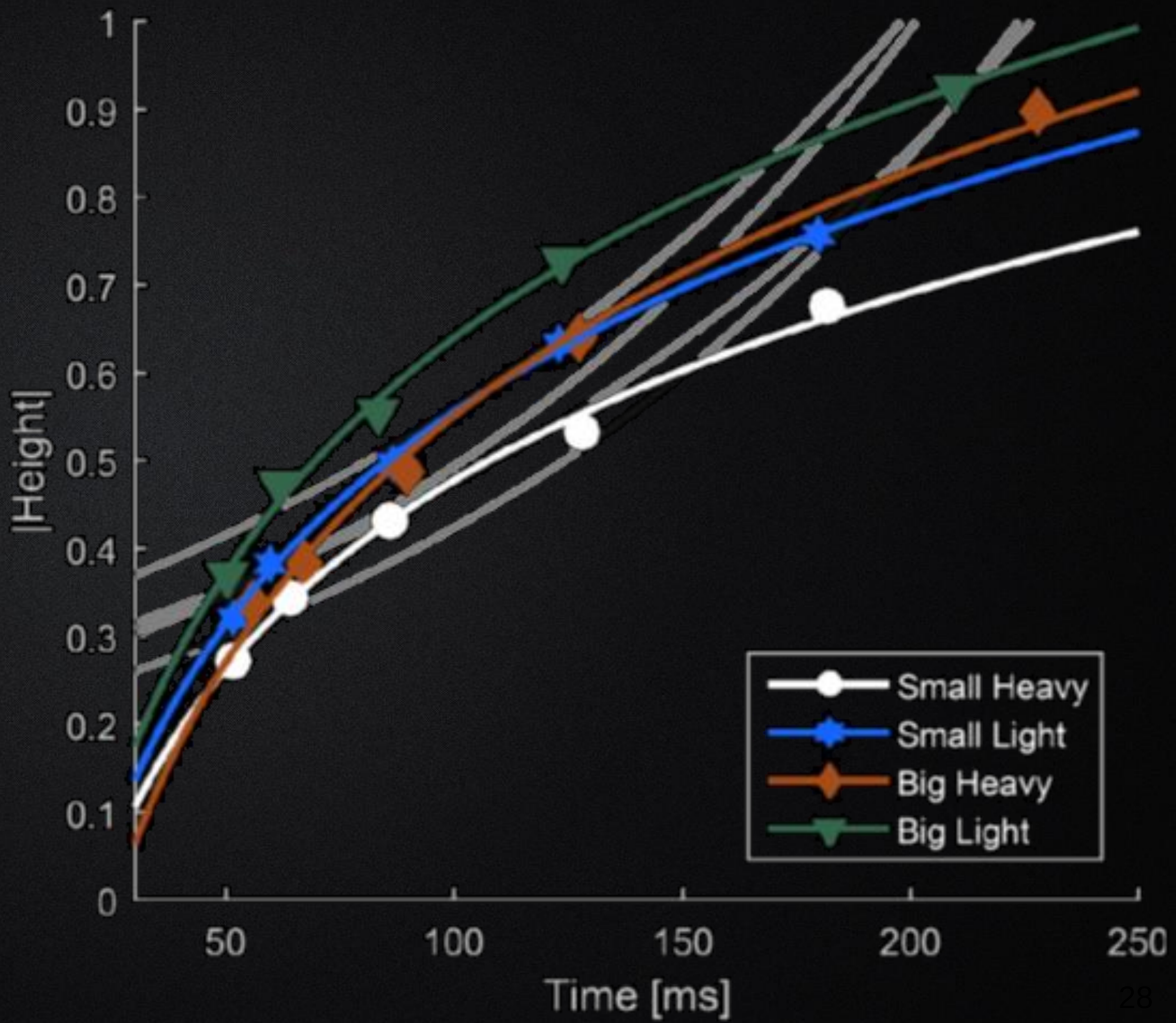
- Fitts' law (gray lines):

$$T_f = a + b \cdot log_2(2D/W)$$

- Better fit with new model ('Inverted' Fitts' law):

$$D = W/2\left[a + b \cdot log_2(T_f)\right]$$

- Fitts' Law does not appear to follow the contours of the experimental data (gray traces)



Human movement is thought to be optimally control

- Human hammering is a difficult control task due to the need to balance energy transfer to the nail with accuracy.
- We hypothesize that the human nervous system determines an optimal tradeoff between maximal impact velocity (complete the task in the most effective manner) and minimal effort.
- We thus determine the optimal joint torques by minimizing the cost function:

