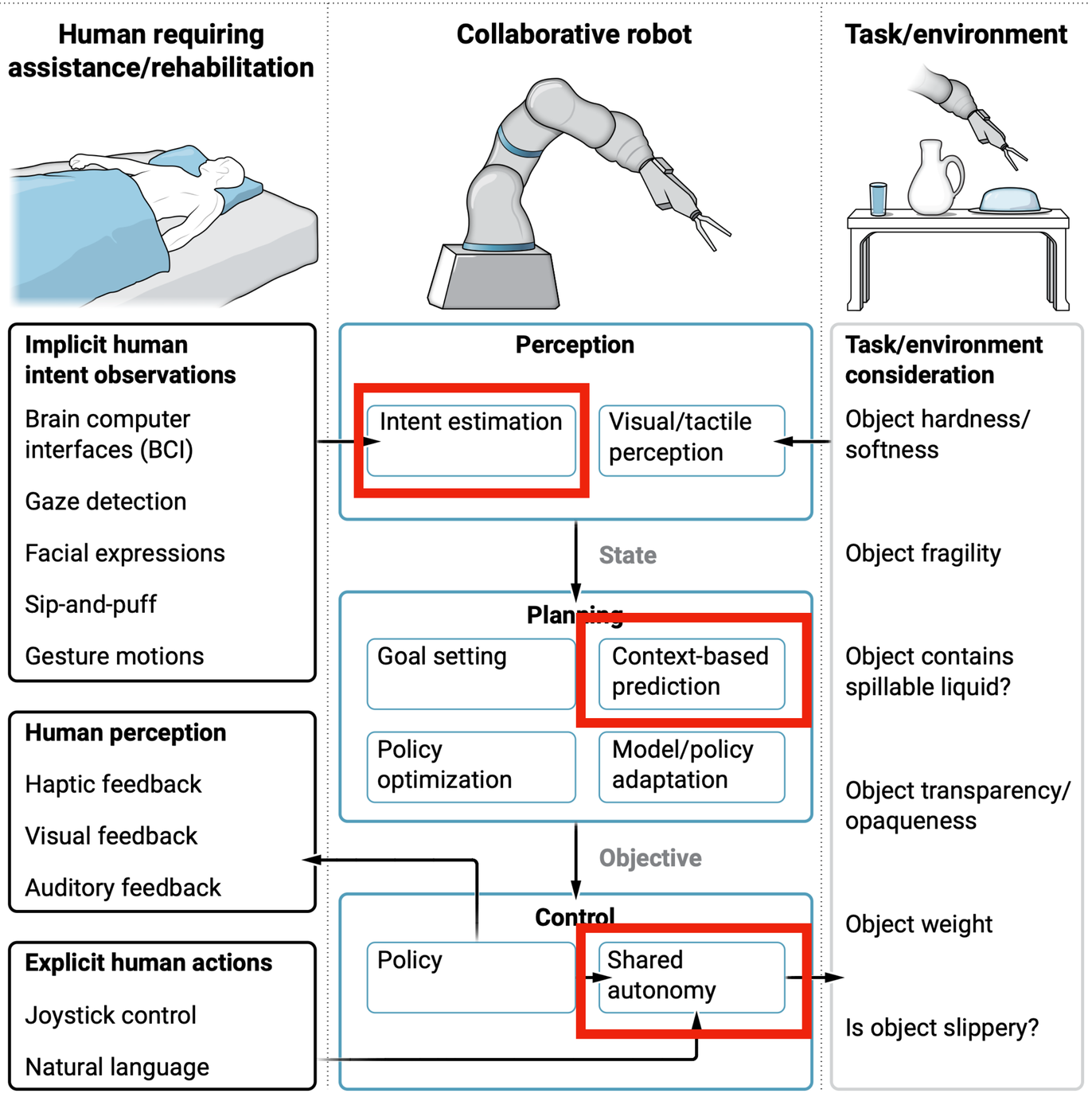
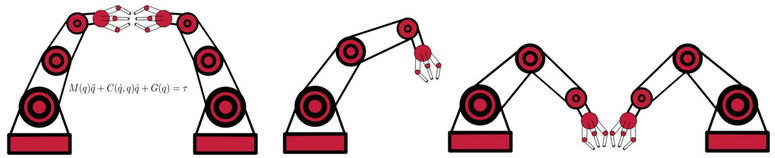
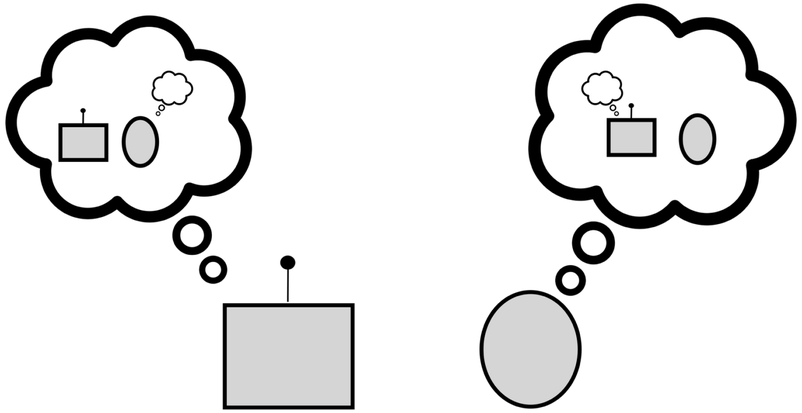
# Assistive Robotics

Prof. Monroe Kennedy III  Assistive Robotics and Manipulation Laboratory, Stanford University



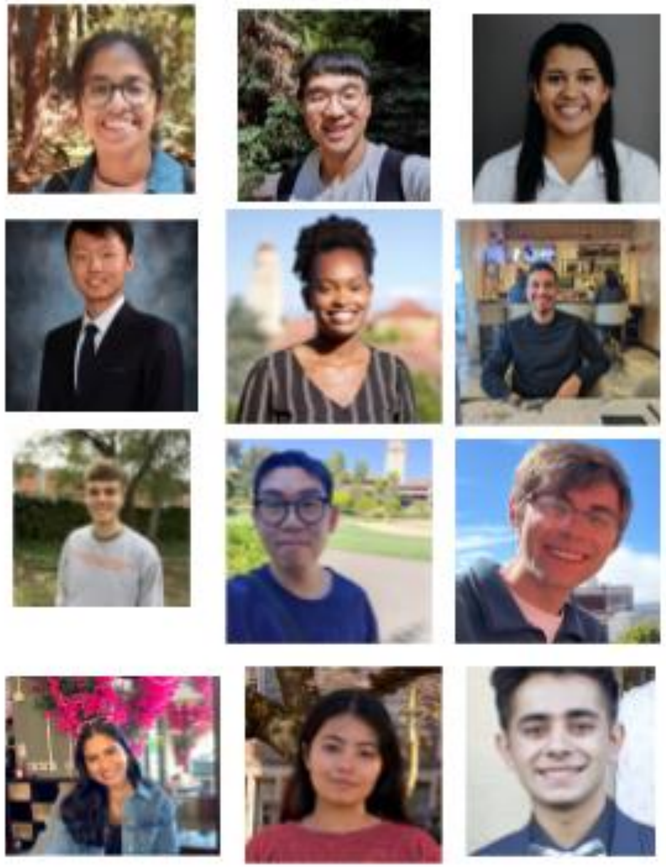

**Assistive Robotics and Manipulation Laboratory**



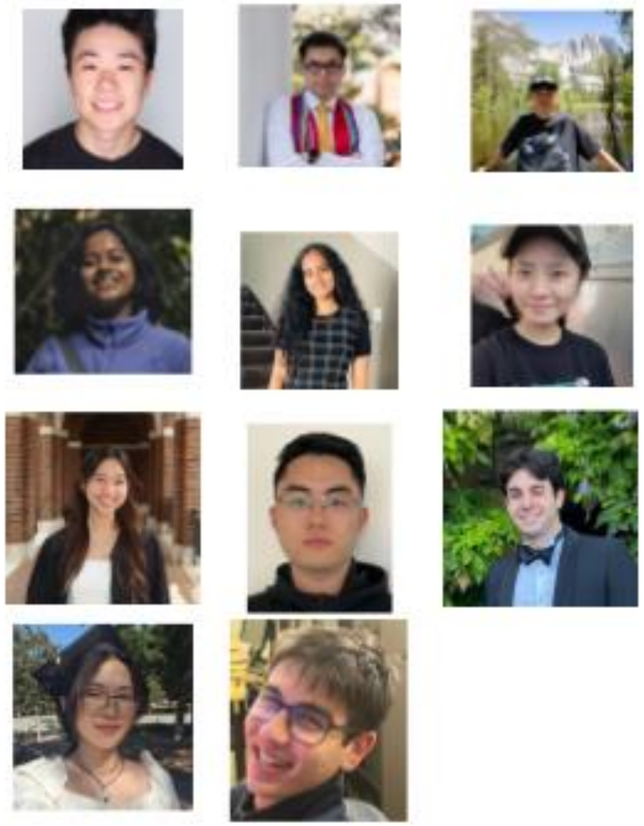
**Collaborative Interaction**

# ARMLab Researchers

PhD



Masters

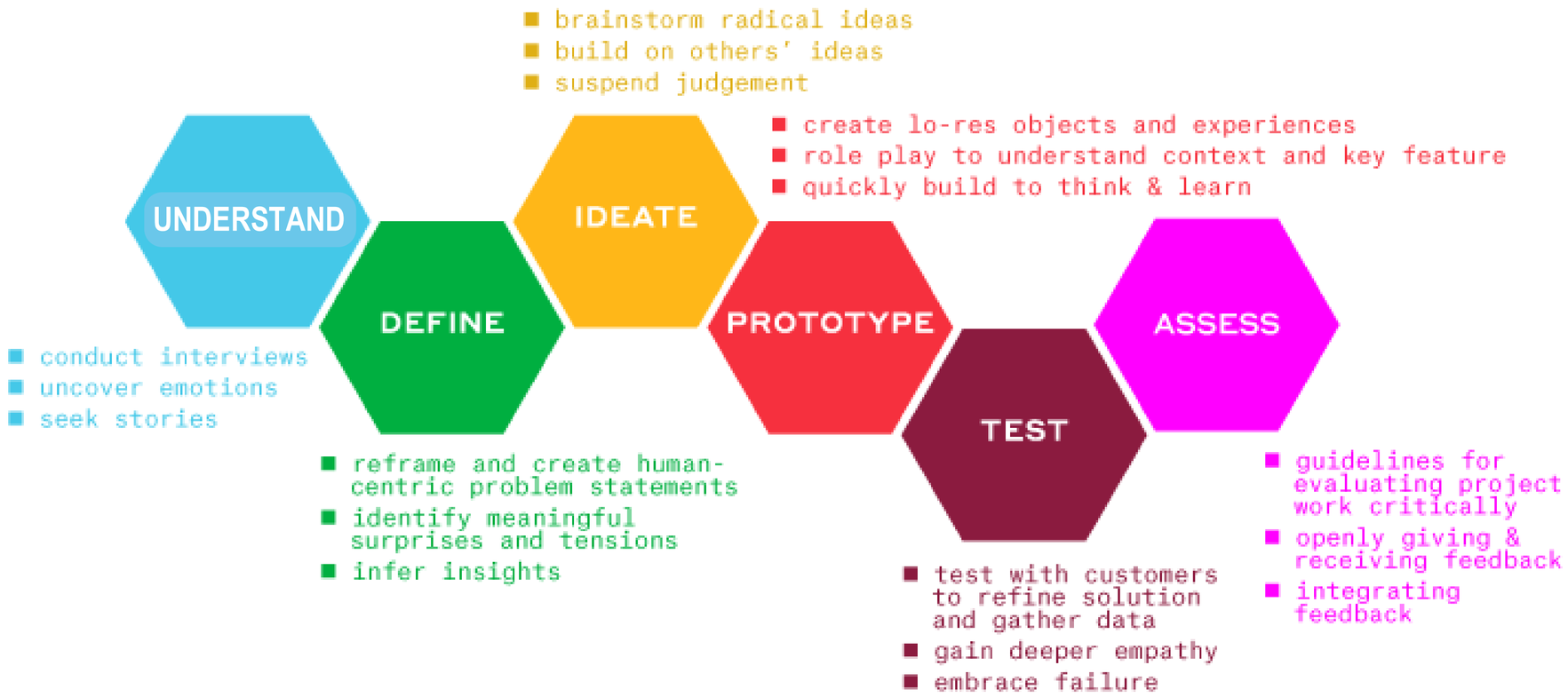


Undergraduates



# Passive versus Active Assistive Devices

# Assistive Technology Design Process




**d.school Executive Education**

Hasso Plattner Institute of Design at Stanford University

*not necessarily linear, apply as needed ©2019

# Assistive Technology

## Passive Devices - Body Powered



Arm Dynamics: https://www.armdynamics.com/upper-limb-library/introduction-to-body-powered-prostheses

