HART Lab

Human-Assistive Robotic Technologies

Individualised Human Models for Cyberphysical Interactions

Ruzena Bajcsy

2016.05.12

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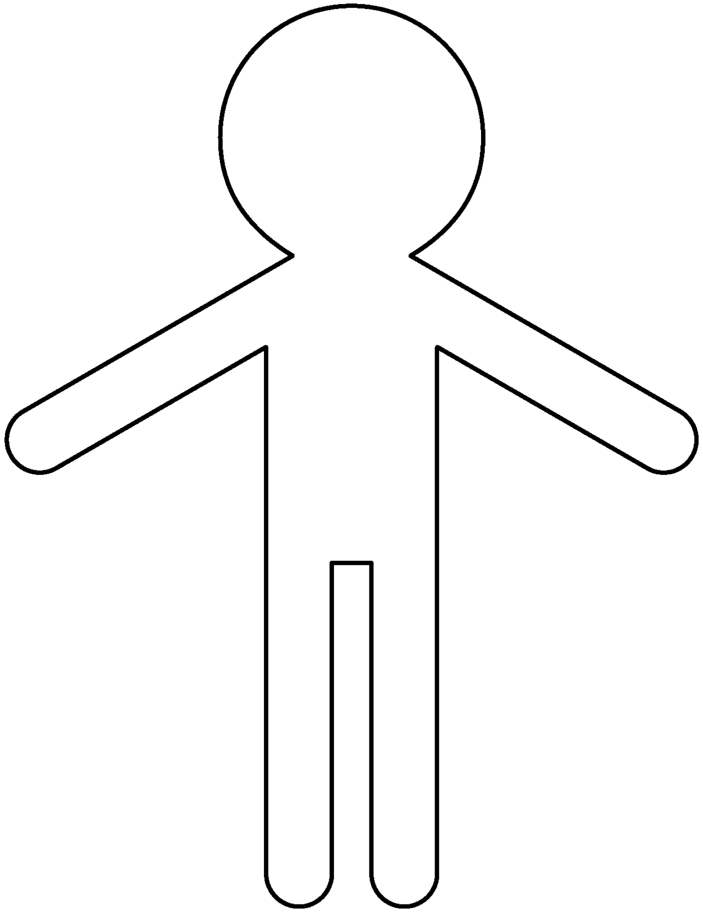
MOTIVATION

Large variations between individuals

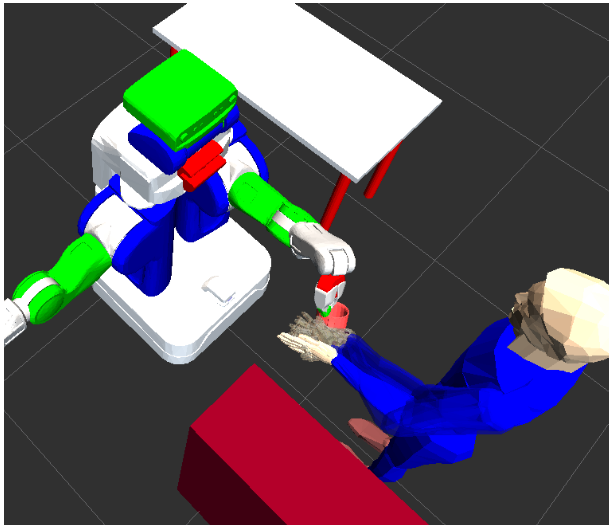
- Genetic variation
- Age
- Illness
- Injury
- Treatment

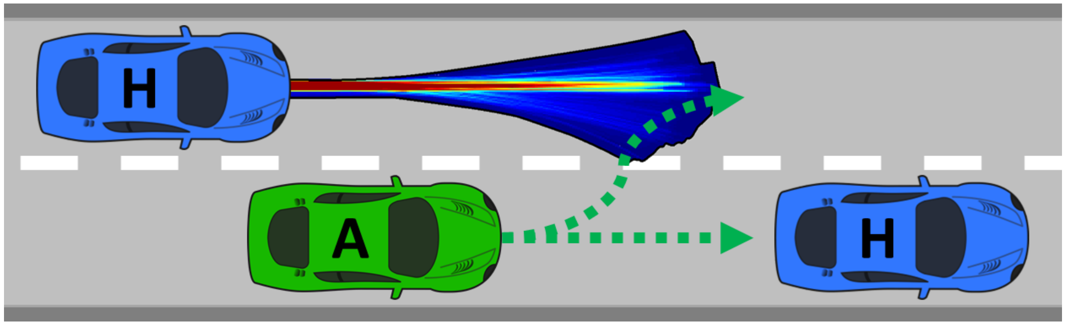


MOTIVATION

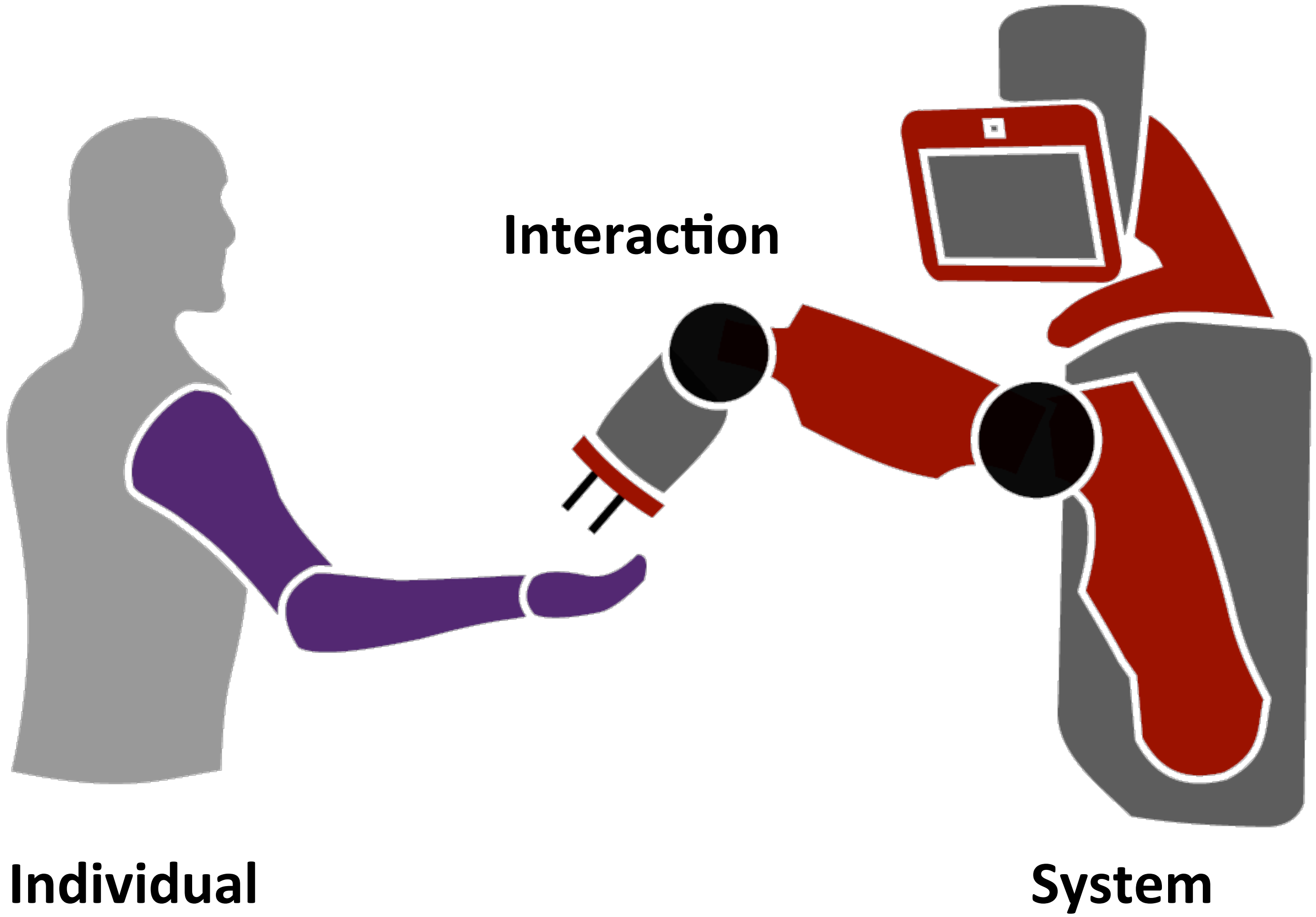
Large variations between individuals, and tasks

- Genetic variation
- Age
- Illness
- Injury
- Treatment





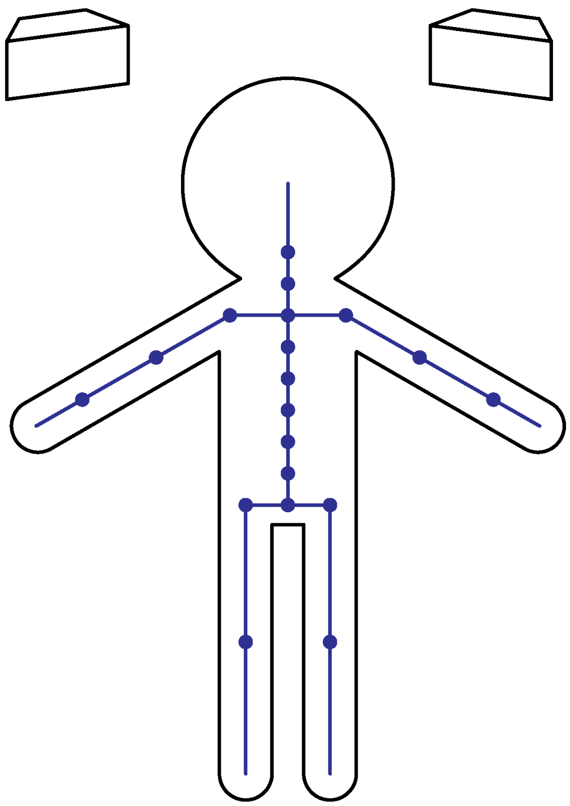
LAB GOALS:



Kinematic Modelling

Kinematics- Motion capture

- Kinect 1, 2, Phasespace Impulse X2
- Adafruit 9DoF IMU
- Recovery via rigid skeletonisation, inverse kinematics



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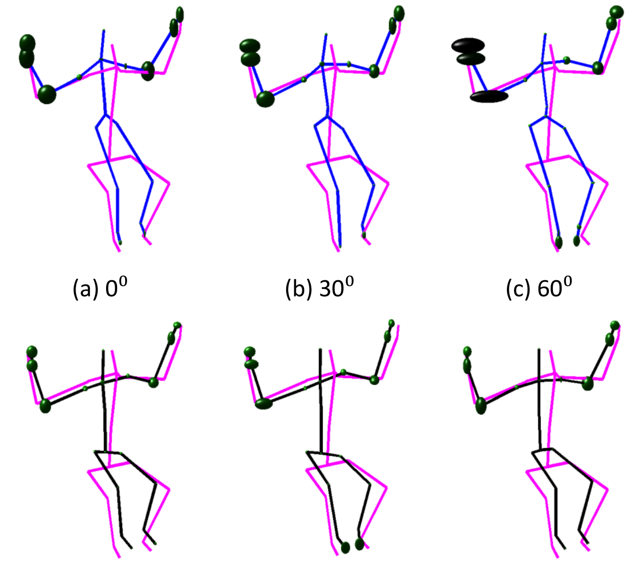
KINEMATIC EVALUATION OF HUMAN MOTION

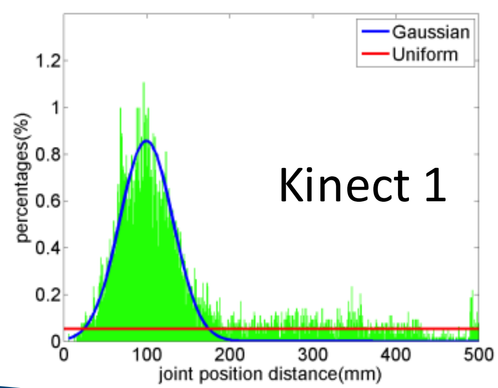
- **Goal: Evaluation of low-cost methods for capturing human motion kinematics**
- We compared Kinect v1 and v2 with motion capture to determine the error distributions for different joints
- Outlier exclusion: using a mixed Gaussian (on-track motion data) and uniform (random motion data due to tracking loss) distribution to model the overall motion data

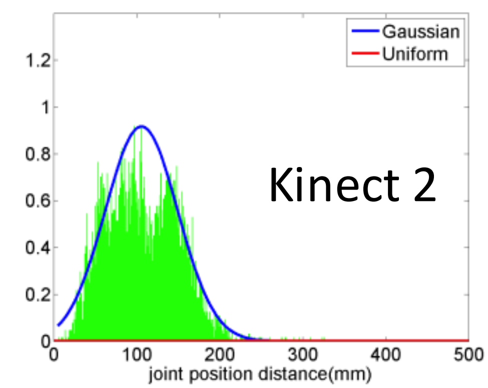
$$p(\theta) = \rho \times N(\mu, \sigma) + (1 - \rho) \times U(x_1, x_2)$$