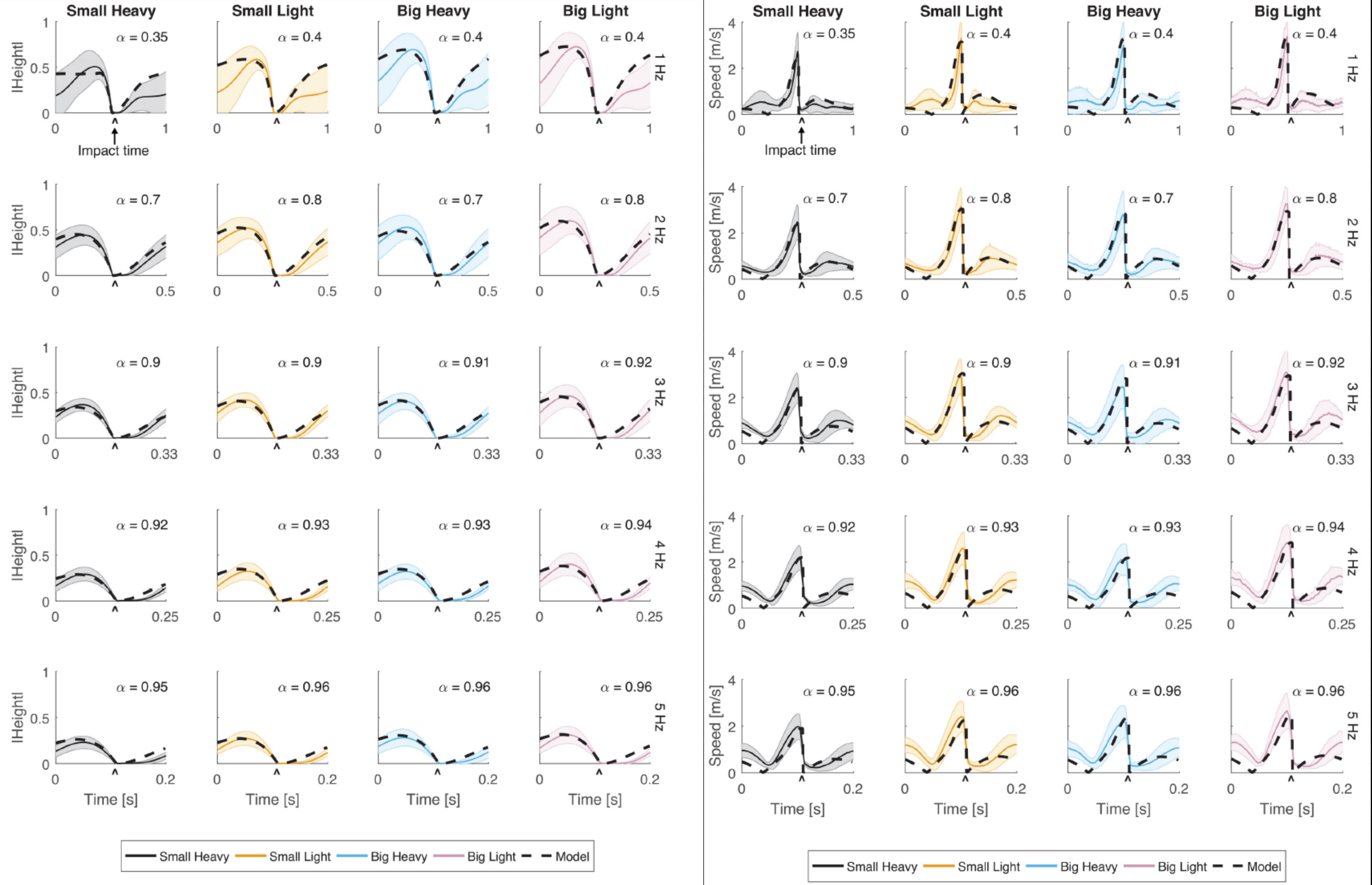
$$Cost = (1 - \alpha)\frac{\sum_{i=1}^{n}\sum_{j=1}^{T}\tau_{i,j}^{2}}{C_{\tau_{max}}} - \alpha\frac{y_{T-1} - y_{T}}{C_{\dot{y}_{max}}}$$