# Assistive Technology

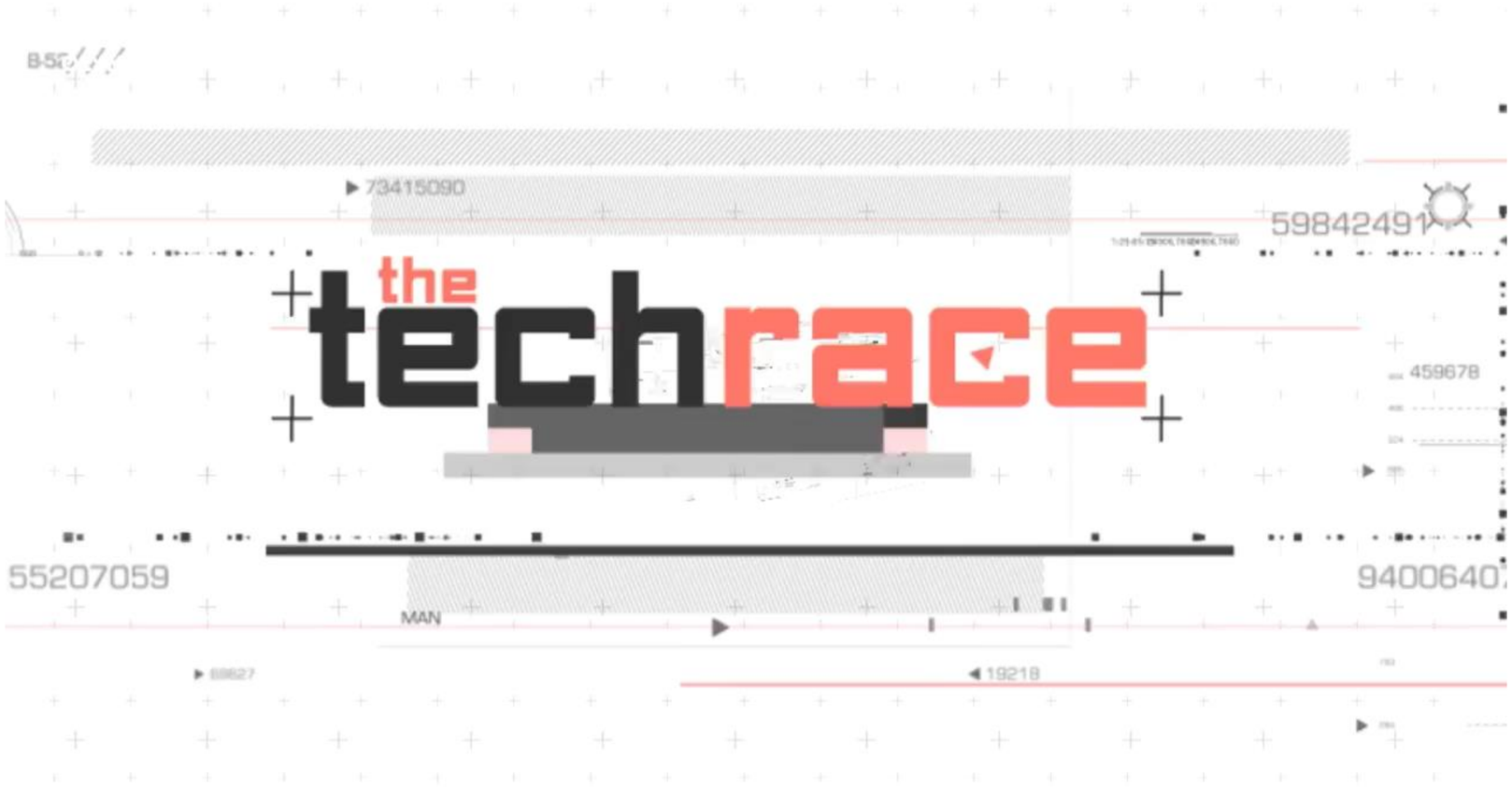
## Passive Devices - Body Powered




https://youtu.be/EodwiLAR3qI (0-40s)

# Assistive Technology

## Passive Devices - Body Powered



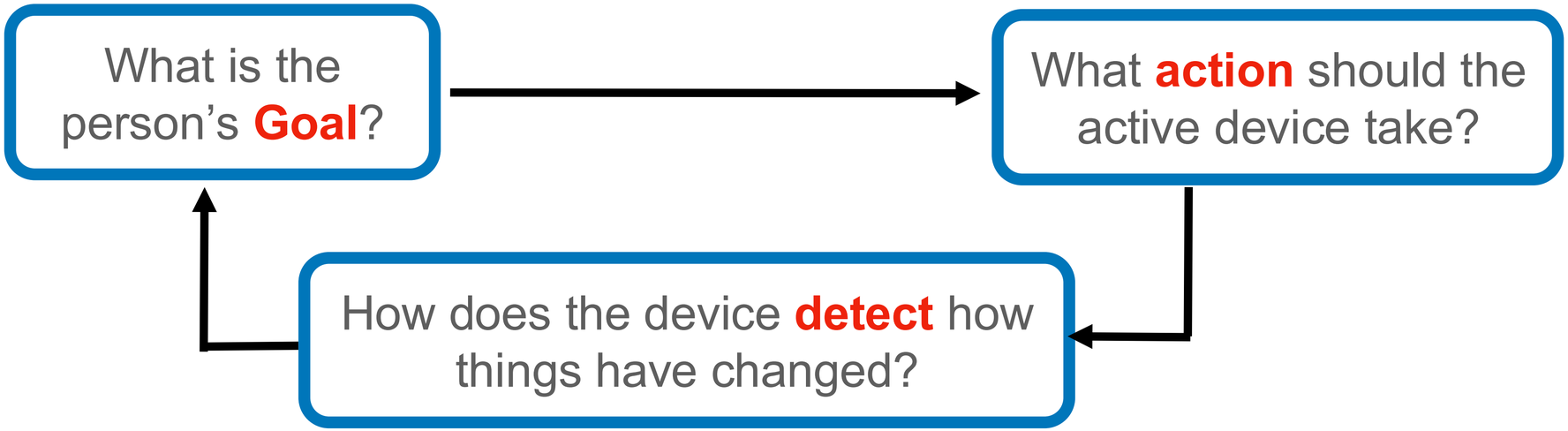

Carbon Fiber Reinforced polymer for running prosthesis

https://youtu.be/42ml6kDvPeE (0-30s)

# Assistive Technology

## Active Devices

What do you do when input does not *passively* map to the desired output/action/result?
Active Control Devices must be employed to reach the target result



# Assistive Technology

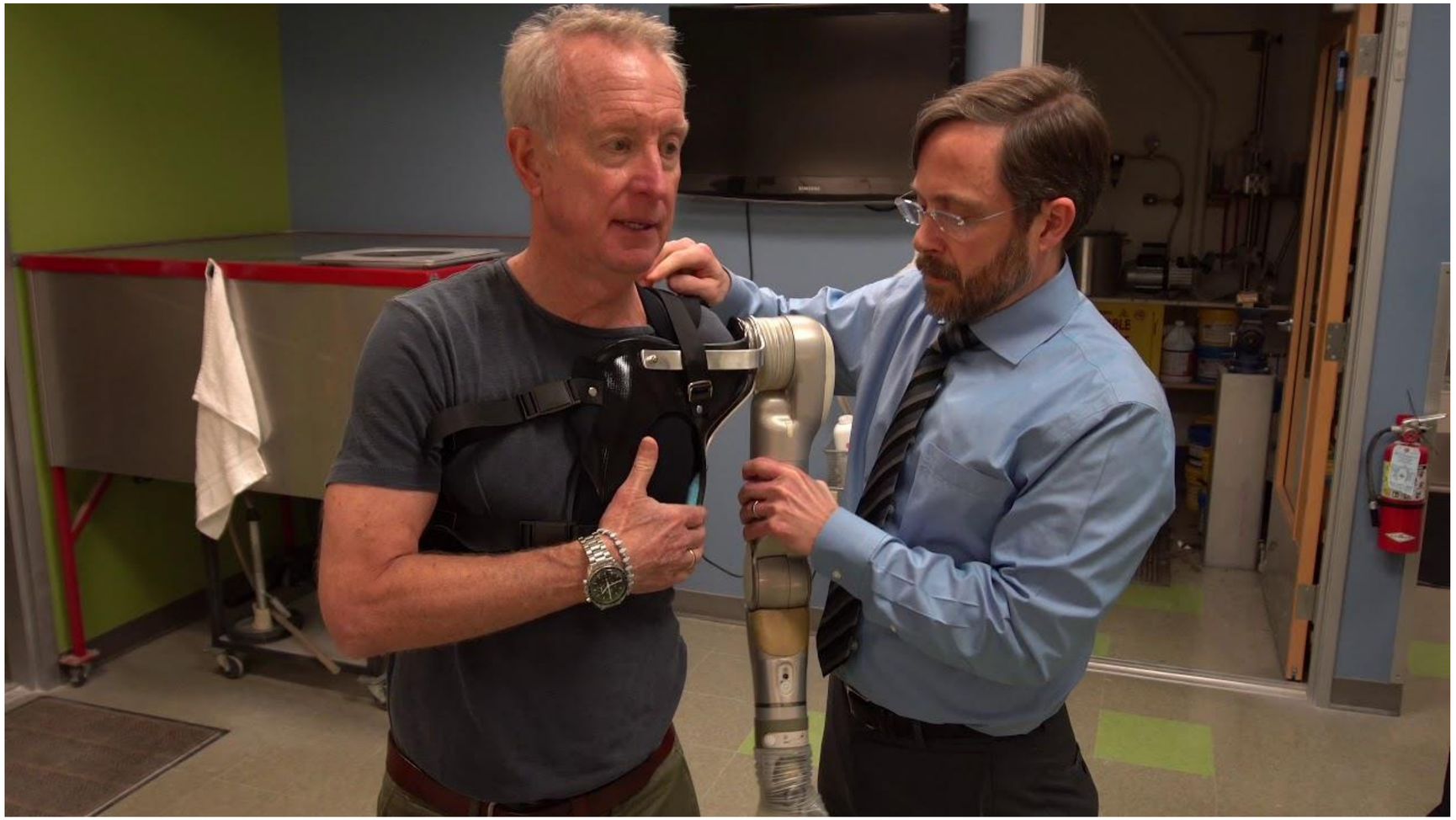
## Active Devices



LiftWare: https://www.liftware.com/; YouTube link: https://youtu.be/YNwfXeLlqsU

# Assistive Technology

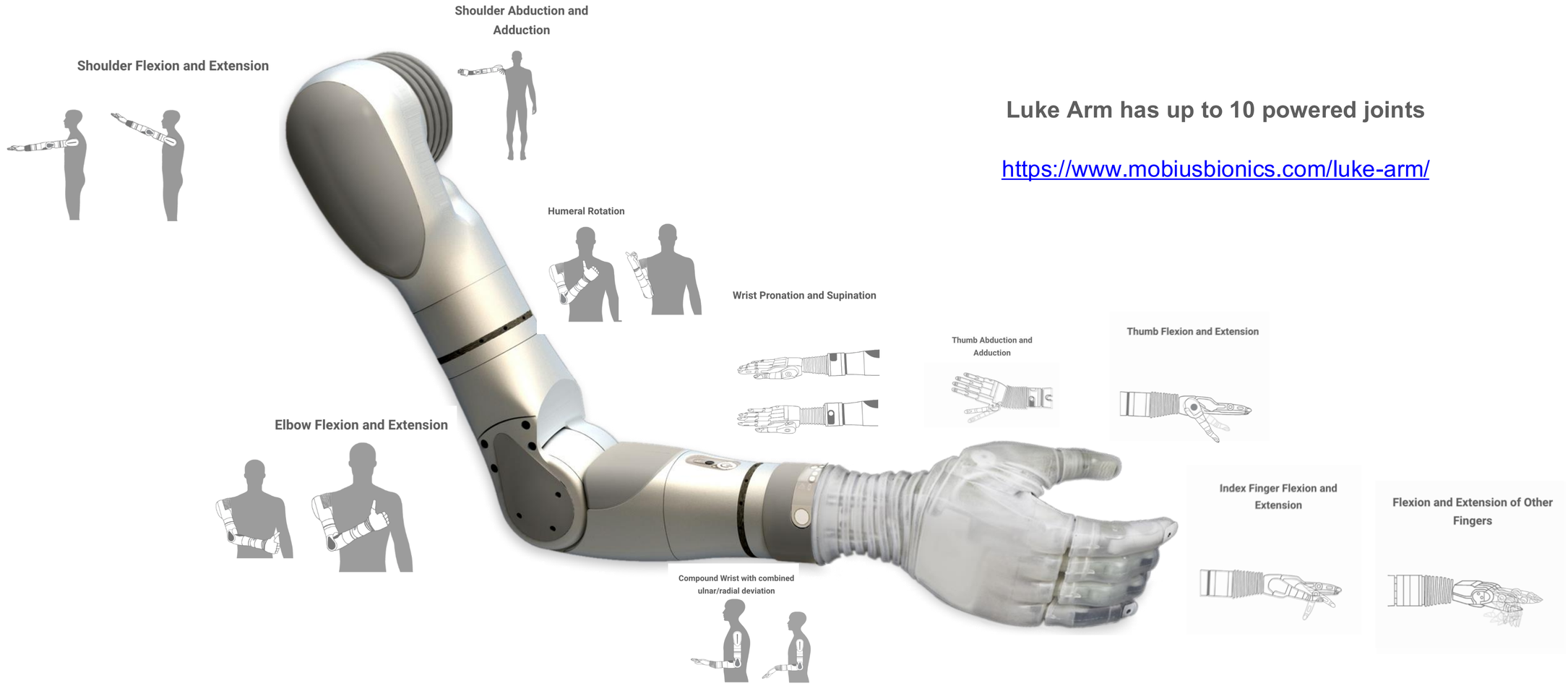
## Active Devices - Luke Arm (Mobius Bionics)