(a) 0^0 (b) 30^0 (c) 60^0

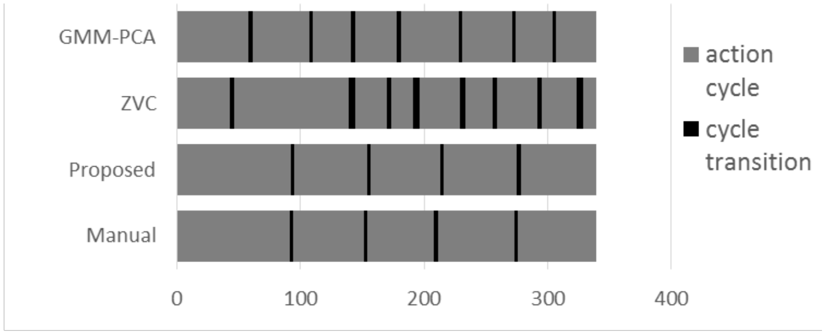
(d) 0^0 (e) 30^0 (f) 60^0

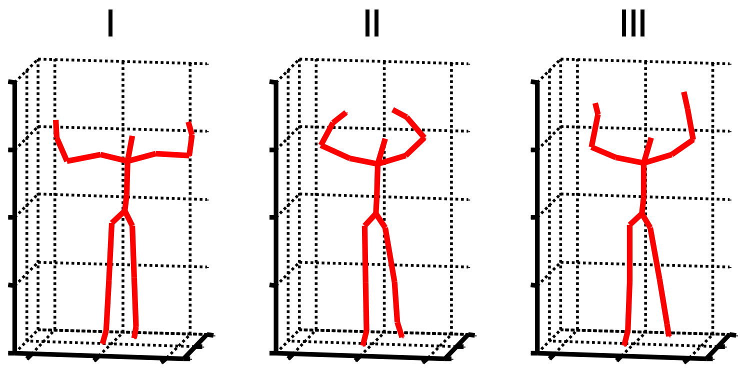




ACTION SEGMENTAION

- **Goal: Develop a robust unsupervised method for segmenting repetitive actions based on the human kinematics**
- We use unscented Kalman filter (UKF) to extract kinematics and reduce effect of noise
- We apply frequency analysis to determine most representative kinematic parameters
- We developed robust method for segmentation using zero-velocity crossing with based k-means classification to determine motion phases
- Applications: Physical rehabilitation, exercise coaching, robotic manipulation





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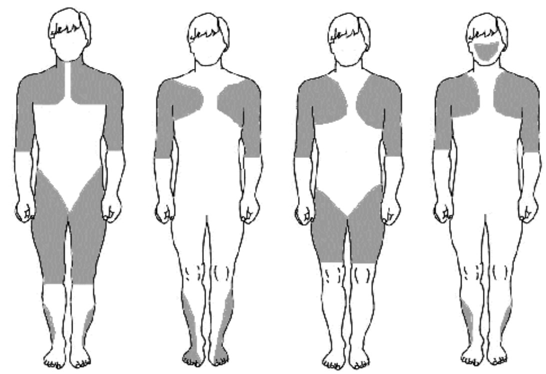
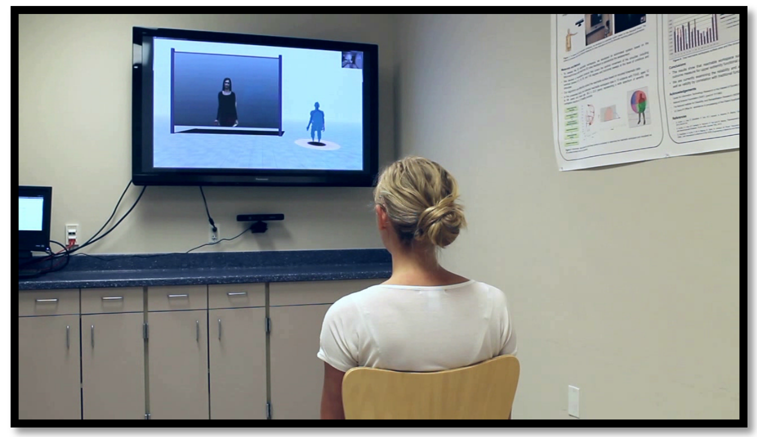
Qifei Wang

APPLICATION: DIAGNOSTICS

- **Goal: Development of new upper-extremity outcome measure for functional evaluation in muscular dystrophy and other disorders.**
- Reachable workspace obtained from kinematic measurements from 3D vision camera (MS Kinect) is used as a proxy of upper-limb function.
- Validation of reachable workspace outcome measure using standardized clinical tests (over 200 controls & patients).
- **Applications:** Physical therapy, testing of drug effectiveness, remote health care, assistive devices, ergonomics.



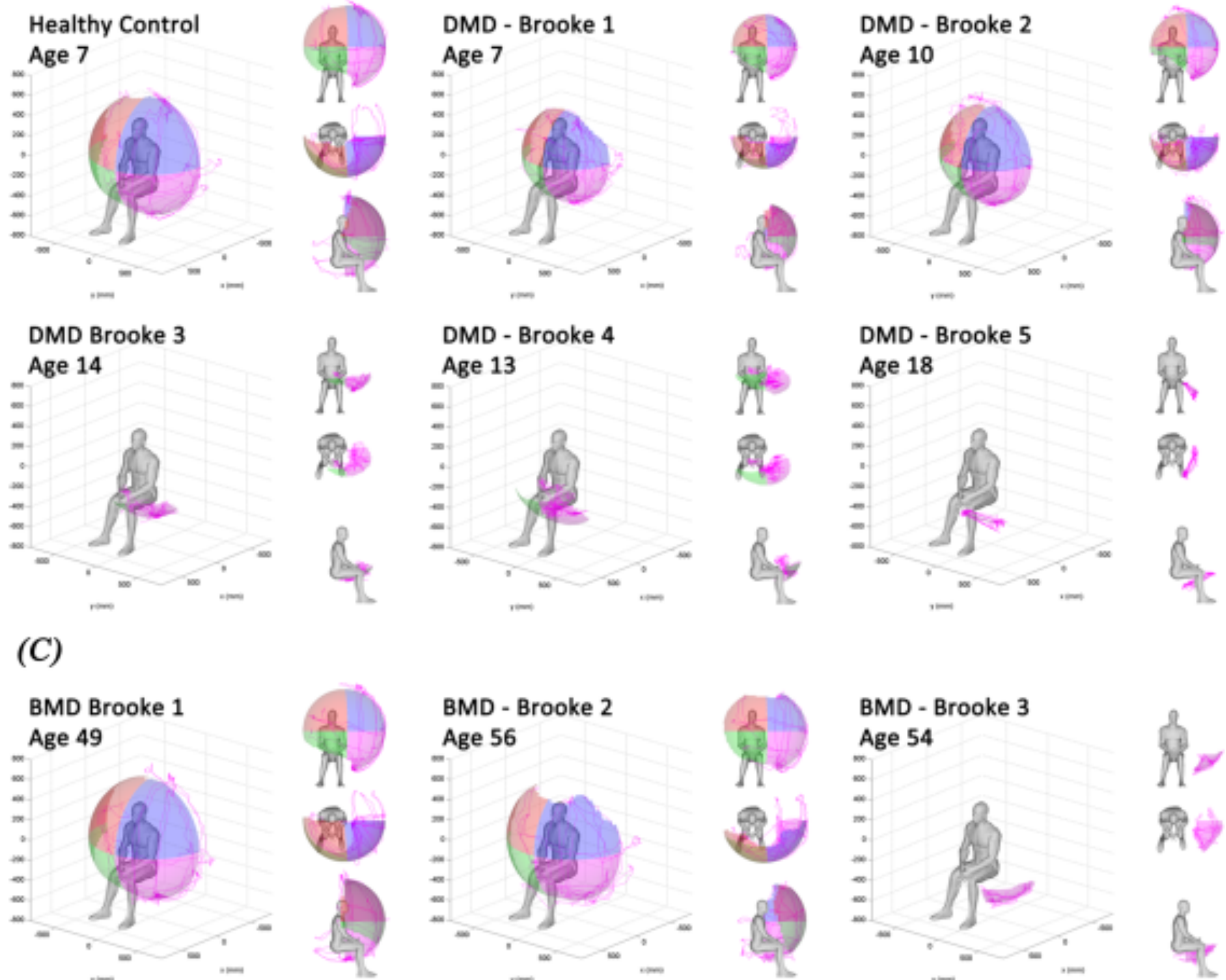


Parent Project Muscular Dystrophy

NIH National Institutes of Health

UC DAVIS MEDICAL CENTER

APPLICATION: DIAGNOSTICS



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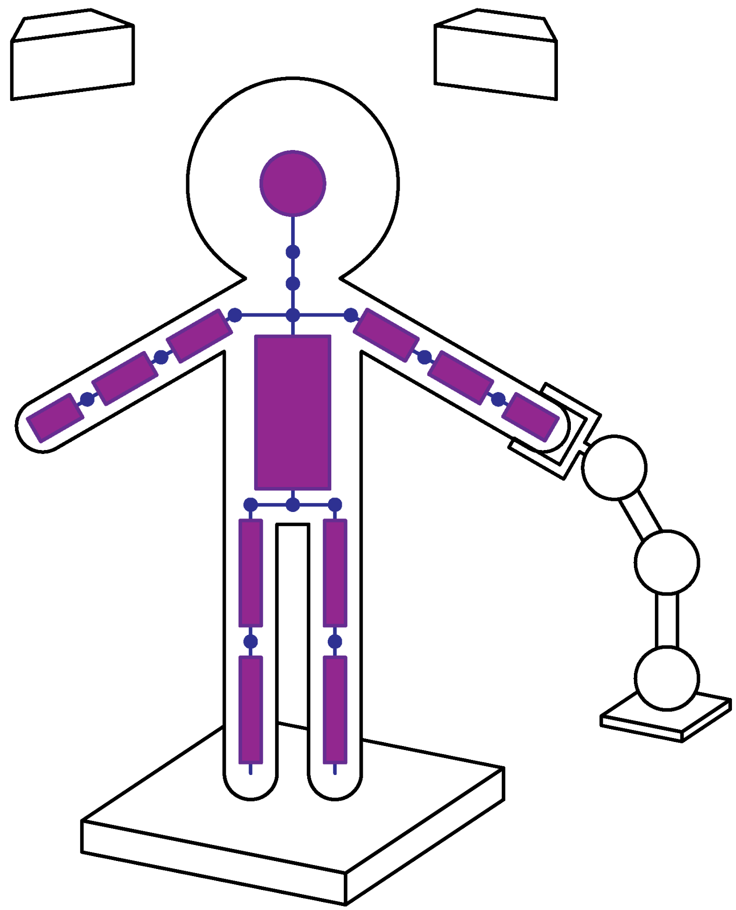
Gregorij Kurillo

Dynamic Modelling

Dynamics- Force sensing

- AMTI Force platform
- ATI Force sensors
- UR5 Robot manipulator



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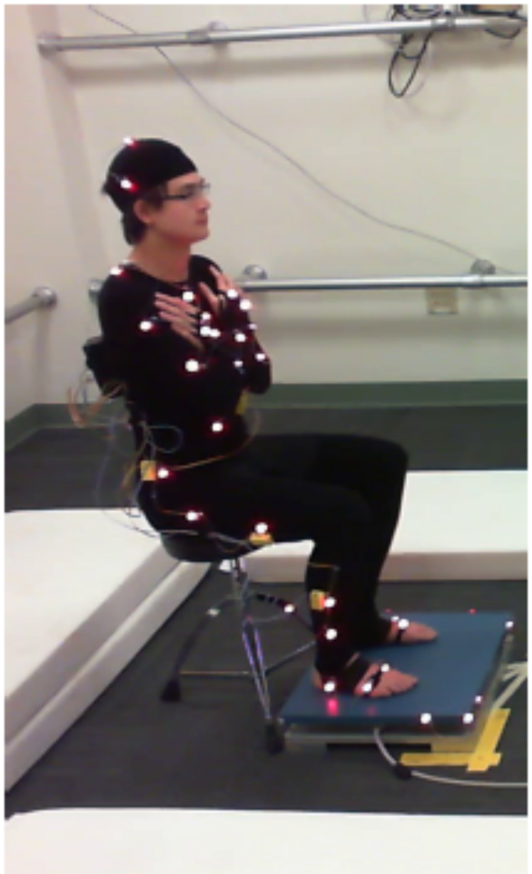
DYNAMIC MODELLING

Investigation into standing

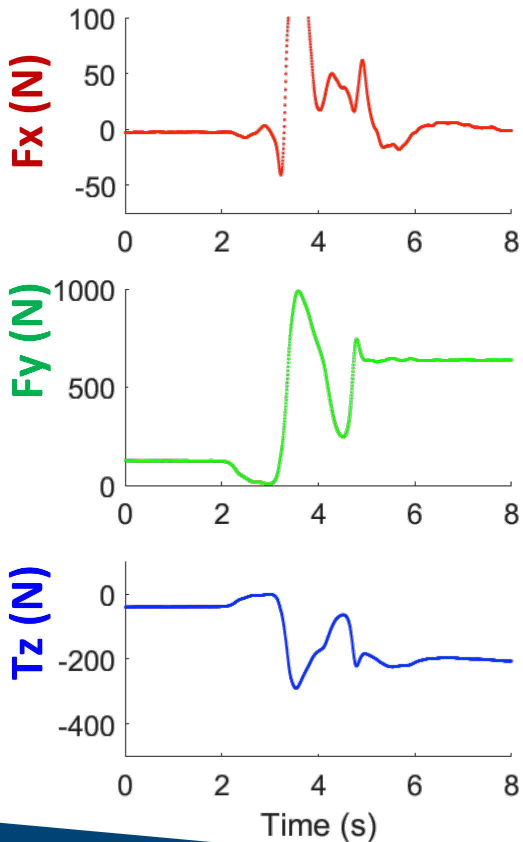
- Given motion capture data and contact force data, can we recover the masses, and skeleton of the user?