Expertise

Maximize energy transfer

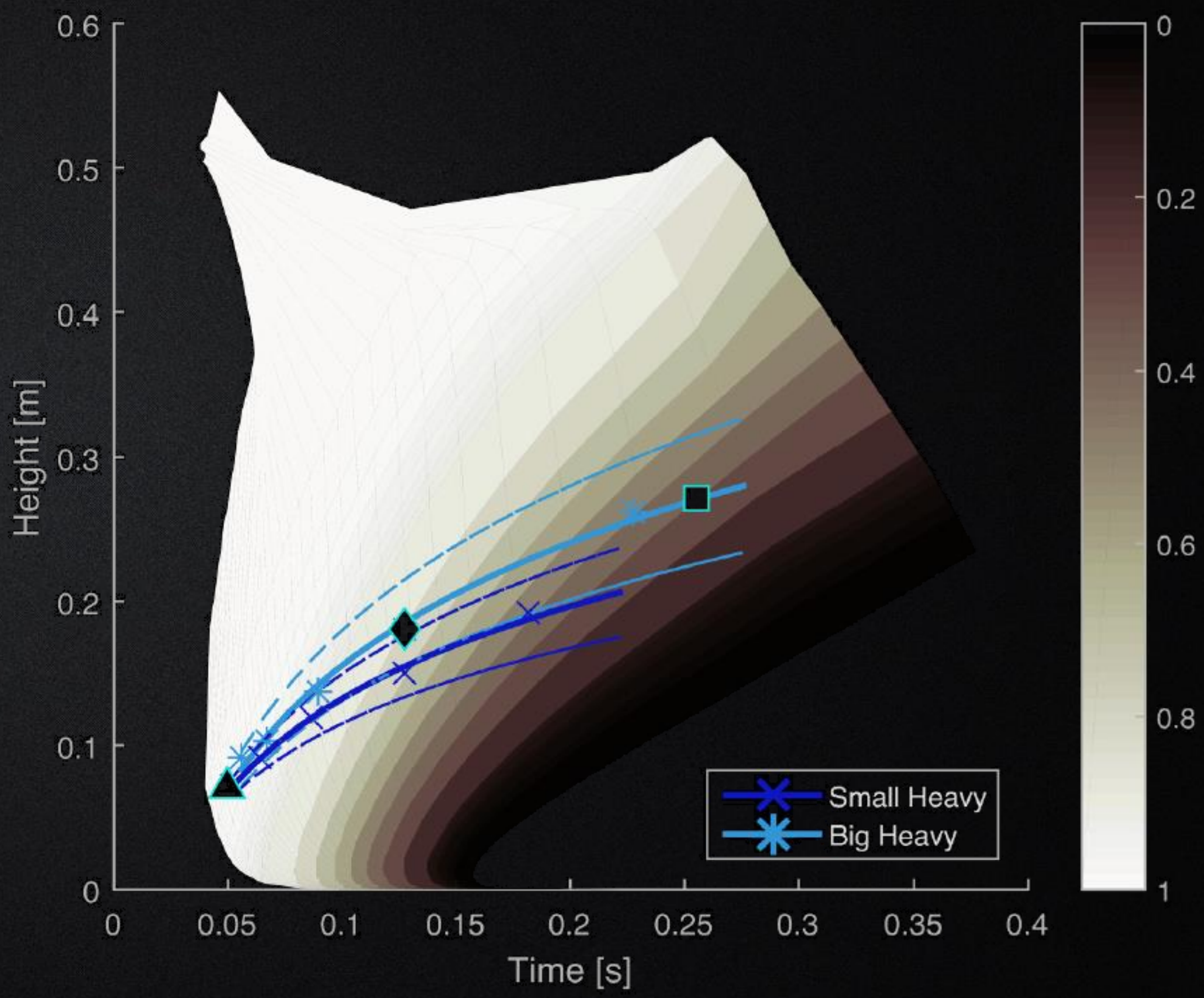
Minimize energy consumption/signal dependent noise

Simulation examples



What was optimized for hammering task

- At low hammering frequencies ■ (greater time between impacts) subjects emphasize effort conservation.
- At high hammering frequencies ▲ (less time between impacts) subjects emphasize energy transfer to the nail.
- No constant relationship for all hammering speeds.



TAKE HOME MESSAGE

Neuromechanical modeling is a powerful tool that can be successfully used as the underlying basis for control of collaborative robots.