https://www.mobiusbionics.com/luke-arm/. Youtube: https://youtu.be/QGPEmtwGqZA

# Assistive Technology

## Active Devices - Luke Arm (Mobius Bionics)




**Luke Arm has up to 10 powered joints**

https://www.mobiusbionics.com/luke-arm/

# Assistive Technology

## Active Devices - Modular Prosthetic Limb (MPL) Johns Hopkins APL



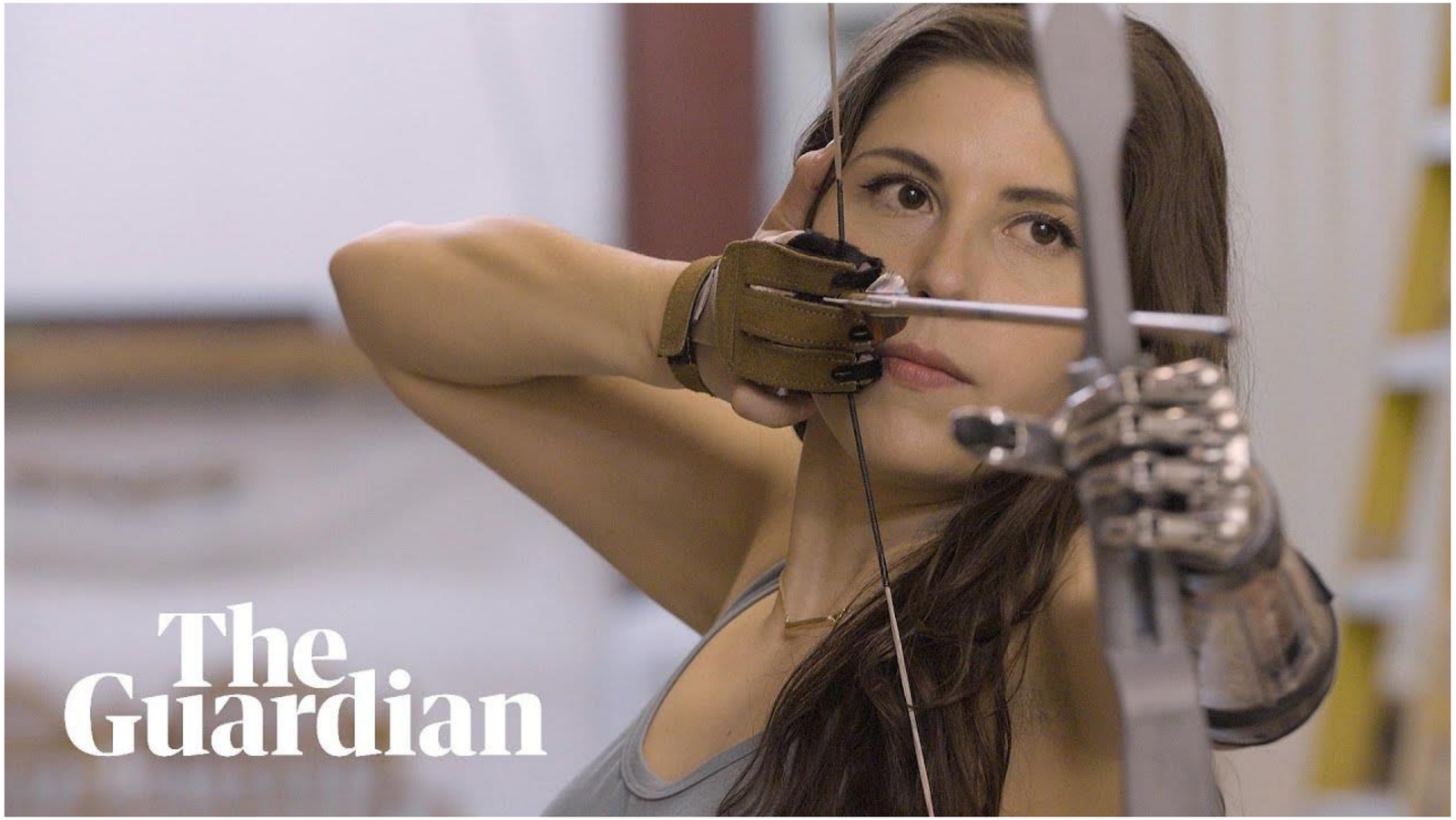

https://www.jhuapl.edu/Prosthetics/ResearchMPL YouTube: https://youtu.be/F_brnKz_2tI (0-1:30)

**An Overview of the Developmental Process for the Modular Prosthetic Limb** Johannes et al. Johns Hopkins tech digest 2011

# Limitations of Existing Assistive Technology

Traditionally, increased functionality has required a degree of invasive procedures to extract human input (e.g. Targeted Muscle Reinnervation (TMR: for motor control); or  Target Sensory Reinnervation (TSR: for sensory feedback)

Is there a way to maintain functionality but reduce invasiveness?



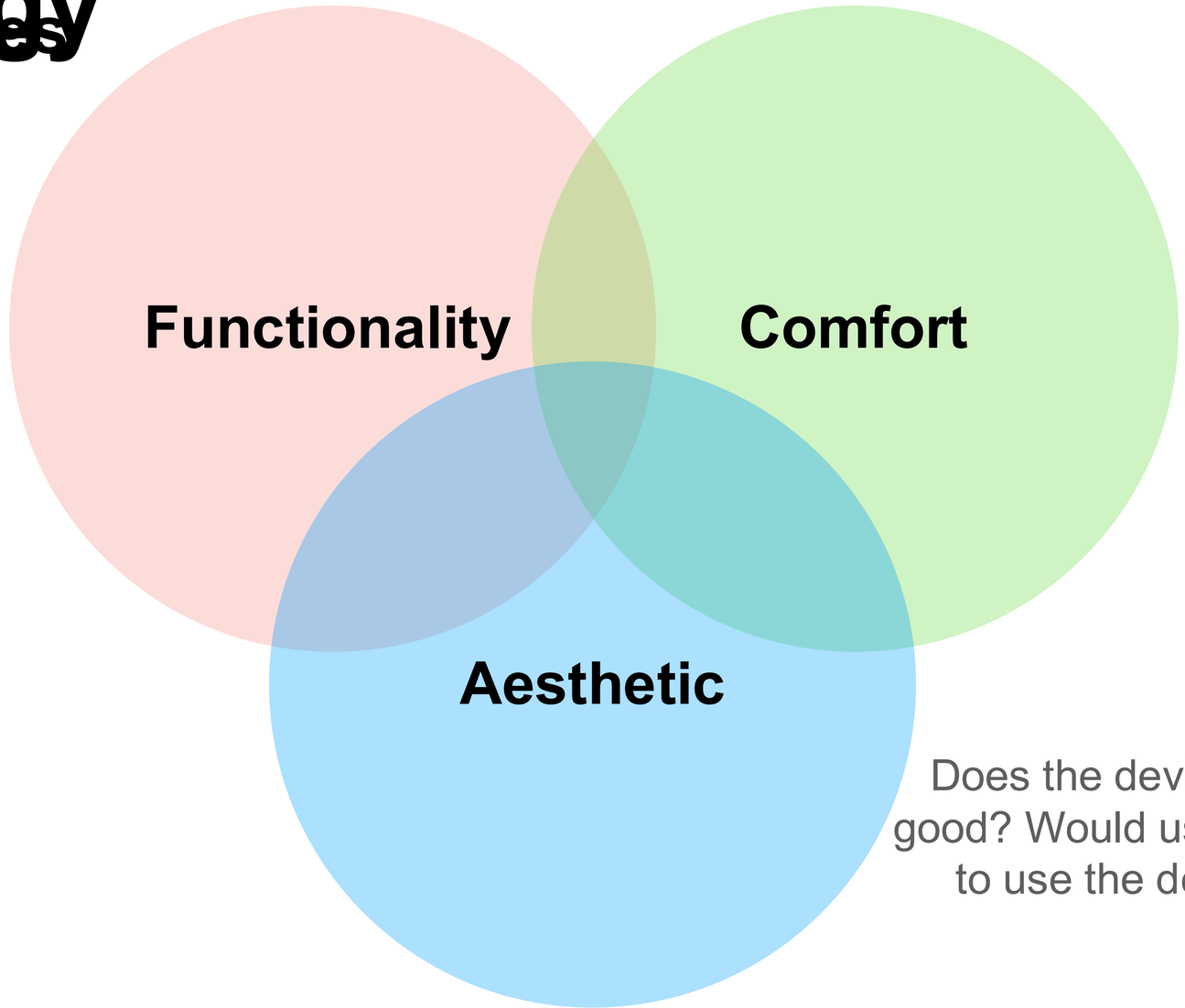

https://youtu.be/GgTwa3CPrIE?t=791. (13:15 - 13:41)

# Limitations of Existing Assistive Technology

## Design priorities

Does the system perform as desired and make it worth use?

Do solutions need to be severely tailored to every case or can an adaptable solution be devised?




Is it comfortable for users?

Does the device look good? Would users want to use the device?

# Limitations of Existing Assistive Technology

## Design priorities

User Dissatisfaction with upper-limb prosthesis

Table II. Prosthesis rates of use and rejection.

| Prosthesis | Currently used | Previously used | Rejection Rate | Primary Prosthesis | Interested in future use |
|---|---|---|---|---|---|
| *Adults* | | | | | |
| Passive hook | 5 | 19 | 74% | 2% | 1% |
| Passive hand | 33 | 62 | 47% | 18% | 10% |
| Body-powered hook | 43 | 87 | 51% | 32% | 2% |
| Body-powered hand | 15 | 43 | 65% | 3% | 3% |
| Electric hook | 13 | 21 | 38% | 3% | 13% |
| Electric gripper | 10 | 24 | 58% | 1% | 10% |
| Electric hand | 58 | 98 | 41% | 41% | 26% |
| Other | 11 | 19 | 42% | – | 11% |
| None | – | – | – | – | 25% |
| *Pediatric* | | | | | |
| Passive hook | 2 | 3 | 33% | 6% | 0% |
| Passive hand | 18 | 46 | 61% | 23% | 10% |
| Body-powered hook | 12 | 23 | 48% | 14% | 2% |
| Body-powered hand | 9 | 17 | 47% | 15% | 7% |
| Electric hook | 0 | 0 | – | 0% | 8% |
| Electric gripper | 0 | 2 | 100% | 0% | 7% |
| Electric hand | 27 | 42 | 36% | 42% | 33% |
| Other | 5 | 14 | 64% | – | 7% |
| None | – | – | – | – | 26% |

Elaine Biddiss, Dorcas Beaton & Tom Chau (2007) Consumer design priorities for upper limb prosthetics, Disability and Rehabilitation: Assistive Technology, 2:6, 346-357, DOI: 10.1080/17483100701714733

# Limitations of Existing Assistive Technology

## Design priorities

Myoelectric versus Body-Powered devices for

- Sensory feedback
- Functionality
- Usage
- Comfort

Table III. Claimed merits of body-powered and myoelectric prostheses.

| | Myoelectric (ME) | Body-powered (BP) |
|---|---|---|
| Sensory feedback | Greater feedback due to auditory cues from motor and vibrations through the close-fitting socket (Northmore-Ball et al. 1980, Silcox et al. 1993) | Better finger position feedback and object visibility (Kruger and Fishman 1993) |
| Function | Preferred by the majority of children (64%) for function (Glynn et al. 1986)<br>Decreased task difficulty and more frequent bilateral use (Weaver et al. 1988)<br>Better grasp of heavy objects (Kruger and Fishman 1993) | Better manipulative function (van Lunteren et al. 1983)<br>Better overall function (voluntary closing mechanism) (Crandall and Tomhave 2002)<br>Less inadvertent activation, and less effort required to open slightly (Kruger and Fishman 1993) |
| Usage | More frequently and actively used (van Lunteren et al. 1983)<br>Decrease from full-time to part-time wear upon exchanging conventional for myoelectric prostheses in a pediatric sample, possibly due to weight and durability issues (Balance et al. 1989).<br>ME wear widely reported in excess of 8 hours per work day in adult populations (Millstein et al. 1986; Datta et al. 1989; Weaver et al. 1988; Kejlaa 1993; Wright et al. 1995). | BP hooks most frequently used (Kruger and Fishman 1993)<br>Active users preferred BP while passive users of active prostheses preferred ME (Kruger and Fishman 1993)<br>Only 30% of children used ME for active prehension and none under the age of 5. (Kruger and Fishman 1993)<br>Full-time use of ME rare before adolescence (Menkveld et al. 1987)<br>BP hook wear widely reported in excess of 8 hours per work day (Millstein et al. 1986; Kejlaa 1993; Scotland and Galway 1983; Weaver et al. 1988; Wright et al. 1995).<br>BP hands less frequently worn (Millstein et al. 1986; Silcox et al. 1993; Kejlaa et al. 1993; Gaine et al. 1997) |
| Comfort | Increased comfort due to freedom from harness – suggests that the greater the aversion to the harness, the greater probability that the ME device will be accepted (Northmore-Ball et al. 1980; Heger et al. 1985) | Reduced weight in comparison with ME (Northmore-Ball et al. 1980; Heger et al. 1985; Kruger and Fishman 1993)<br>Reduced noise levels (Kruger and Fishman 1993)<br>Preferred for overall comfort (Kruger and Fishman 1993) |