- Can we predict contact forces from just this model and motion capture?



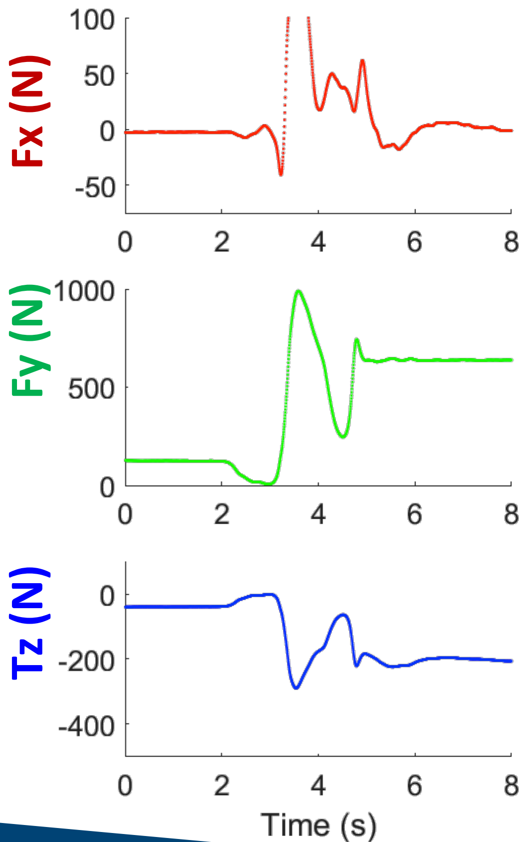
Dynamic Modelling

Measure contact forces

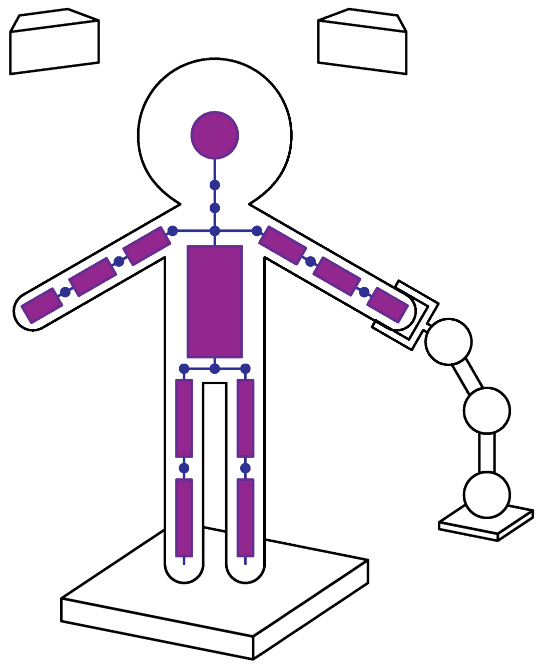


Dynamic Modelling

Measure contact forces

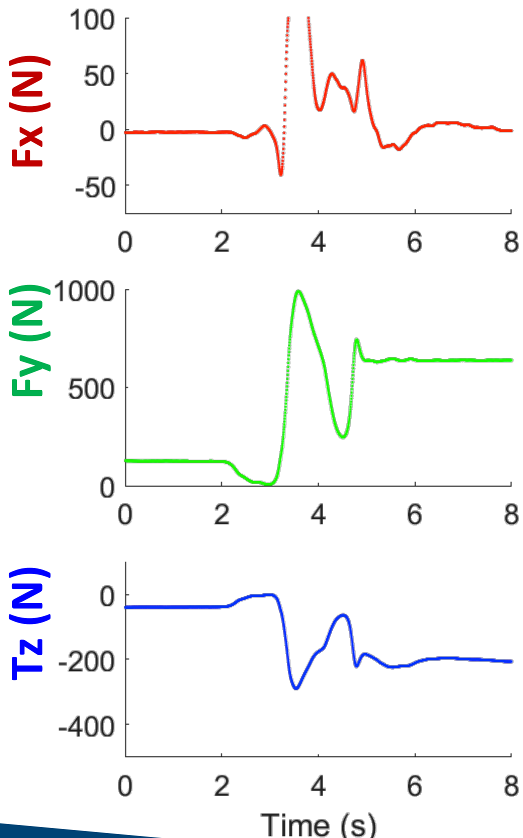


Recover Dynamic Parameters

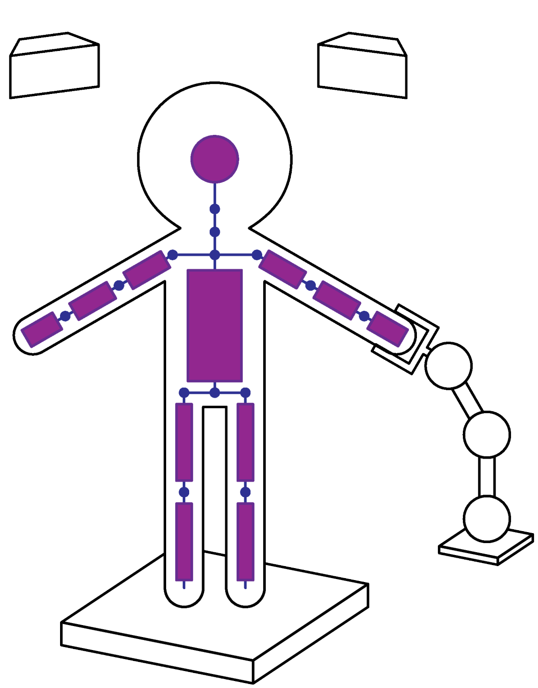


Dynamic Modelling

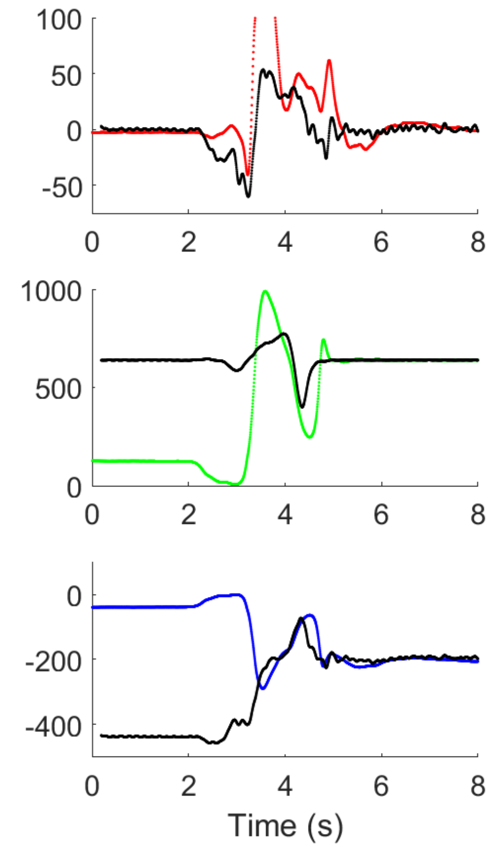
Measure contact forces



Recover Dynamic Parameters



Validate recovered forces



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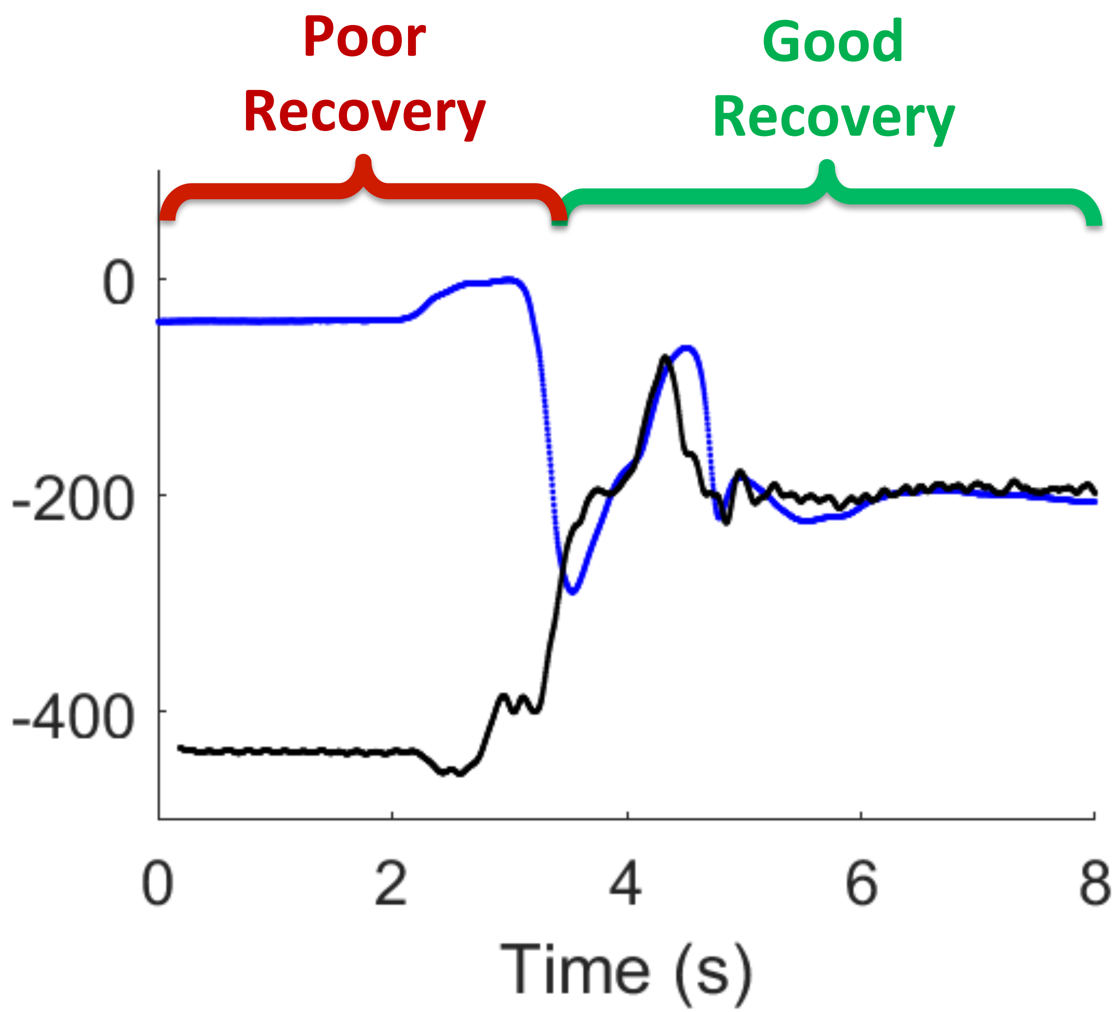
Robert Matthew

Dynamic Modelling

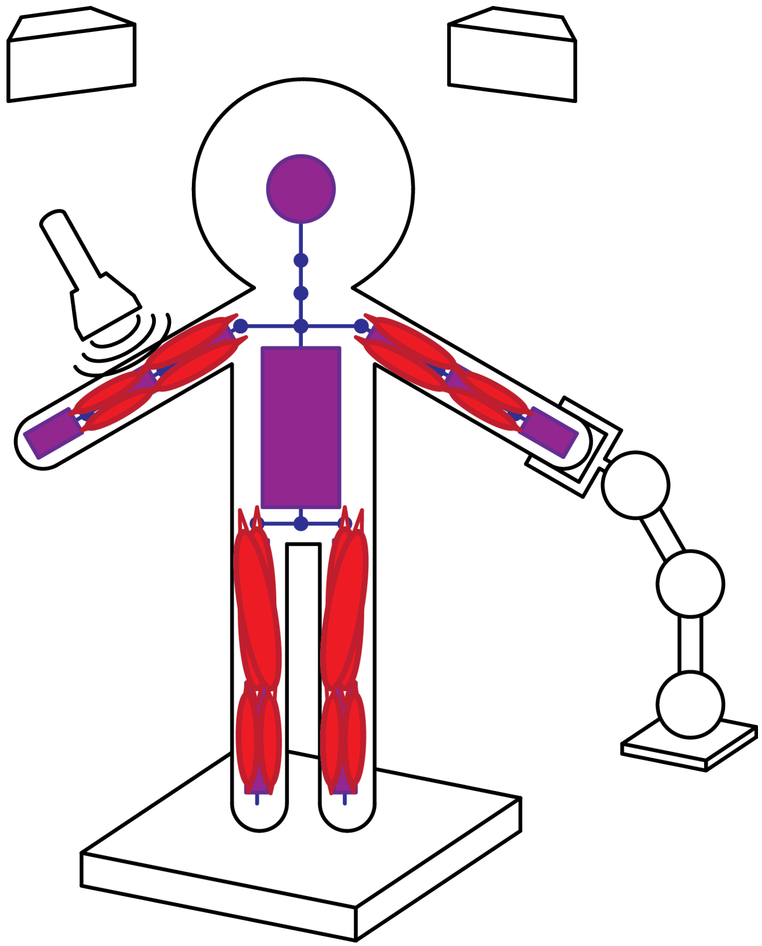
- Presence of two hybrid modes:
  - In contact with chair,
  - Not in contact with chair



Muscle Modelling

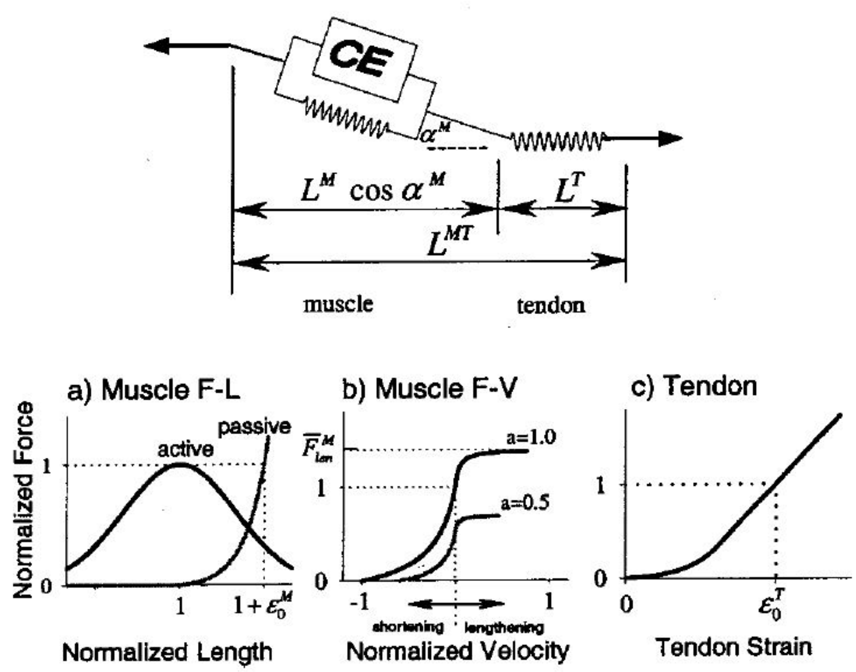
Muscle sensing

- Electromyography
- Near Infrared Sensing
- Ultrasound



MUSCLE MODELLING

- Estimation of muscle force from is an open problem
- Hill model used extensively
  - Highly parameter sensitive- tendon length
  - Typically EMG driven- highly noisy

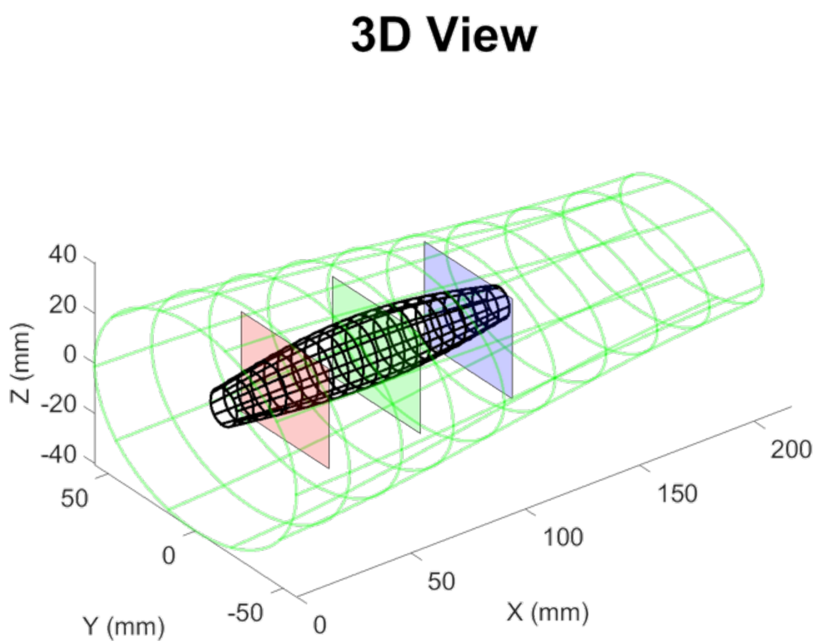


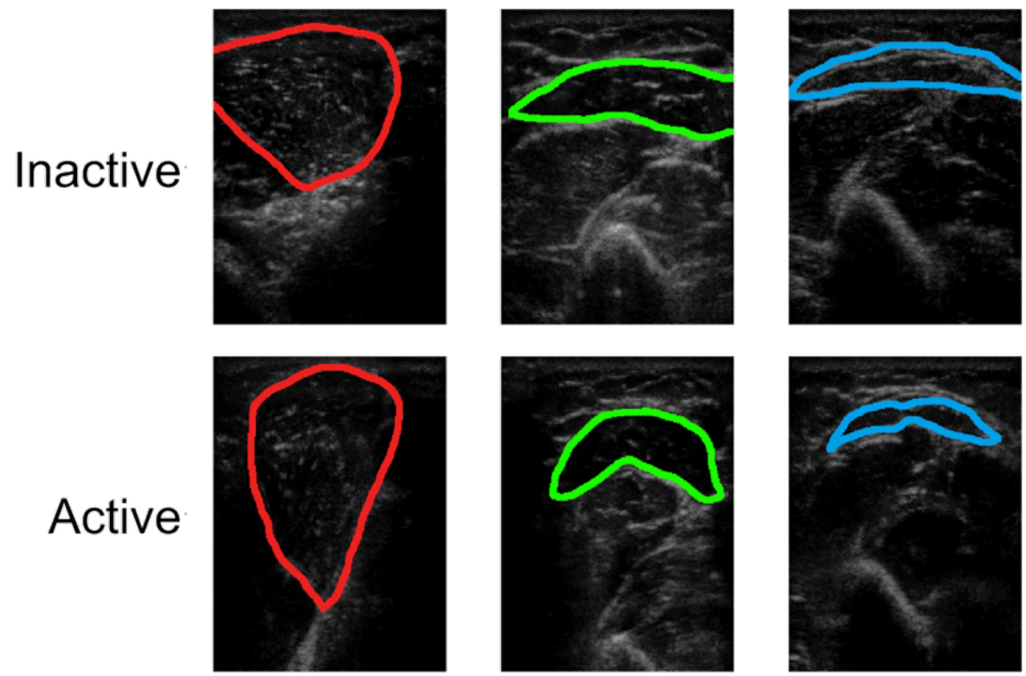
Hill Muscle Model

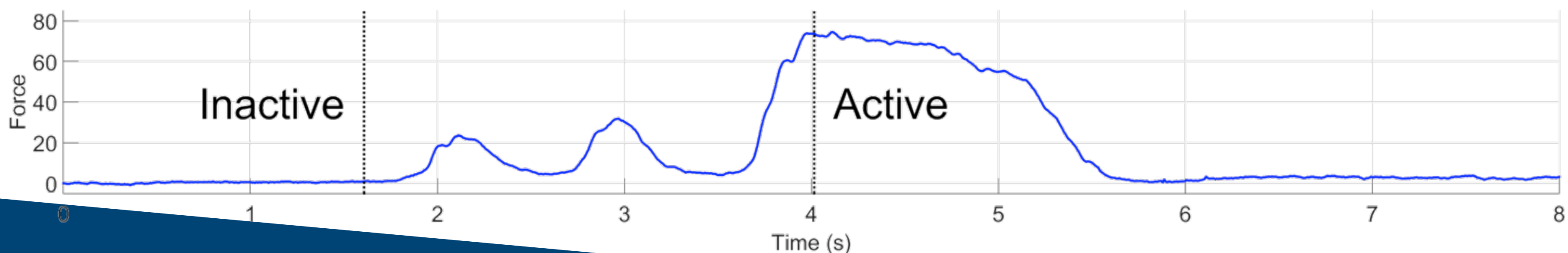
Hill, A. V. "The heat of shortening and the dynamic constants of muscle." Proceedings of the Royal Society of London B: Biological Sciences 126.843 (1938): 136-195.

Zajac, Felix E. "Muscle and tendon: properties, models, scaling, and application to biomechanics and motor control." Critical reviews in biomedical engineering 17.4 (1988): 359-411.

Muscle Modelling







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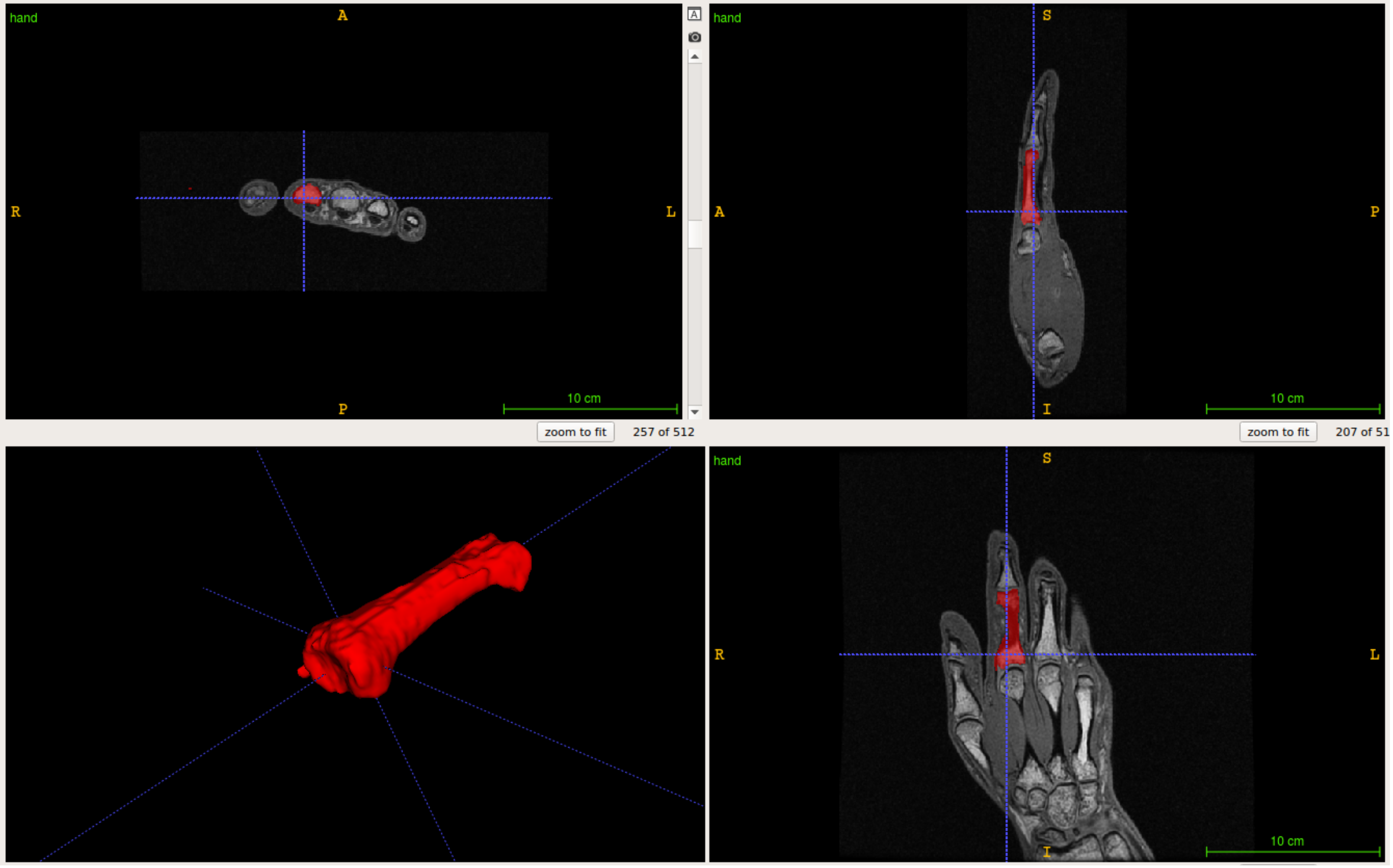
Laura Hallock

VERIFICATION: MRI



Laura Hallock

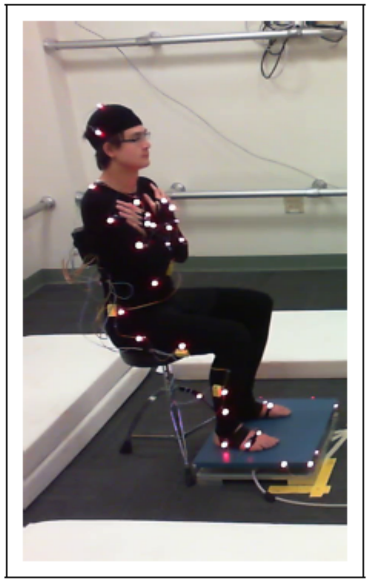
Stability of the Individual

Falling

- 2.5 million ED visits per year
- Cause over 95% of hip fractures
- Annual cost ~$34 billion