Biddiss, E. A., & Chau, T. T. (2007). Upper limb prosthesis use and abandonment: A survey of the last 25 years. Prosthetics and Orthotics International, 31(3), 236–257. https://doi.org/10.1080/03093640600994581

# Limitations of Existing Assistive Technology

## Design priorities

Study was performed with veterans to describe and compare satisfaction by prosthesis and terminal device type and to identify factors associated with satisfaction

**Table 2.** Prosthesis use characteristics.

| | Body-powered N=334 | Myoelectric/hybrid N=93 | Cosmetic N=22 |
|---|---|---|---|
| Frequency of prosthesis use | | | |
| Daily | 257 (78.1) | 72 (78.3) | 14 (63.6) |
| Weekly | 43 (13.1) | 8 (8.7) | 5 (22.7) |
| Monthly | 14 (4.3) | 5 (5.4) | 0 (0.0) |
| Every few months | 11 (3.3) | 2 (2.2) | 1 (4.6) |
| 1 to 2 times per year | 4 (1.2) | 5 (5.4) | 2 (9.1) |
| Intensity of prosthesis use (h) | | | |
| <2 | 68 (20.6) | 12 (13.0) | 4 (18.2) |
| 2 to <4 | 29 (8.8) | 11 (12.0) | 2 (9.1) |
| 4 to <8 | 58 (17.6) | 20 (21.7) | 5 (22.7) |
| 8 to <12 | 64 (19.4) | 18 (19.6) | 3 (13.6) |
| ⩾12 | 111 (33.6) | 31 (33.7) | 8 (36.4) |
| Most recent prosthesis received | | | |
| <2 years ago | 135 (40.4) | 53 (57.0) | 6 (27.3) |
| 2+ years ago | 198 (59.3) | 39 (41.9) | 16 (72.7) |
| Unknown | 1 (0.3) | 1 (1.1) | 0 (0.0) |
| Number of prostheses used | | | |
| One | 229 (68.6) | 41 (41.1) | 14 (63.6) |
| Two or more | 105 (31.4) | 52 (55.9) | 8 (36.4) |
| Number of terminal devices used | | | |
| One | 209 (62.6) | 30 (32.3) | 17 (77.3) |
| Two or more | 123 (36.8) | 60 (64.5) | 4 (18.2) |
| Unknown | 2 (0.6) | 3 (2.9) | 1 (4.7) |
| Primary type of terminal device used | | | |
| Body-powered hook | 334 (100.0) | 0 (0.0) | 0 (0.0) |
| Greifer | 0 (0.0) | 6 (6.5) | 0 (0.0) |
| Power hook (ETD) | 0 (0.0) | 15 (16.1) | 0 (0.0) |
| Sensor speed hand | 0 (0.0) | 9 (9.7 | 0 (0.0) |
| I-Limb/Michaelangelo hand/Bebionic hand | 0 (0.0) | 40 (43.0) | 0 (0.0) |
| Cosmetic | 0 (0.0) | 0 (0.0) | 22 (100.0) |
| Unknown | 0 (0.0) | 23 (24.7) | 0 (0.0) |
| DOF of primary terminal device | | | |
| No DOF (cosmetic) | 0 (0.0) | 0 (0.0) | 22 (100.0) |
| Single DOF | 334 (100.0) | 30 (32.3) | 0 (0.0) |

*(Continued)*

Resnik, L., Borgia, M., Heinemann, A. W., & Clark, M. A. (2020). Prosthesis satisfaction in a national sample of Veterans with upper limb amputation. Prosthetics and Orthotics International, 44(2), 81–91. https://doi.org/10.1177/0309364619895201

# Limitations of Existing Assistive Technology

## Design priorities

Study was performed with veterans to describe and compare satisfaction by prosthesis and terminal device type and to identify factors associated with satisfaction

**Table 2.** (Continued)

| | Body-powered N=334 | Myoelectric/hybrid N=93 | Cosmetic N=22 |
|---|---|---|---|
| Multi-DOF | 0 (0.0) | 40 (43.0) | 0 (0.0) |
| Unknown | 0 (0.0) | 23 (24.7) | 0 (0.0) |
| Received training to use initial prosthesis | | | |
| Yes | 254 (76.1) | 75 (80.7) | 11 (50.0) |
| No | 77 (23.1) | 18 (19.4) | 10 (45.5) |
| Unknown | 3 (0.9) | 0 (0.0) | 1 (4.9) |
| Received training to use current prosthesis | | | |
| Yes | 216 (64.7) | 75 (76.3) | 7 (31.8) |
| No | 113 (33.8) | 21 (22.6) | 15 (68.2) |
| Unknown | 5 (1.5) | 1 (1.1) | 0 (0.0) |
| How many times was your prosthesis repaired in the past 12 months? | | | |
| 0 | 138 (42.6) | 37 (40.2) | 12 (57.1) |
| 1 | 85 (26.2) | 14 (15.2) | 6 (28.6) |
| 2–3 | 68 (21.0) | 22 (23.9) | 3 (14.3) |
| ⩾4 | 33 (10.2) | 19 (20.7) | 0 (0.0) |
| How many times did you visit a prosthetist for adjustment to your socket in the past 12 months? | | | |
| 0 | 217 (66.4) | 49 (53.3) | 12 (60.0) |
| 1 | 42 (12.8) | 16 (17.4) | 4 (20.0) |
| 2–3 | 46 (14.1) | 19 (20.7) | 1 (5.0) |
| ⩾4 | 22 (6.7) | 8 (8.7) | 3 (15.0) |
| **Prosthetic users with two or more prostheses** | **Body-powered N=98** | **Myoelectric/hybrid N=59** | **Cosmetic N=8** |
| Secondary type of prosthesis used | | | |
| Body-powered | 43 (41.0) | 28 (53.9) | 1 (12.5) |
| Myoelectric/hybrid | 50 (47.6) | 12 (23.1) | 3 (37.5) |
| Cosmetic | 1 (1.0) | 1 (1.9) | 3 (37.5) |
| Sports/recreation | 8 (7.6) | 9 (17.3) | 1 (12.5) |
| Unknown | 3 (2.9) | 2 (3.9) | 0 (0.0) |
| Frequency of secondary prosthesis use | | | |
| Daily | 23 (21.9) | 16 (30.8) | 4 (50.0) |
| Weekly | 45 (42.9) | 22 (42.3) | 1 (12.5) |
| Monthly | 11 (10.5) | 5 (9.6) | 1 (12.5) |
| Every few months | 12 (11.4) | 3 (5.8) | 0 (0.0) |
| 1 to 2 times per year | 14 (13.3) | 4 (7.7) | 2 (25.0) |
| Unknown | 0 (0.0) | 2 (3.9) | 0 (0.0) |

ETD: electronic terminal devices; DOF: degrees of freedom.

Resnik, L., Borgia, M., Heinemann, A. W., & Clark, M. A. (2020). Prosthesis satisfaction in a national sample of Veterans with upper limb amputation. Prosthetics and Orthotics International, 44(2), 81–91. https://doi.org/10.1177/0309364619895201

# Limitations of Existing Assistive Technology

## Human Input

How many advanced human-machine interfaces rely on bio signals to interpret user's intentions to control the corresponding prosthesis

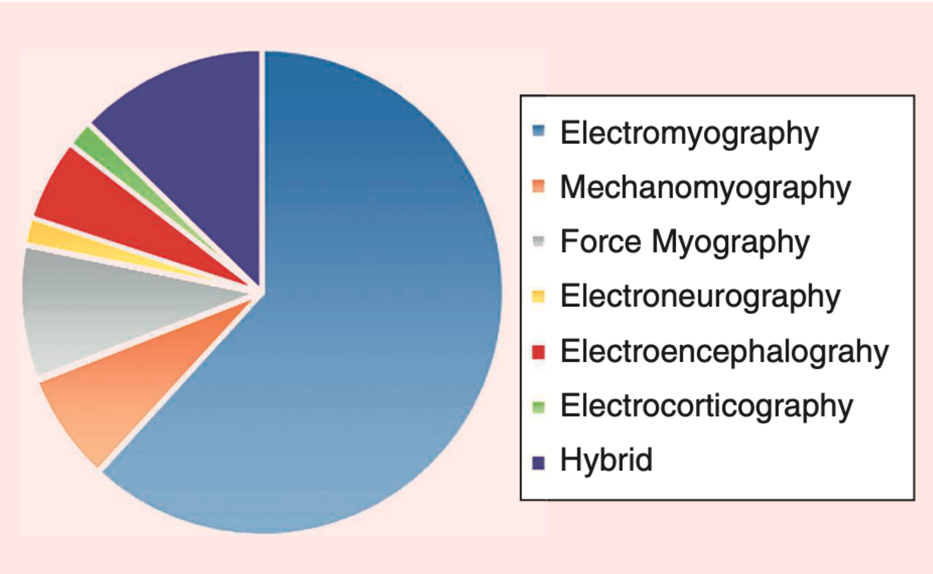



**FIGURE 1.** The prevalence of different types of biosignals used as the basis of HMIs in selected papers.

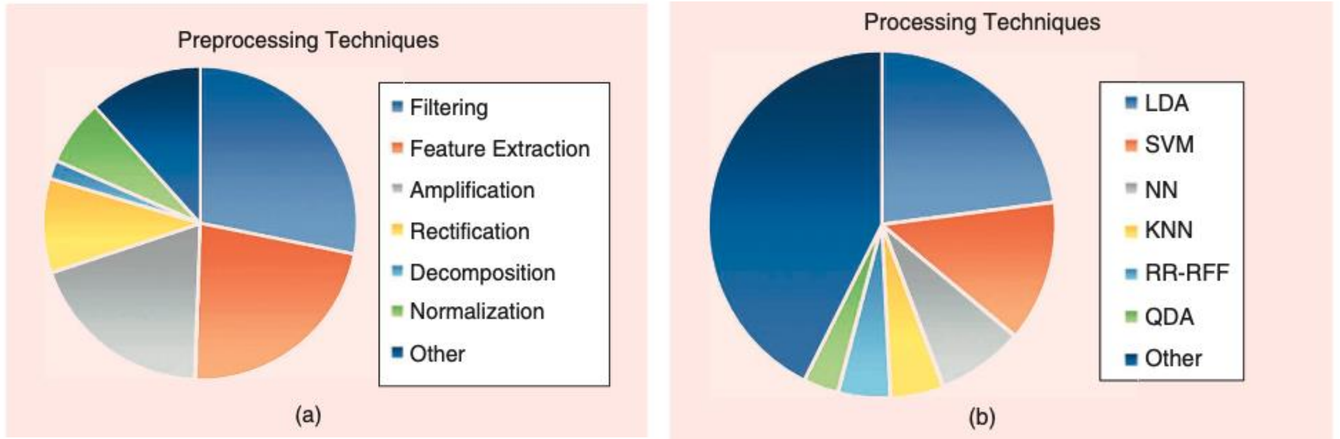



**FIGURE 2.** The prevalence of (a) preprocessing and (b) processing techniques used in EMG-based studies. LDA: linear discriminant analysis; SVM: support vector machine; NN: neural network; KNN: k-nearest neighbors; RR-RFF: ridge regression with random Fourier features; QDA: quadratic discriminant analysis.

C. Ahmadizadeh, M. Khoshnam and C. Menon, "Human Machine Interfaces in Upper-Limb Prosthesis Control: A Survey of Techniques for Preprocessing and Processing of Biosignals," in IEEE Signal Processing Magazine, vol. 38, no. 4, pp. 12-22, July 2021, doi: 10.1109/MSP.2021.3057042.

# Limitations of Existing Assistive Technology

Obtaining input from a human can be expensive (computationally) and taxing (to the human - cognitive load). How can we provide a mechanism that provides high functionality while preserving non-invasive, low cognitive demand interfacing?