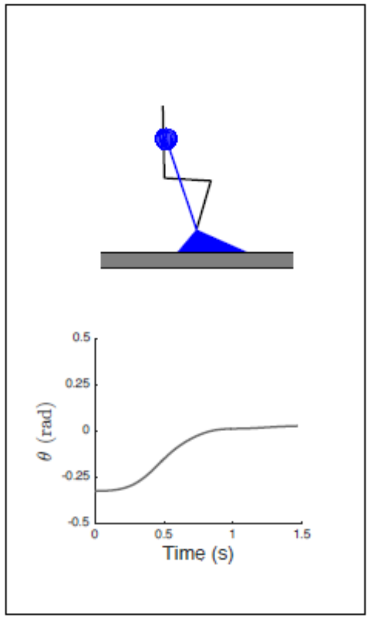
- Multiple causes for falls
- Can fall while walking
- Can fill while trying to stand
- Focusing work on Sit-to-Stand (STS) stability

Stability of the Individual



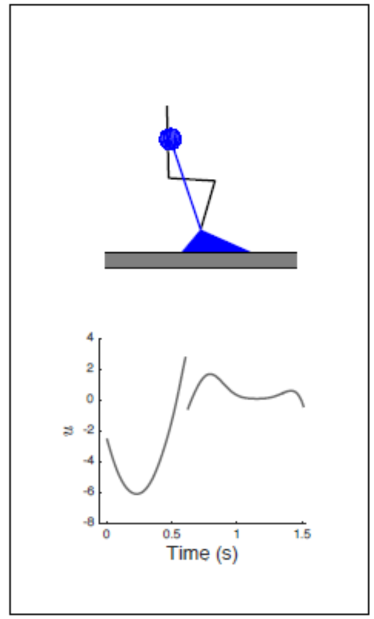
Data Collection

⇒



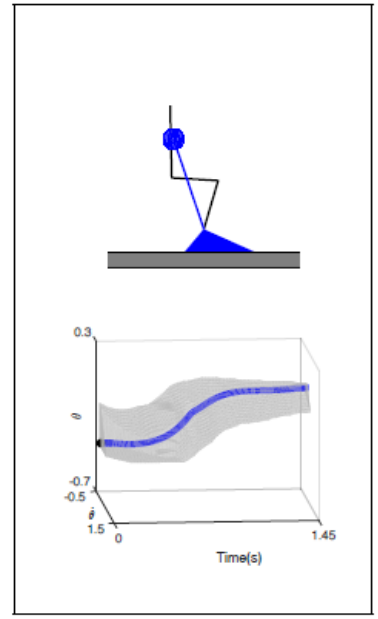
Modeling

⇒



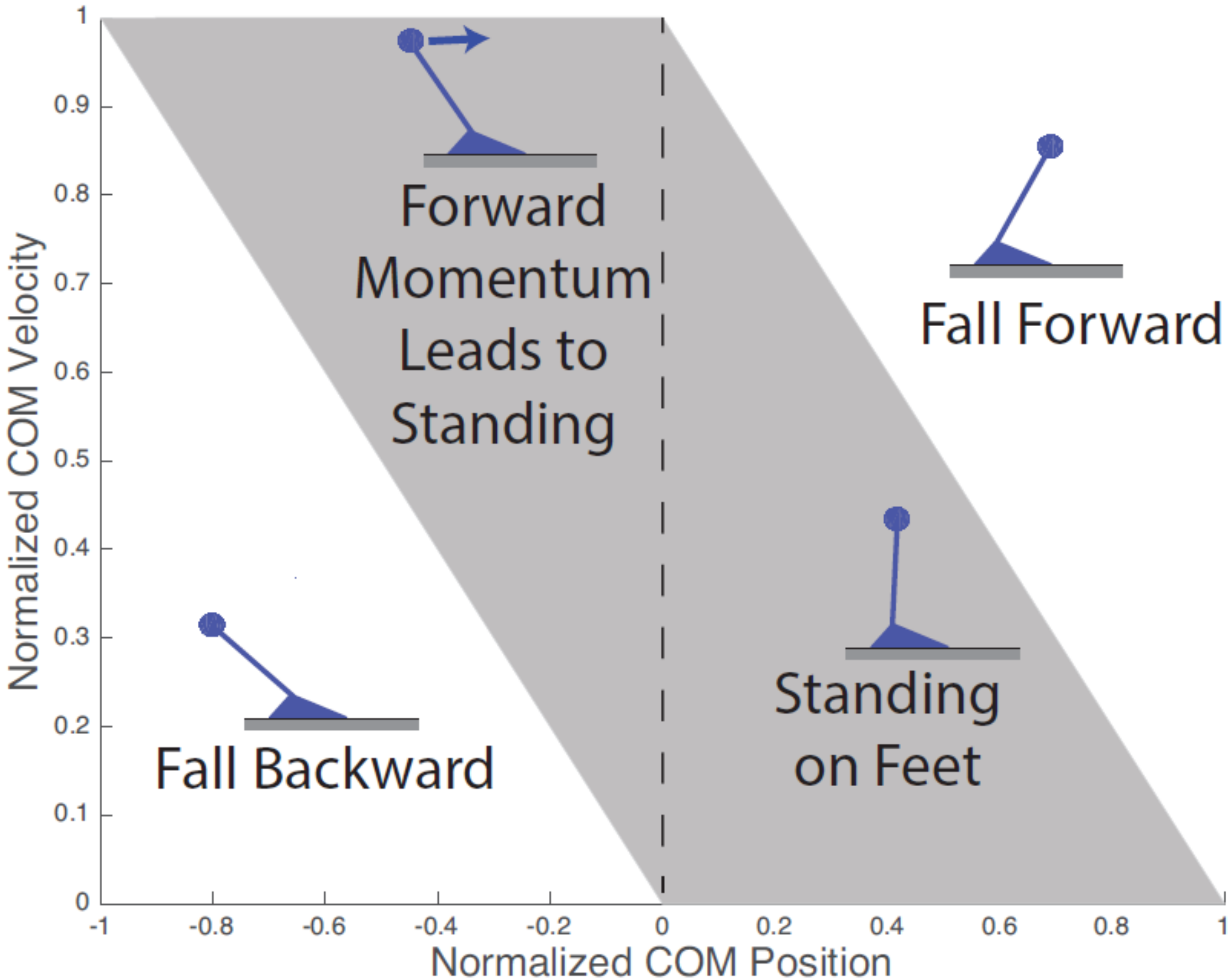
Input ID

⇒

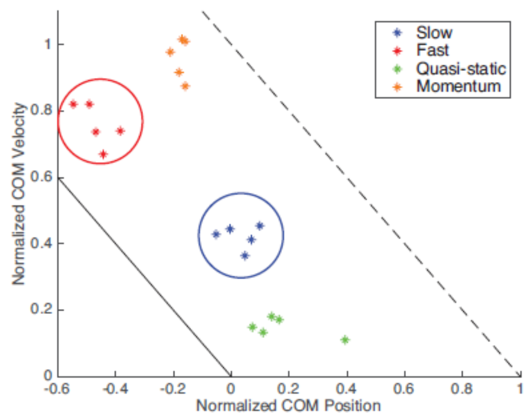


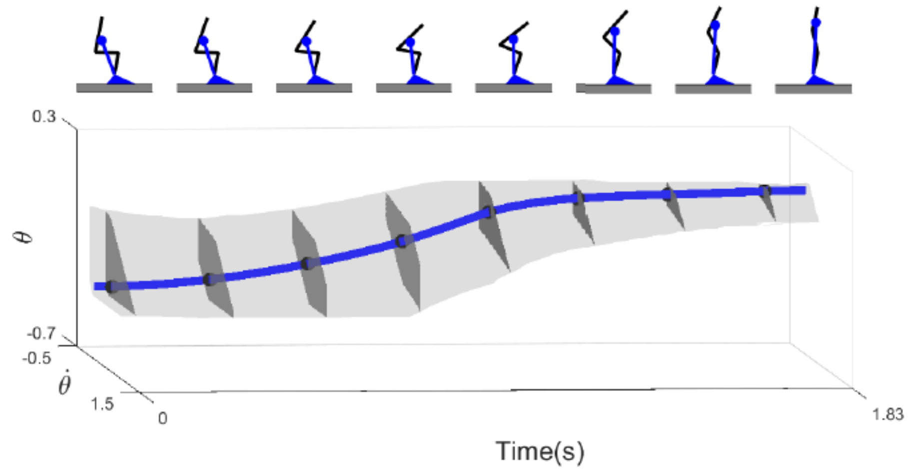
Compute BOS

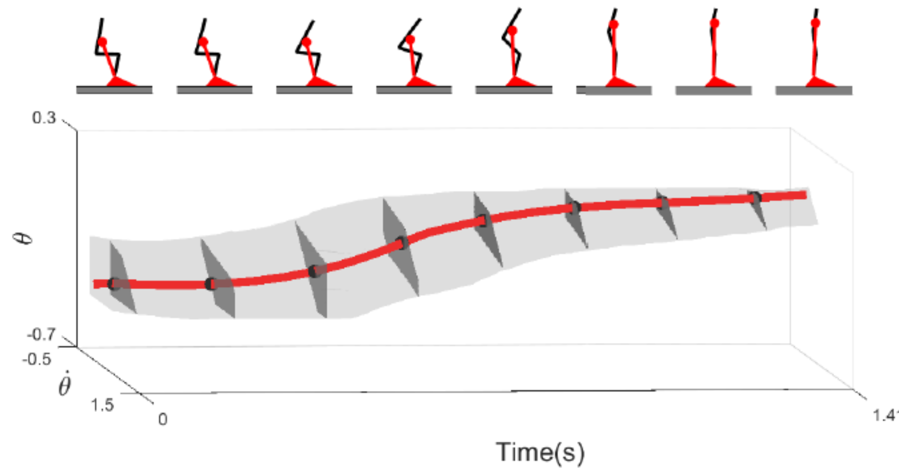
Stability of the Individual



Stability of the Individual



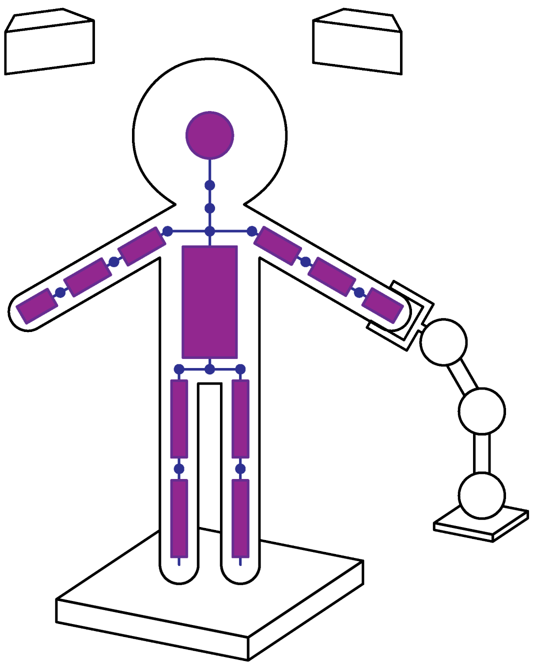




Prescription of Assistive Devices

MEASUREMENT

- Kinematics
- Dynamics

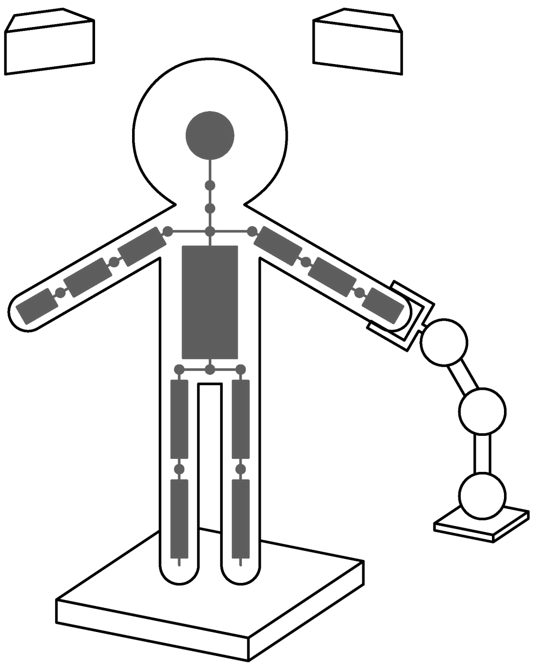


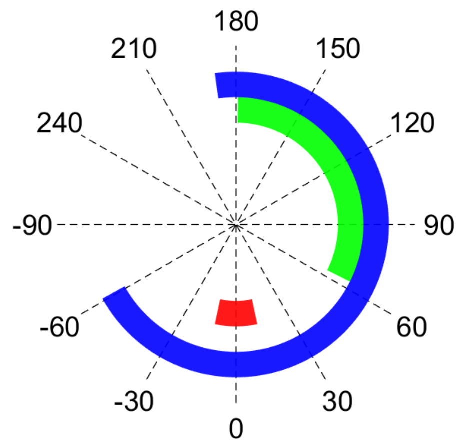
PRESCRIPTION OF ASSISTIVE DEVICES

MEASUREMENT → PRESCRIPTION

- Kinematics
- Dynamics

- Customise assistance





k=34mNm/deg

θ_0=319deg

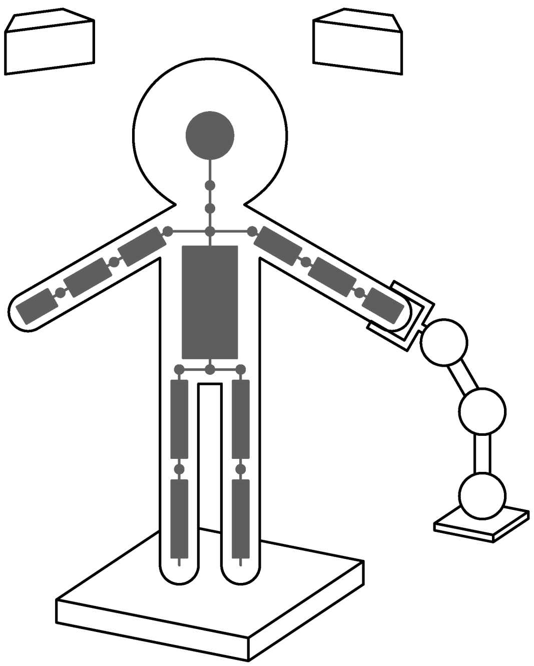
PRESCRIPTION OF ASSISTIVE DEVICES

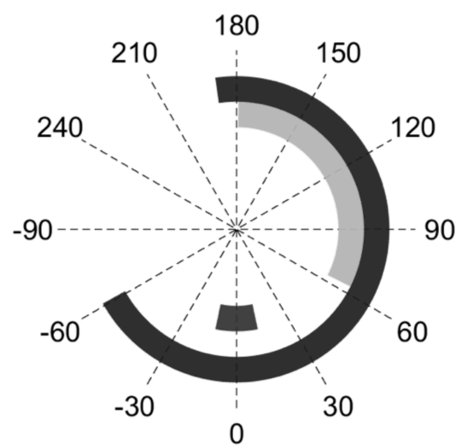
MEASUREMENT → **PRESCRIPTION** → **INTERVENTION**

- Kinematics
- Dynamics

- Customise assistance

- Optimise actuation





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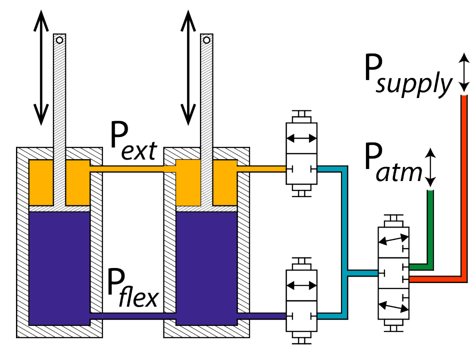
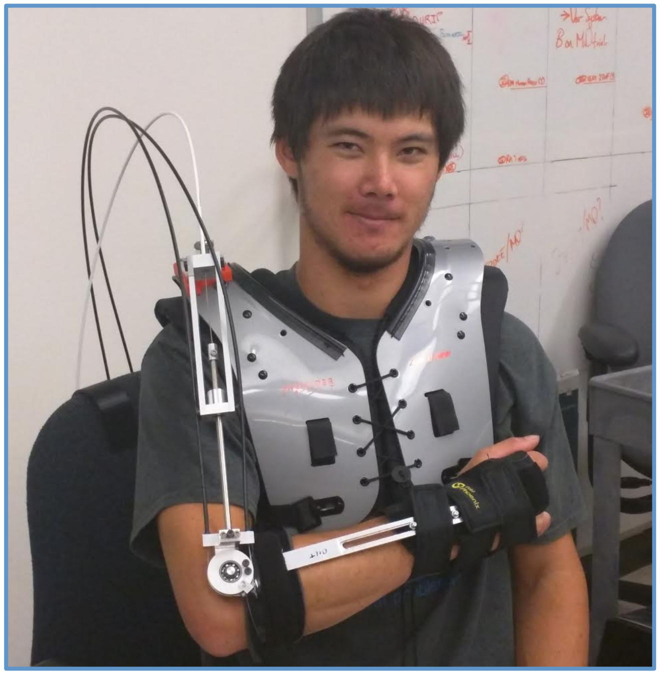


Variable stiffness actuation

PRESCRIPTION OF ASSISTIVE DEVICES

- Implement **optimal device**
  - Novel, **low-power** actuators
  - **Variable** device stiffness
  - Stiffness passively maintained: **energy only required to actively change stiffness**



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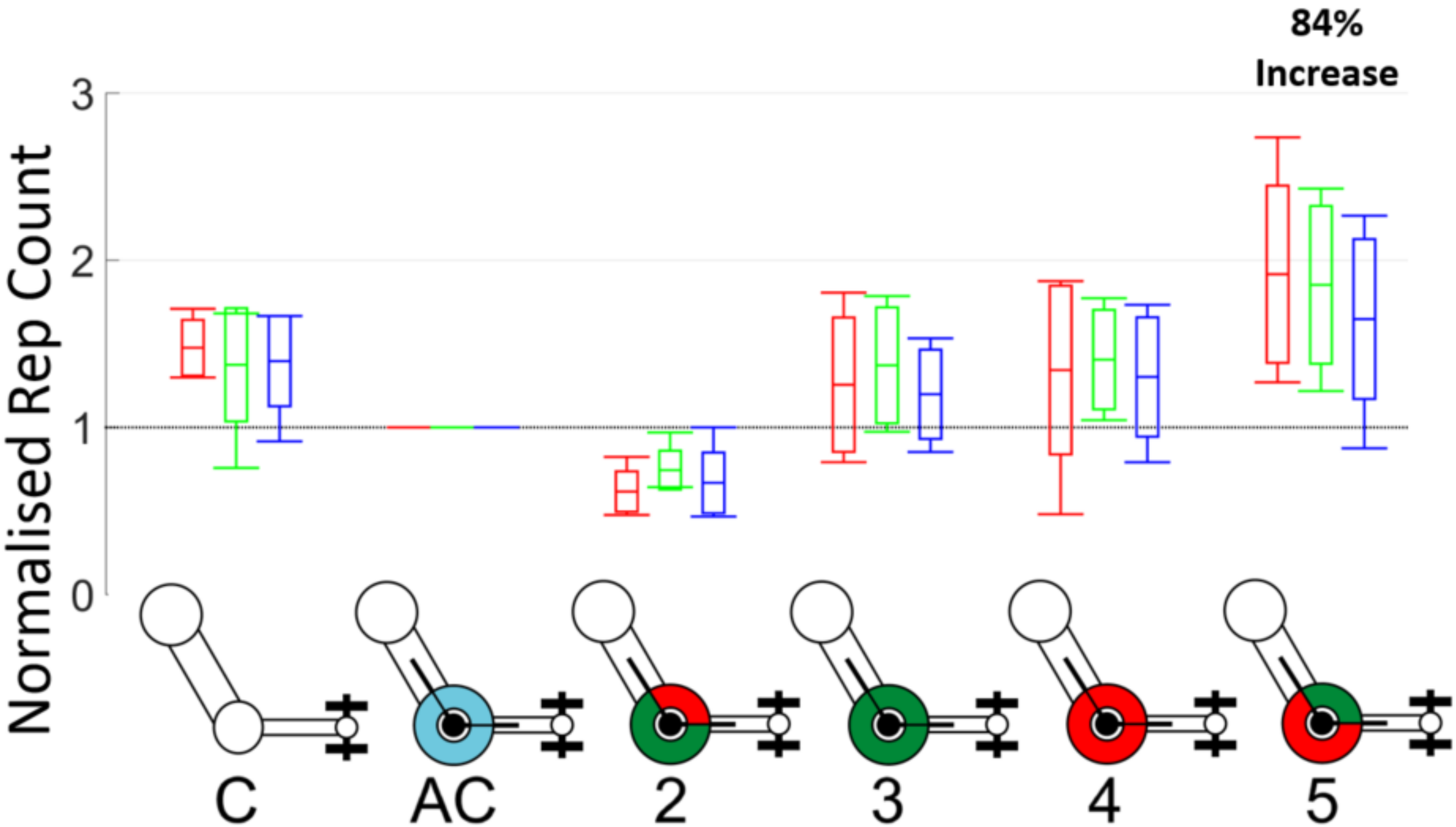
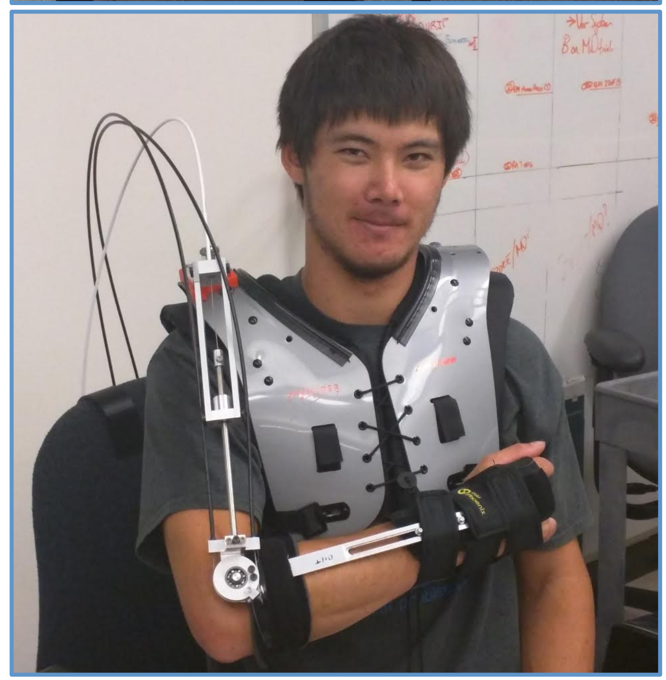
Robert Matthew

Prescription of Assistive Devices



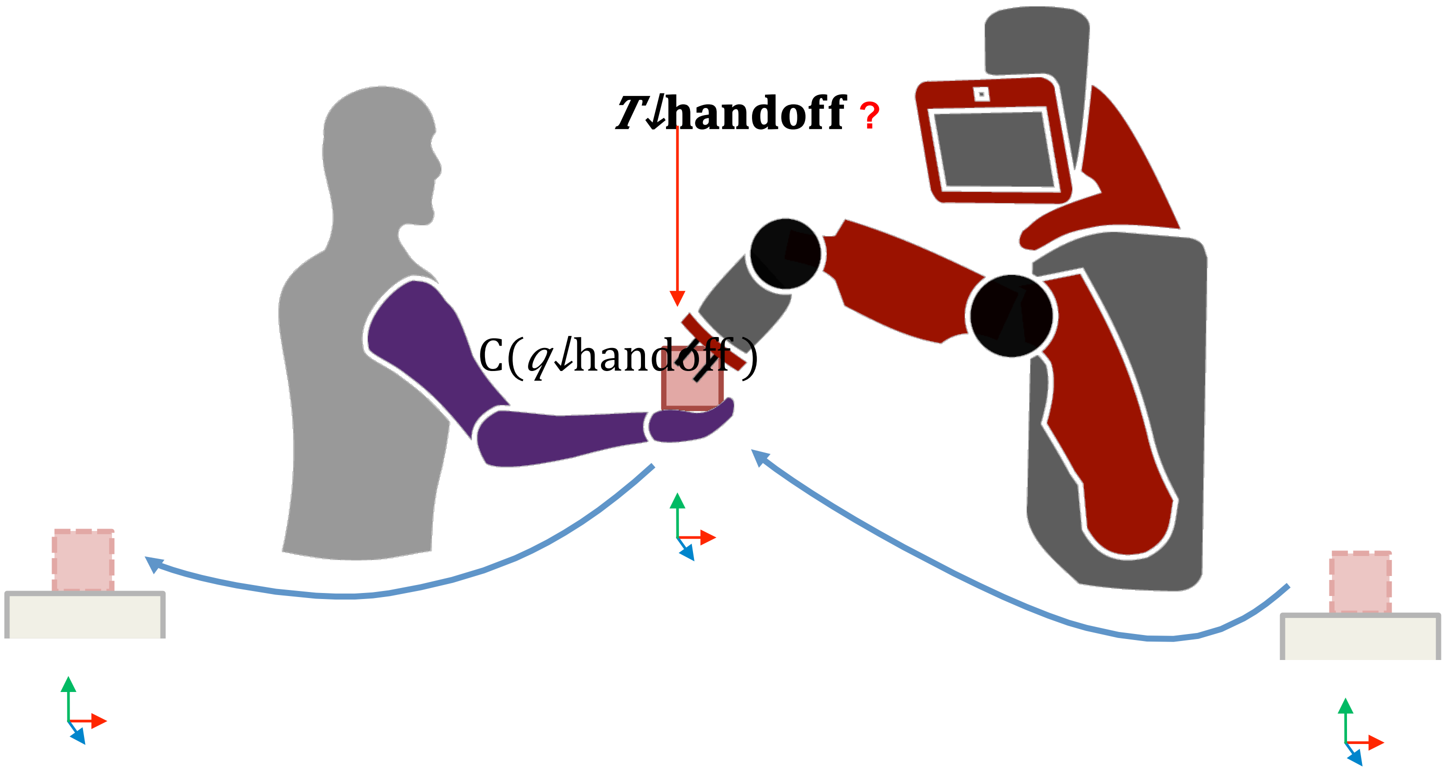
PRESCRIPTION OF ASSISTIVE DEVICES

- **Low mass**
  - 2.54kg total
  - 0.39kg on arm
- **Low power**
  - 12g CO_2
  - 9V Battery
  - no energy required during operation
- **Low cost**
  - <$1,000