Robotic Autonomy

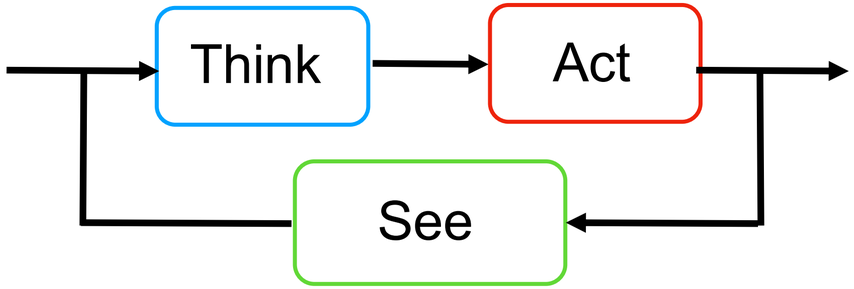
# Robotics - Thinking Machines

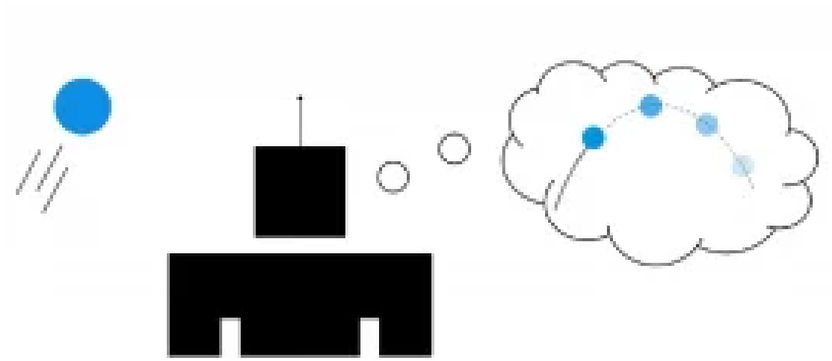
# Overview of Robotics Considerations

## See - Think - Act

The Key Elements of Robotics

- **See** (Perception - sense your environment)
- **Think** (Planning - given experience what should be done?)
- **Act** (Execution - perform the action according to the plan)

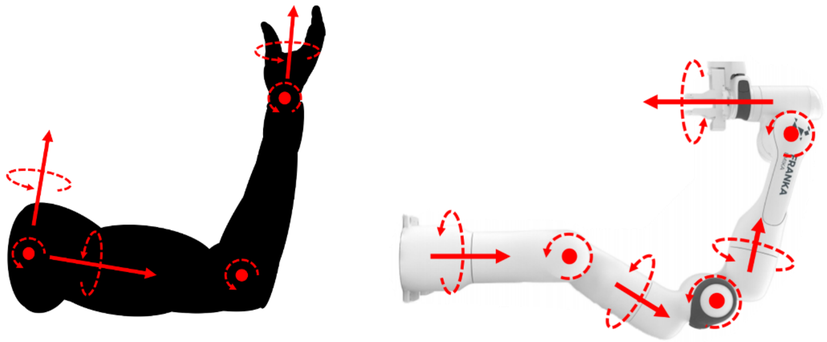


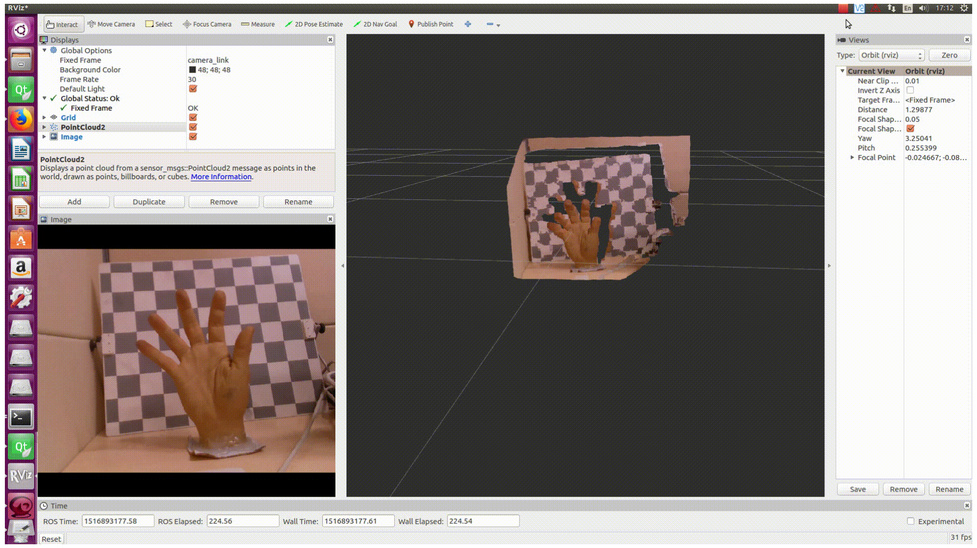
Li, A., Wu, P., & Kennedy III, M. (2021). Replay Overshooting: Learning Stochastic Latent Dynamics with the Extended Kalman Filter. *IEEE International Conference on Robotics and Automation (ICRA)*

# Robotic Perception

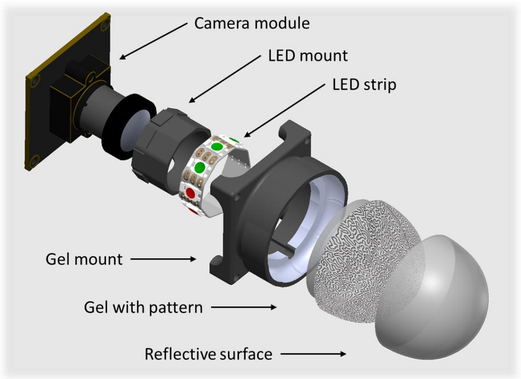
## Ego or Environment Observation

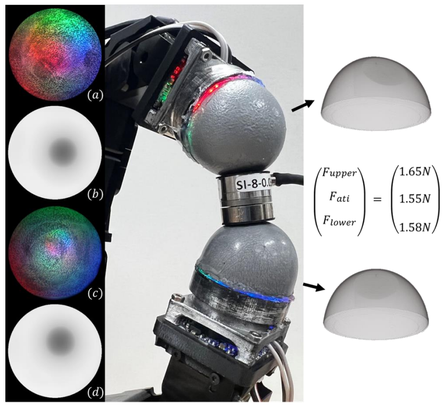


**Proprioception**: sense of embodiment - perception/awareness of the position and movement of the body



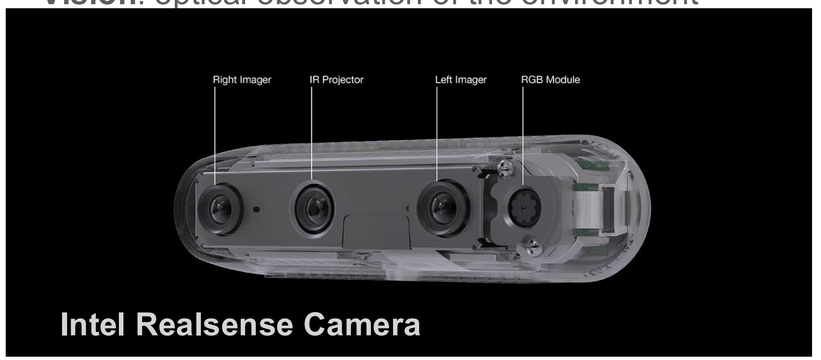

**Touch**: tactile feedback of environment (Shown: ARMLab DenseTact sensor)




Do, W. K., Jurewicz, B., & Kennedy, M. (2022, September). **DenseTact 2.0: Optical Tactile Sensor for Shape and Force Reconstruction**. ICRA 2023 accepted

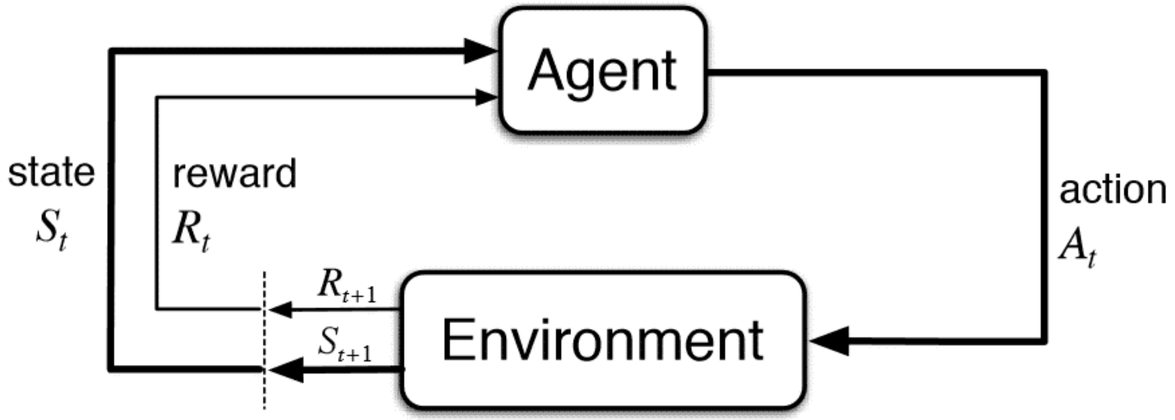
**Vision**: optical observation of the environment



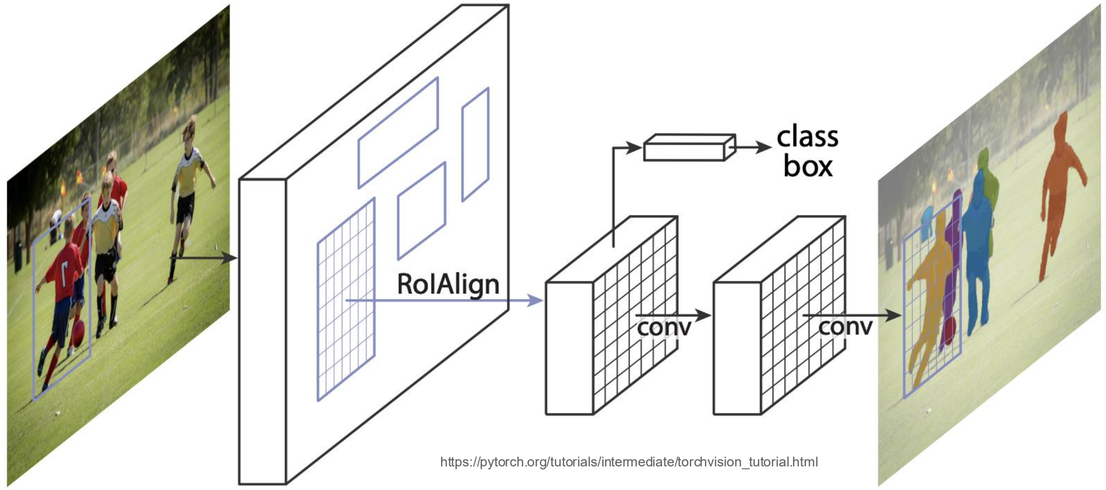

Do, W. K., & Kennedy III, M. (2022). **DenseTact: Optical Tactile Sensor for Dense Shape Reconstruction**. *IEEE*, 6188-6194.

# Robotic Intelligence

## Ego, Teammate and Task/Environment Modeling

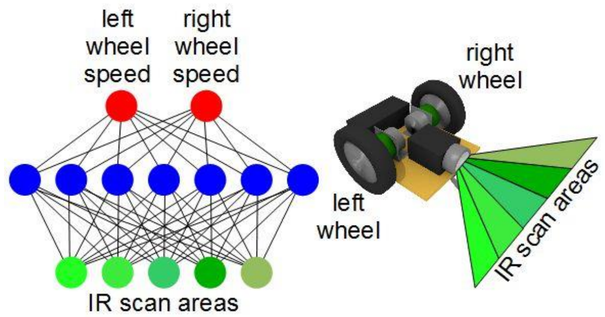



Reinforcement Learning Paradigm:
What action leads to the best reward?




https://pytorch.org/tutorials/intermediate/torchvision_tutorial.html

**Vision interpretation:** Shown is a Convolutional Neural Network (CNN) determining the location of people in an image




Neural Network (multi-layer perceptron) for decision making

https://rimstar.org/science_electronics_projects/neural_networks.htm

# Robotic Action

## Analytical versus Data Driven Approaches

Given an observation (z) of an environment state (a person or task) (s) how does the robot determine what action (a) to take?