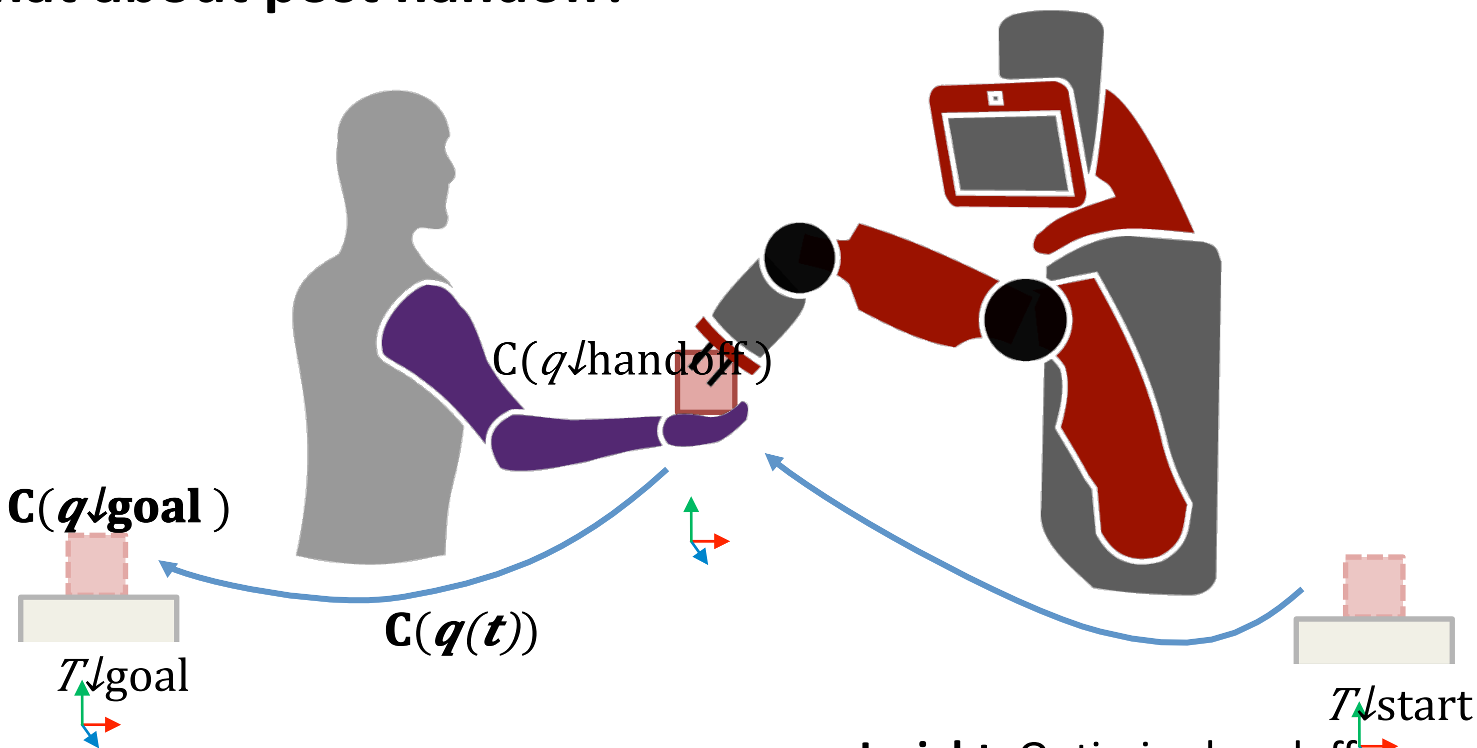
Robots: Human–Robot Interactions

Existing Work: Static handoff pose planning



Robots: Human–Robot Interactions

What about post handoff?



Problem: Human grasp affects task ergonomics post-handoff

Insight: Optimize handoff pose w.r.t. C(q_{goal}) and C($q(t)$) in addition to C($q_{handoff}$)

Idea: Optimize the *robot's* motion with respect to the *human's* ergonomic cost function

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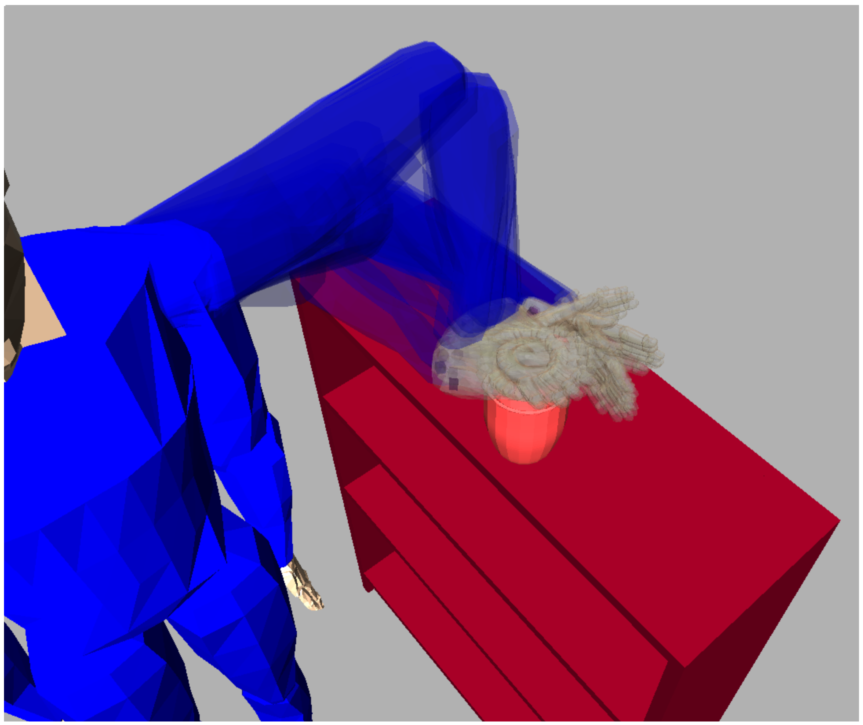
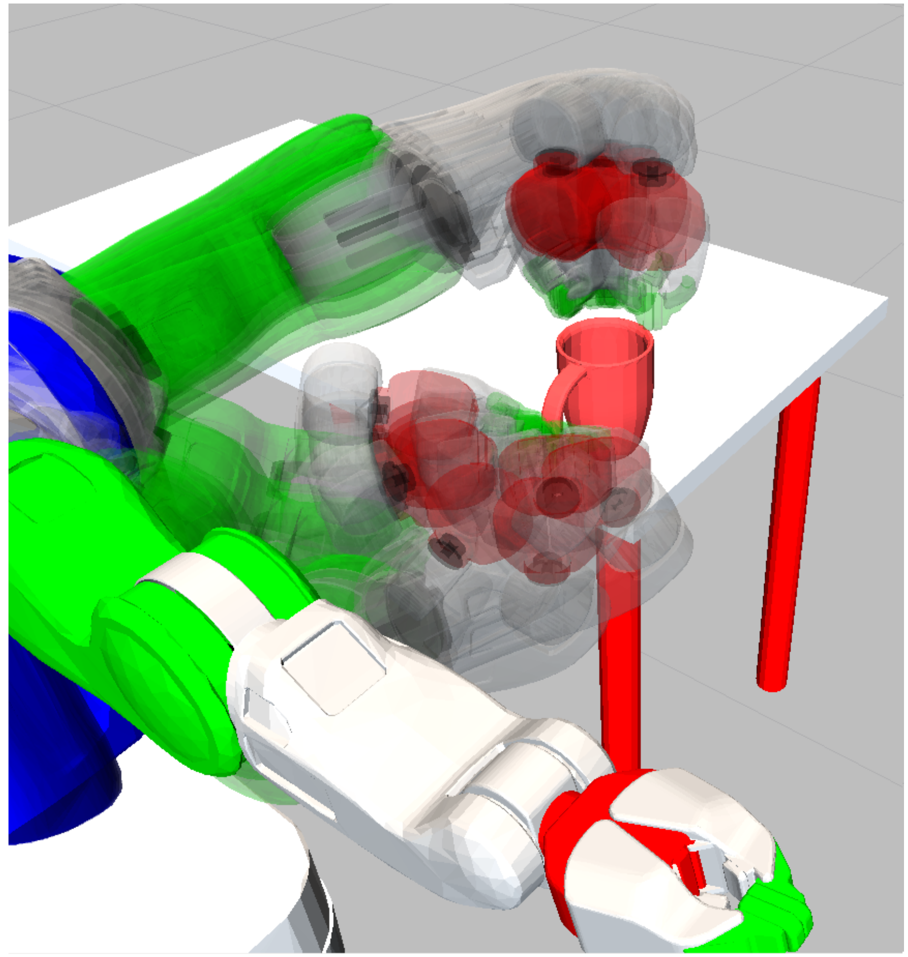
Aaron Bestick

ROBOTS: HUMAN–ROBOT INTERACTIONS

Step 1: Sample Start/End Goals



$G\downarrow H$

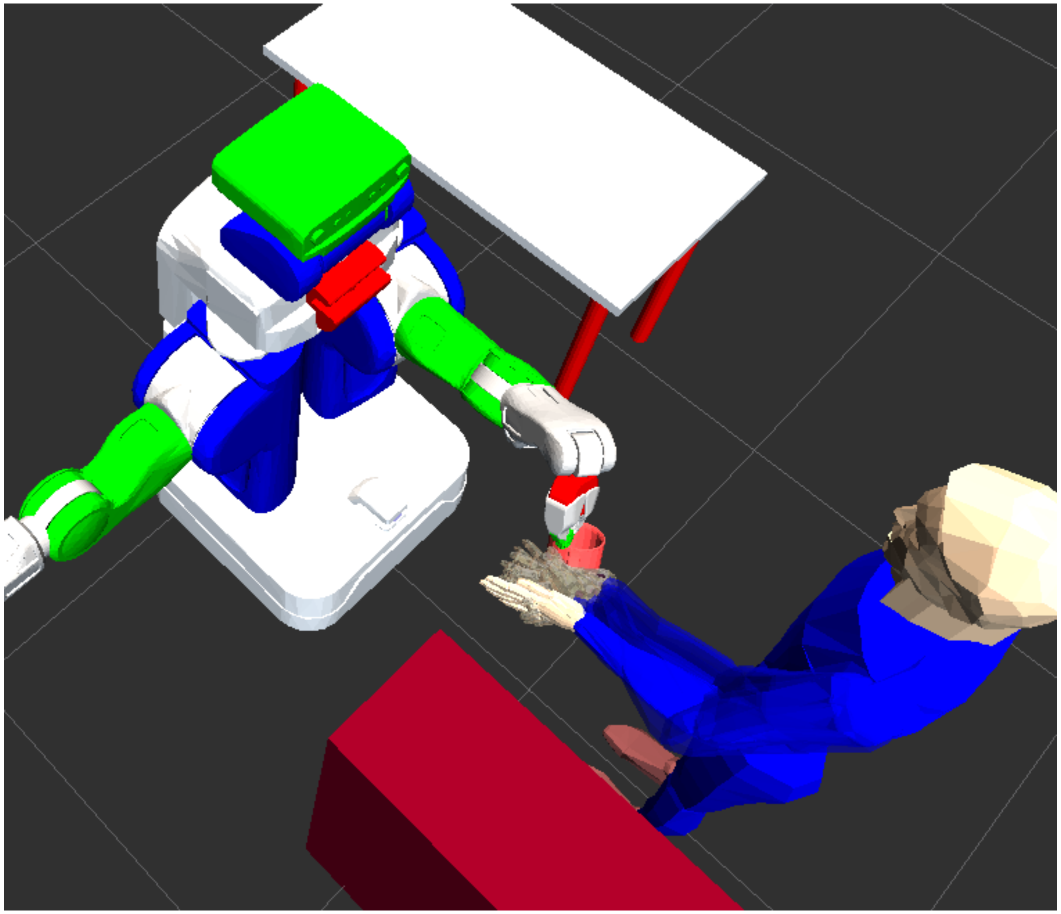


$G\downarrow R$

ROBOTS: HUMAN–ROBOT INTERACTIONS

Step 2: Find feasible human grasps

Compute H
$\forall\ g_R \in G_R,$
$\forall\ T_{handoff}^{w} \in SE(3)$



$H(g_R, T_{handoff}^{w})$

Robots: Human–Robot Interactions

Step 3: Find optimal handoff pose

Choose the optimal g_r and T_{handoff}^{w} according to:

1) $\max |H(g_R, T_{\text{handoff}}^{w})| \;\; s.t. \;\; h^* \in H$ (most options and allows ergonomically optimal choice)

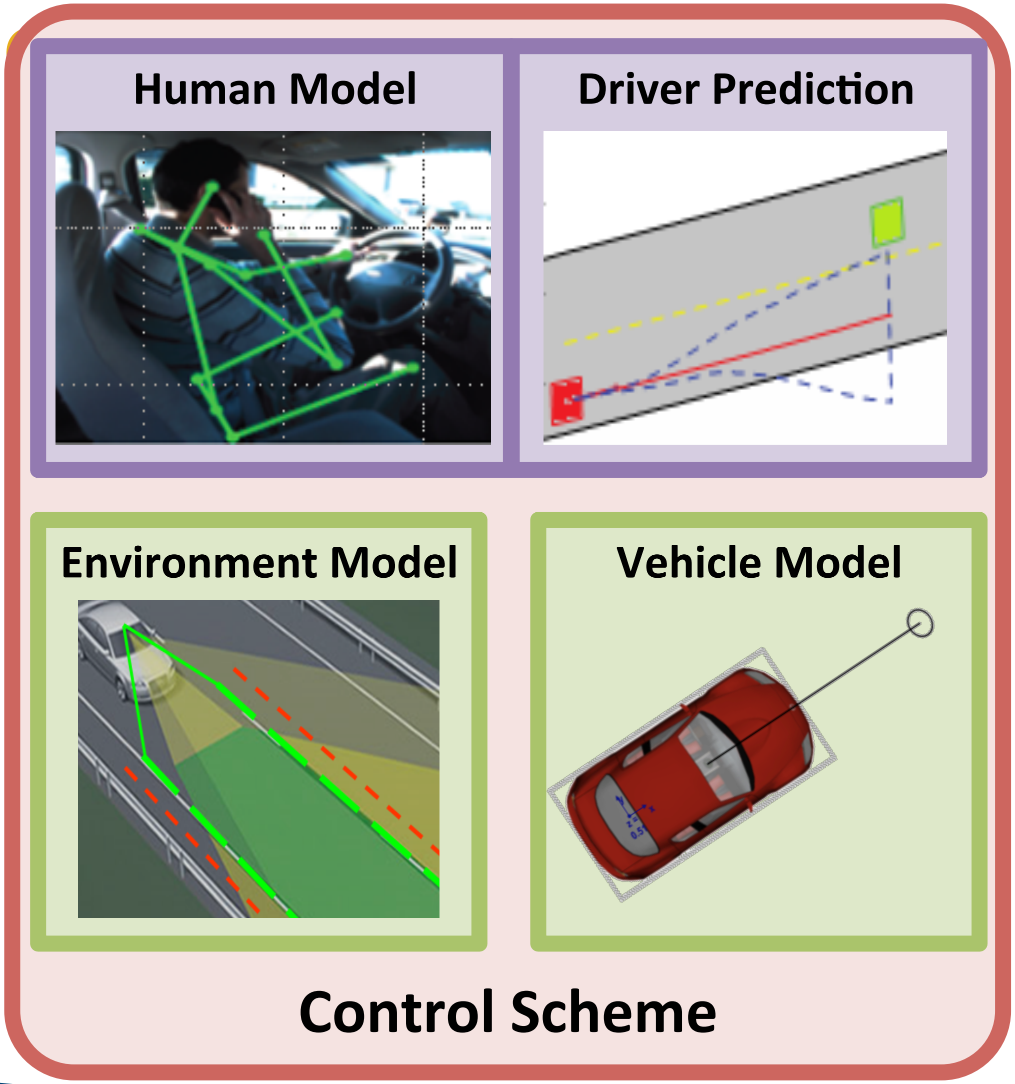
2) $\min |H(g_R, T_{\text{handoff}}^{w})| \;\; s.t. \;\; h^* \in H$ (least options and allows ergonomically optimal choice)

3) $\max |H(g_R, T_{\text{handoff}}^{w})|$ (most options)

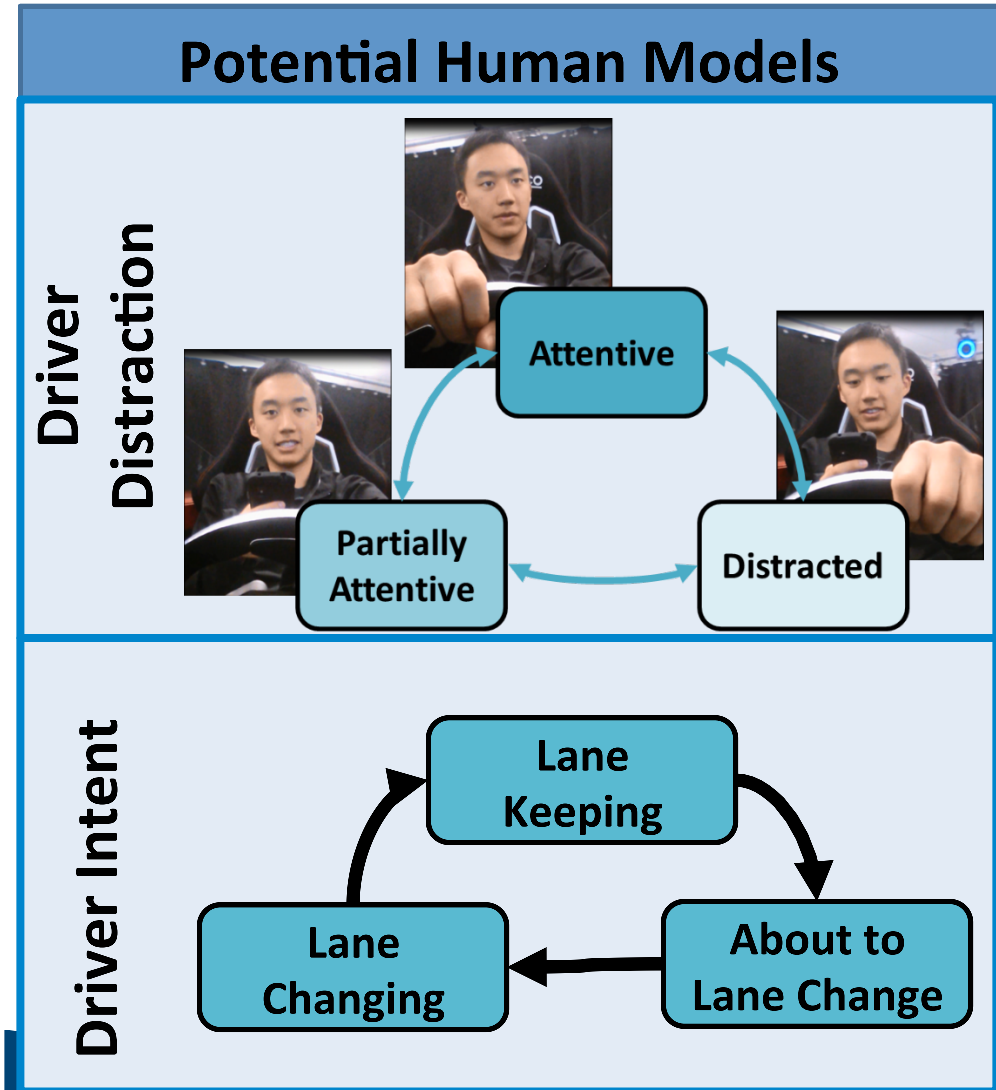
4) $\min \sum_{h \in H(g_R, T_{\text{handoff}}^{w})} C(h) / |H(g_R, T_{\text{handoff}}^{w})|$ (minimum average ergonomic cost)

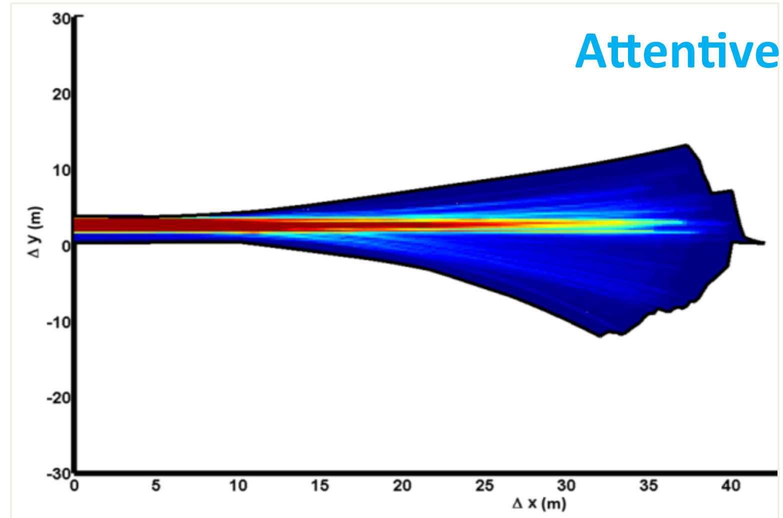
Driving: Human in the loop

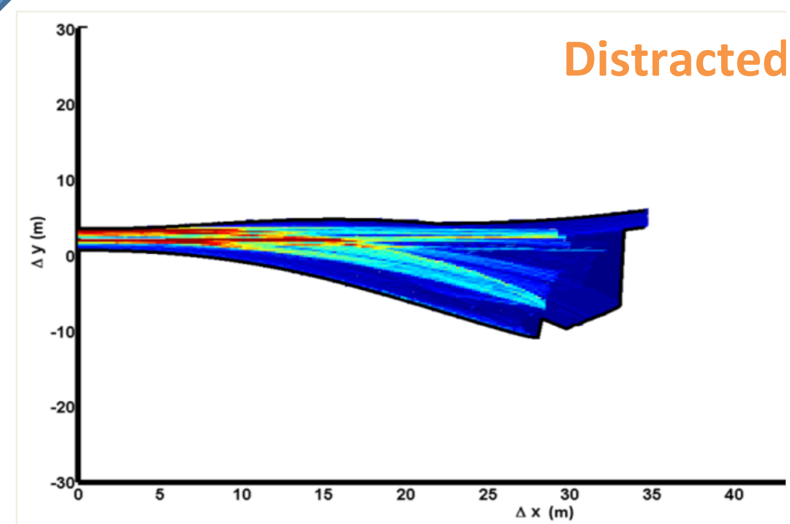
Interventi



Driving: Predicting Behavior





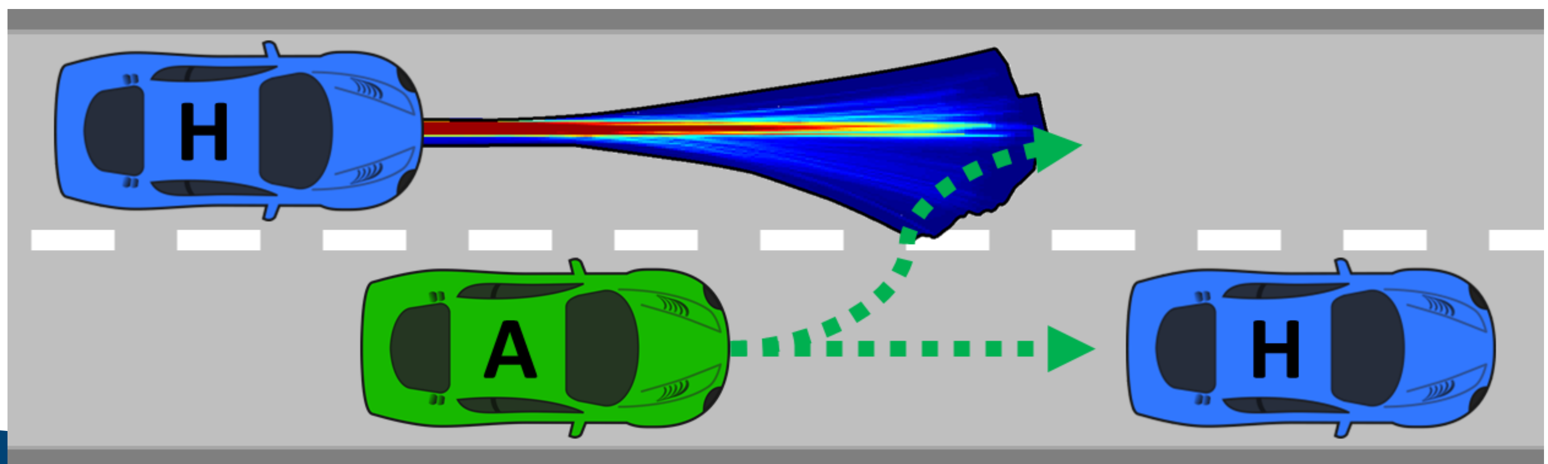


Driving: Agent Interactions

$$\operatorname{argmin}_{\Delta \subset \mathbb{R}^n} \quad |\Delta_H|$$

subject *to* $\quad P[(X_H(k) - x_H(0)) \subset \Delta_H(\mathcal{O},\mathcal{I}) \mid s_A] \geq \alpha$

$\quad \forall k \in \{0, \dots, N\}$



Thank You

HART Lab

Human-Assistive Robotic Technologies

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