Analytical Approach

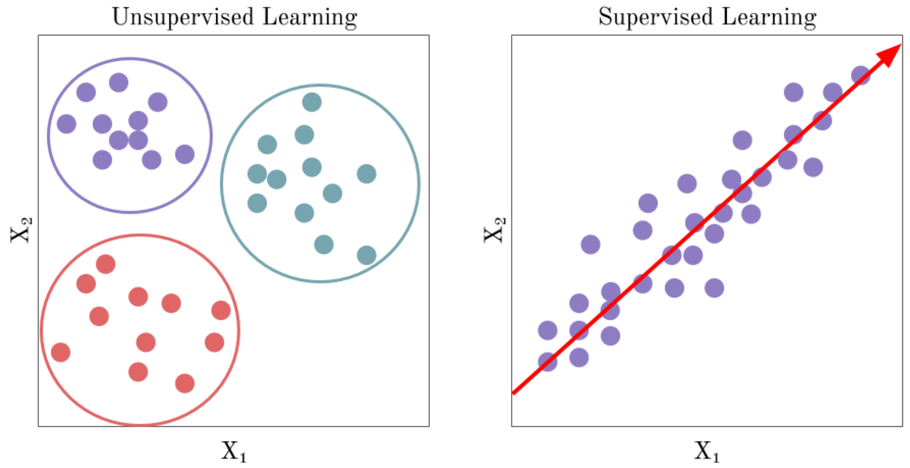
Have an explicit analytical function that maps the observation to the action

$$a_t = g(z_t)$$

This form of $g(\cdot)$ must be known, and may be hard to adapt to new information

Data Driven Approach

Leverage history of observations (and new observations) to drive behavior in either a supervised or unsupervised paradigm

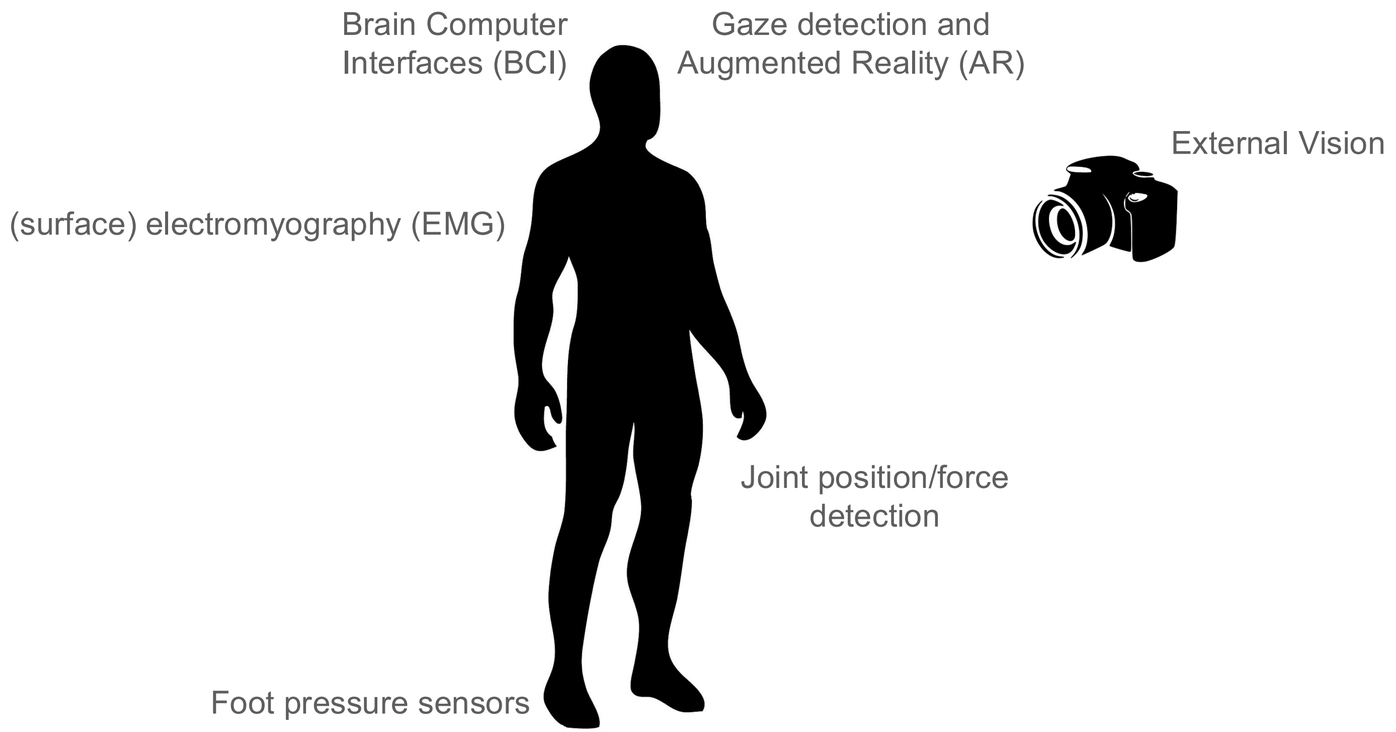



https://towardsdatascience.com/a-brief-introduction-to-unsupervised-learning-20db46445283

# Robotic Perception

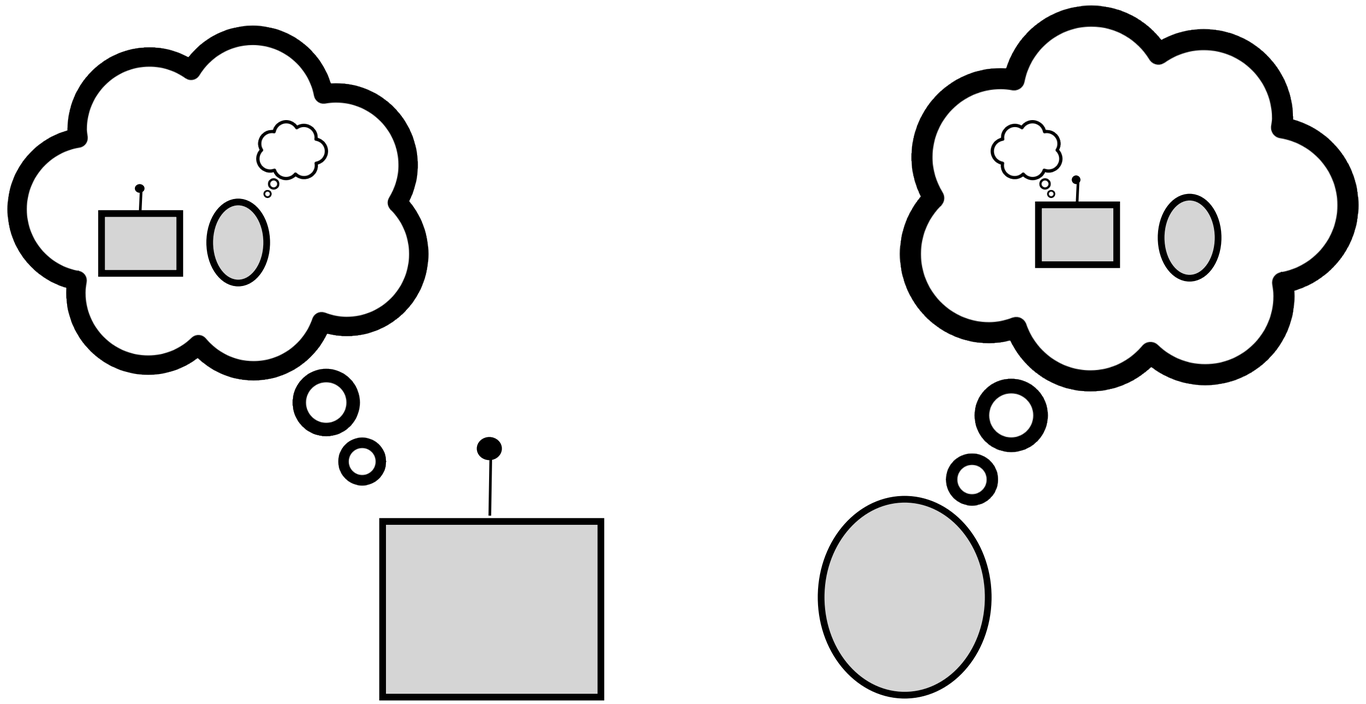
## Human Perception

For assistive robotics, the human must be observed either passively (from external sensors e.g. cameras) or actively (from wearable or implanted sensors)



Do agents share the same goals (objectives)?

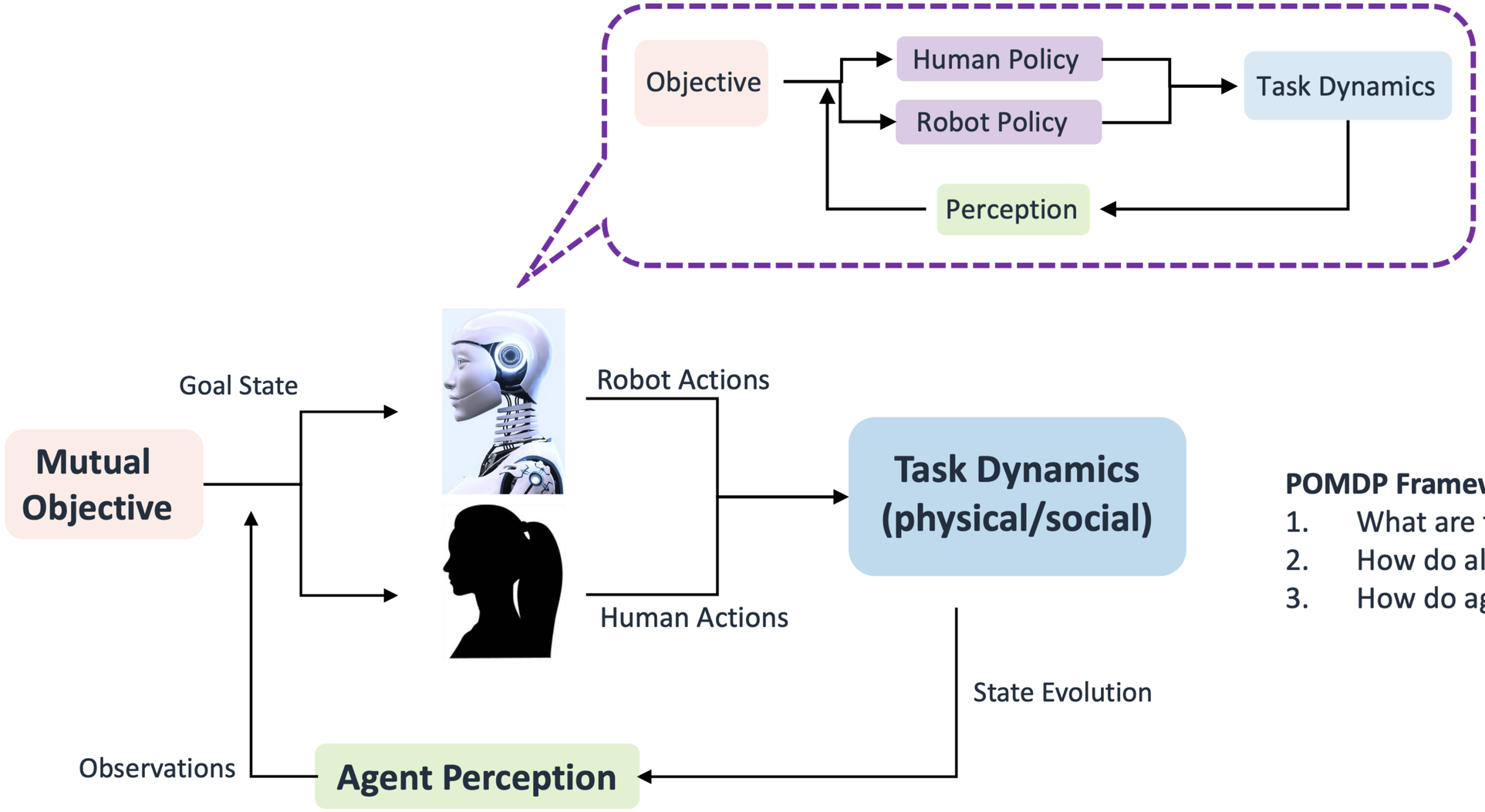
Who (if anyone) is in charge?



Collaborative Interaction

If the robot is predicting multiple partners sequence of future actions how can this be done efficiently?

Where does task domain knowledge come from?




**POMDP Framework:**

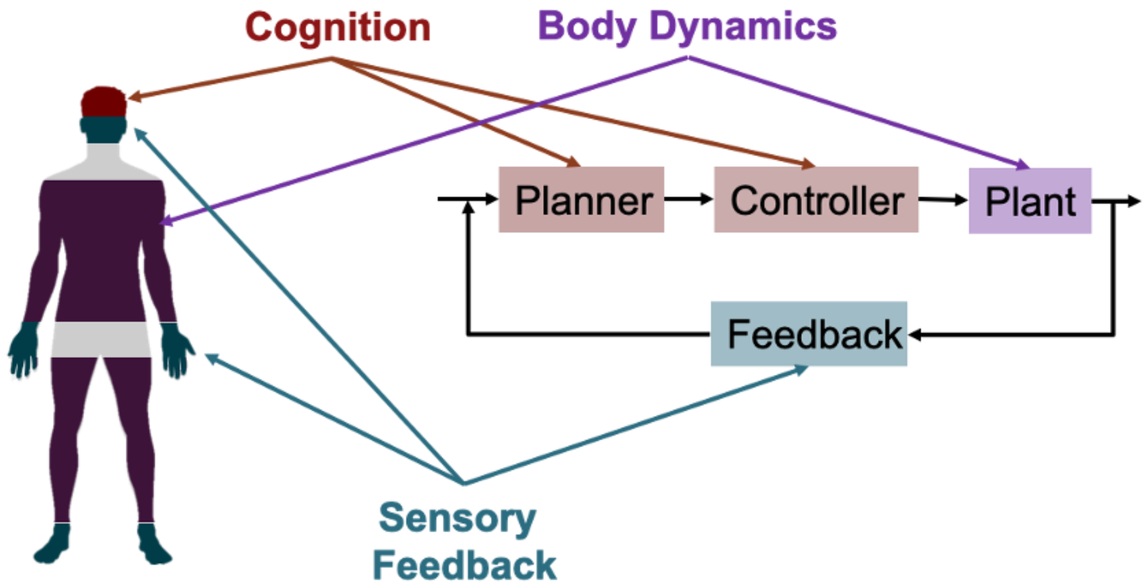
1. What are the dynamics of the task?
2. How do all agents perceive the world?
3. How do agents make decisions?

# Robotics Role in Assistive Technology

# When is Robotics the Best Option?

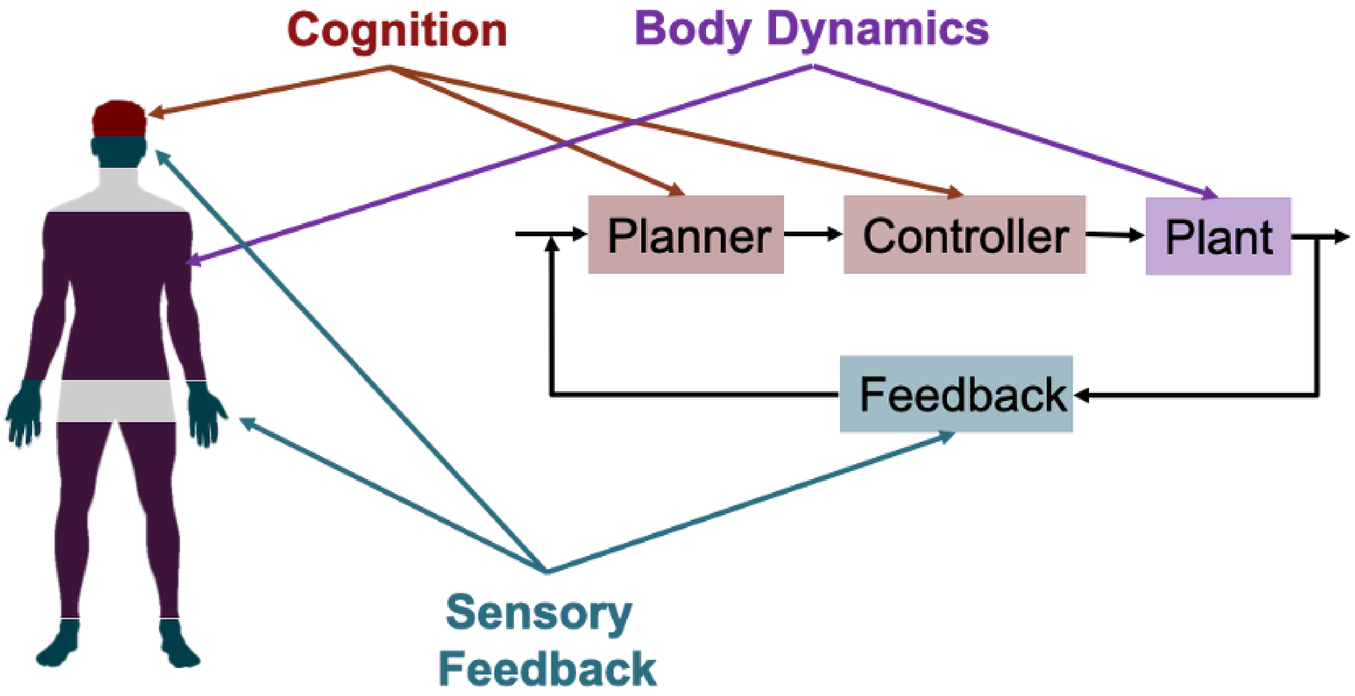
Robotics serve as a useful tool when the task requires

- High operational complexity (decisions/actions are not obvious)
- Human control/input that is limited for the complexity of the desired task



# Robotics Fills the Gap

## Wearable Robotics

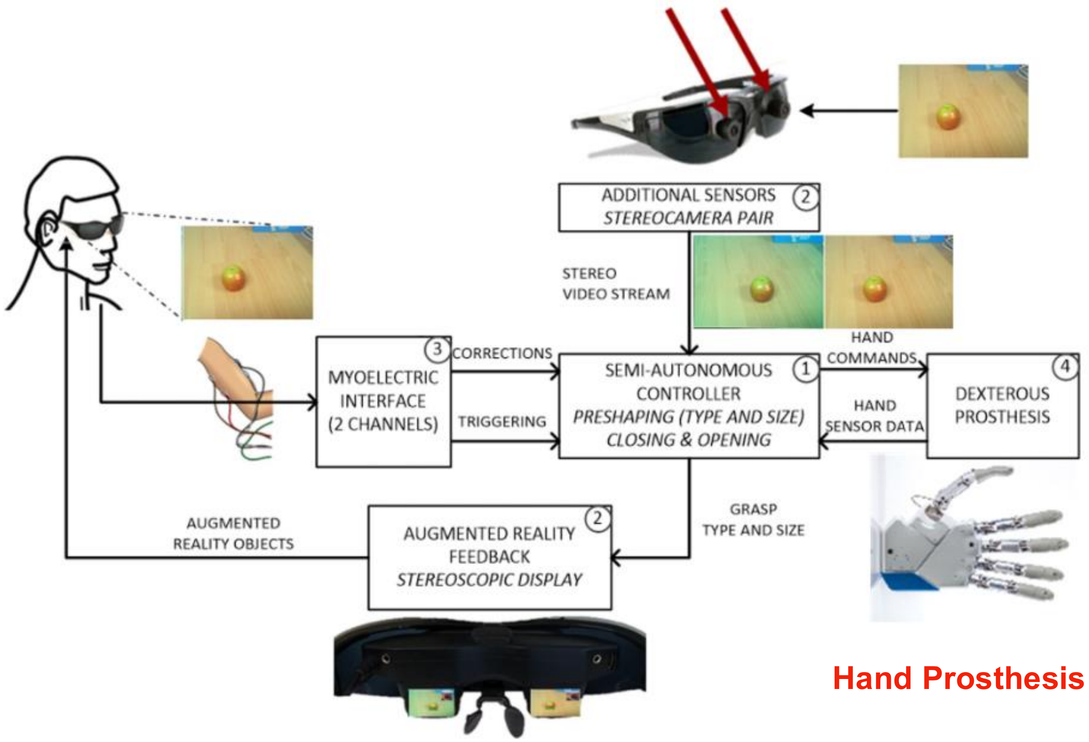



**Particularly for wearables, what part of the human is being augmented or substituted?**

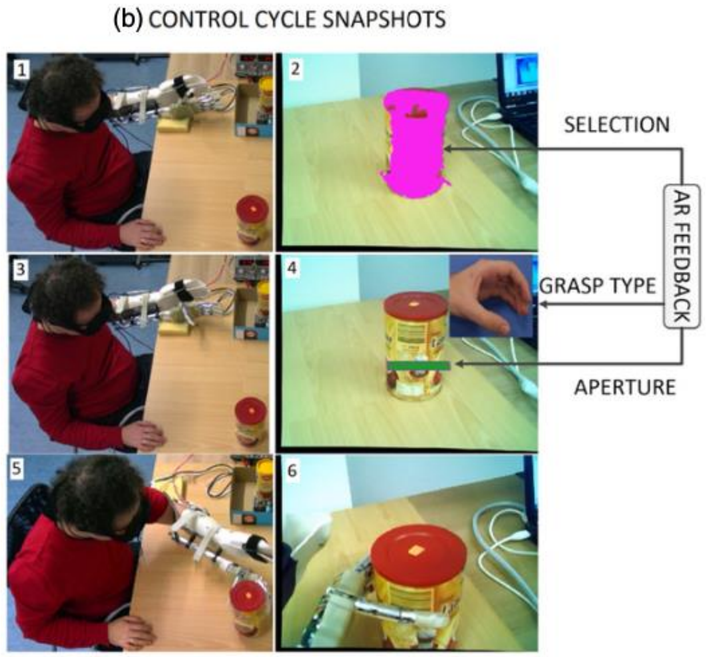
1. **Is the robotic augmentation functionally adequate?**
2. **Does the presence of the robot feel 'natural' (easy to use)?**

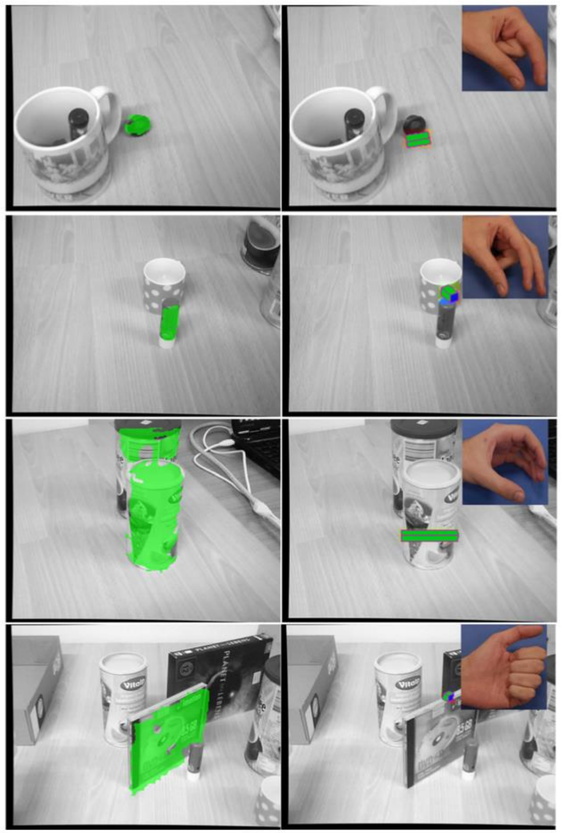
# Robotics Fills the Gap

## Robotics for Prosthesis: AR + Perception + Planning + Controls




Hand Prosthesis



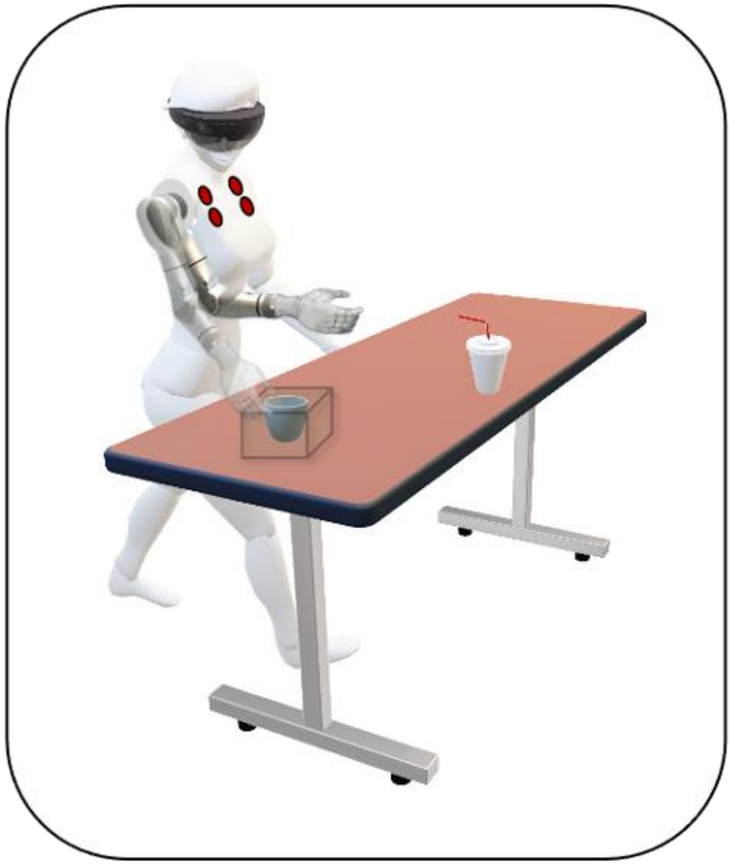



Markovic, Marko, et al. "Stereovision and augmented reality for closed-loop control of grasping in hand prostheses." *Journal of neural engineering* 11.4 (2014): 046001.

# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Intelligent Prosthetic Arm



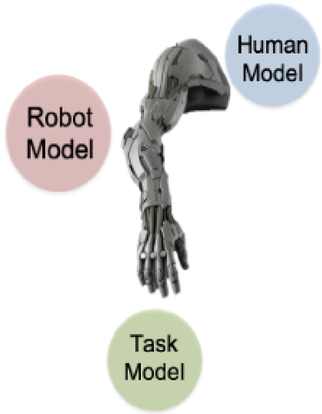
ARMLab Project:
Intelligent Prosthetic Arm

# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Intelligent Prosthetic Arm

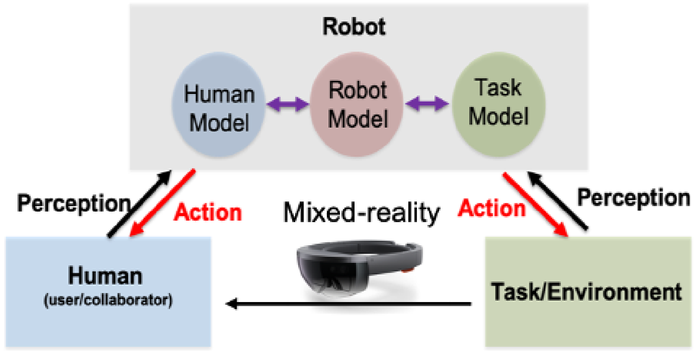
ARMLab Project:
Intelligent Prosthetic Arm







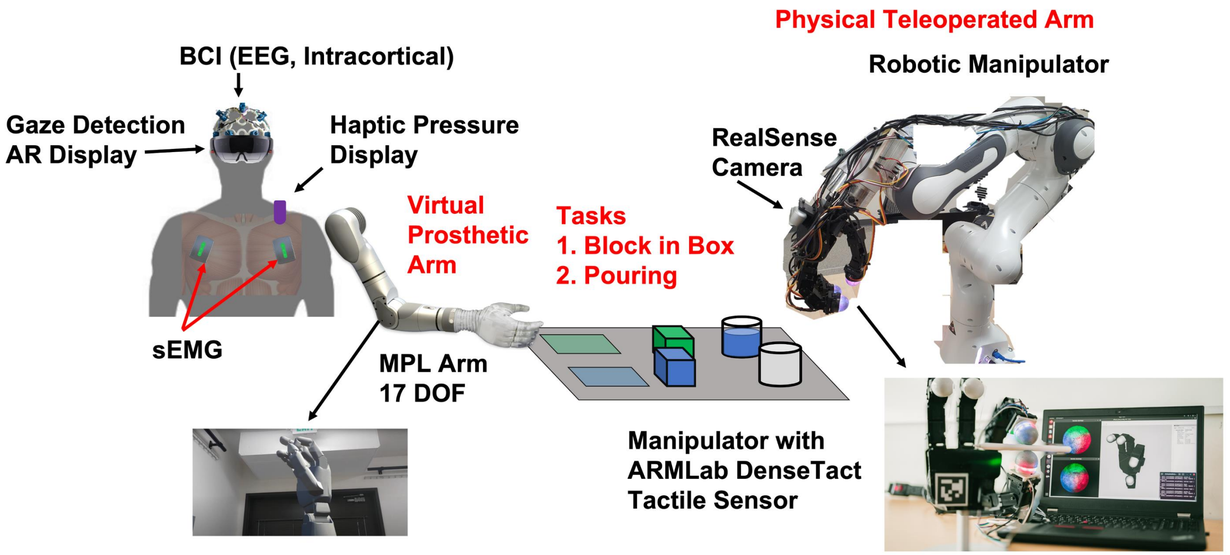

EMG Measurements

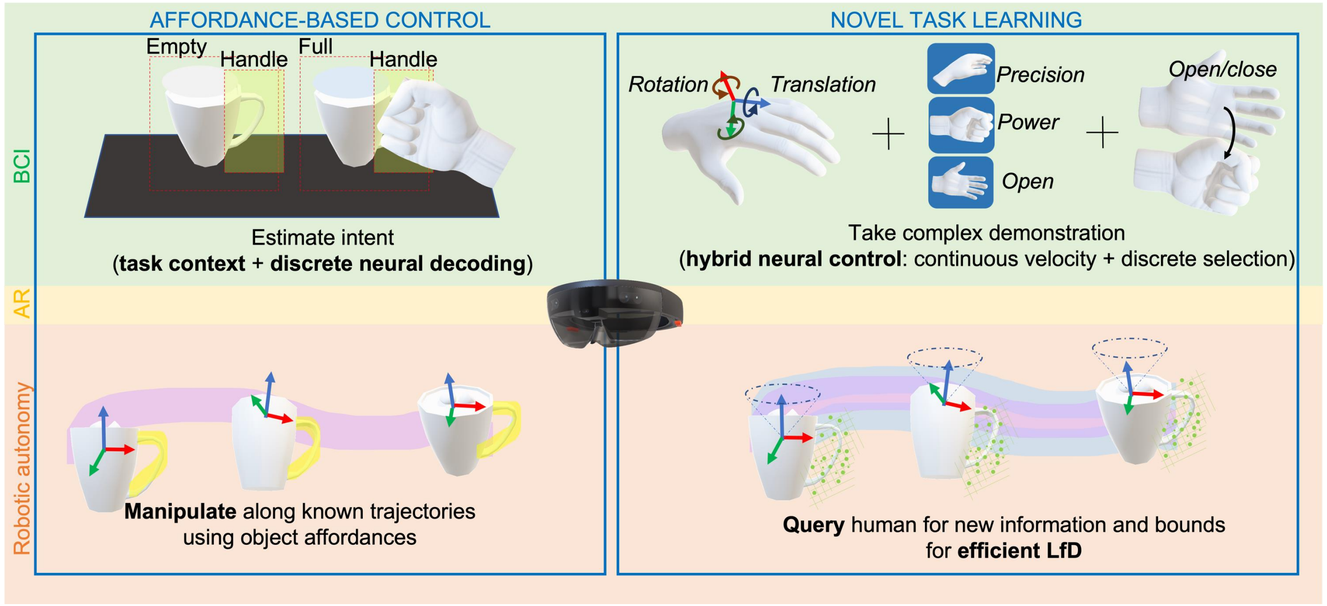


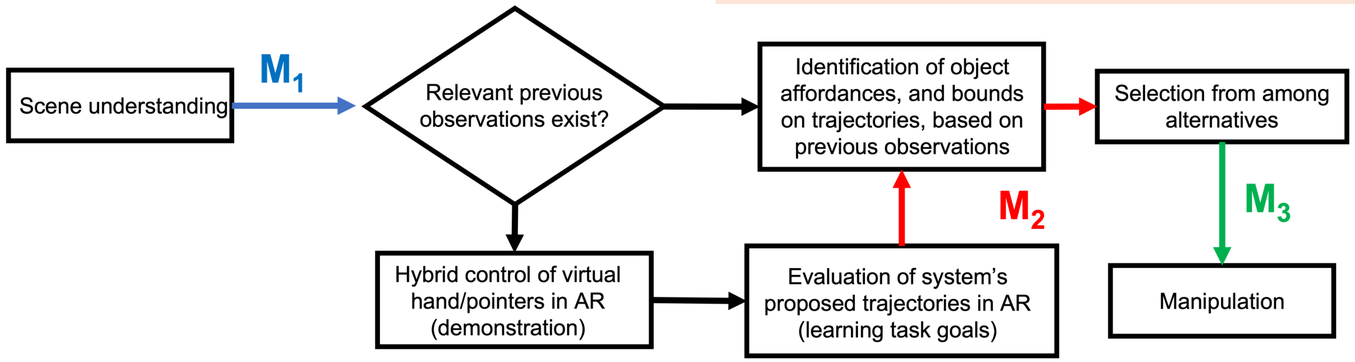

Visuo-Tactile Measurements

# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Intelligent Prosthetic Arm

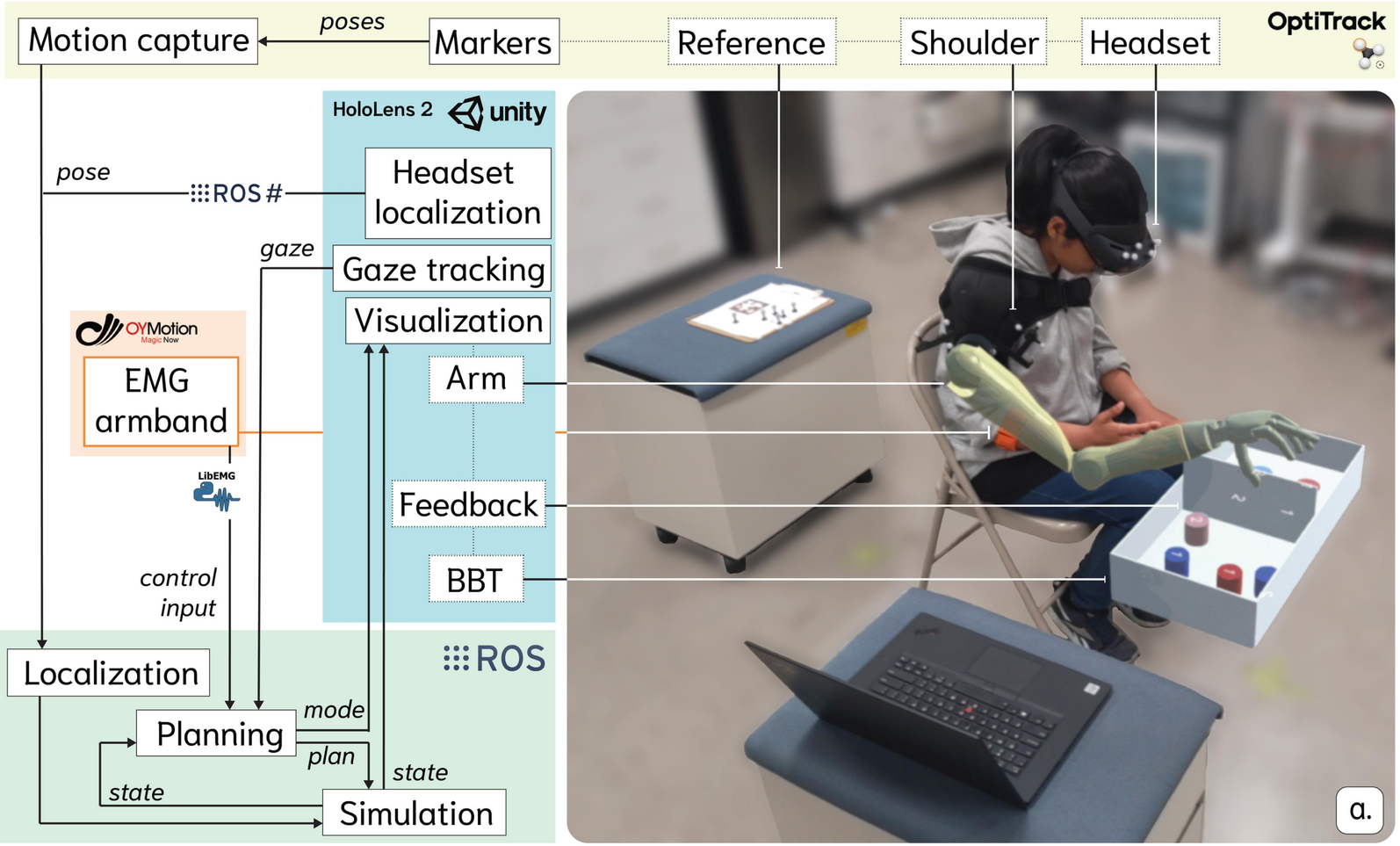


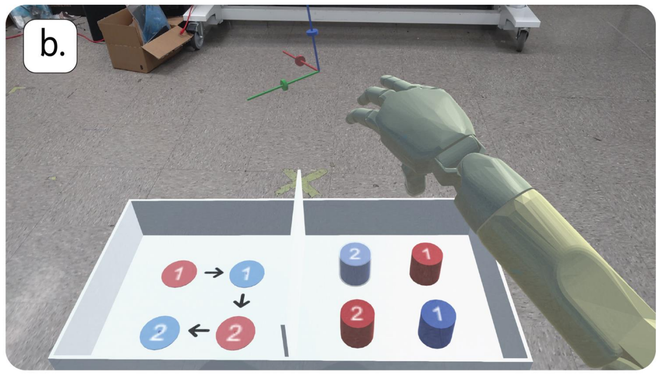



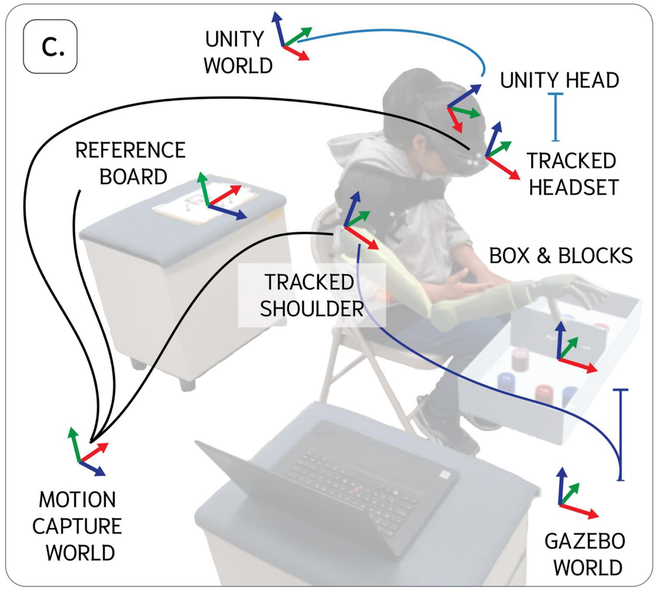



# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Intelligent Prosthetic Arm



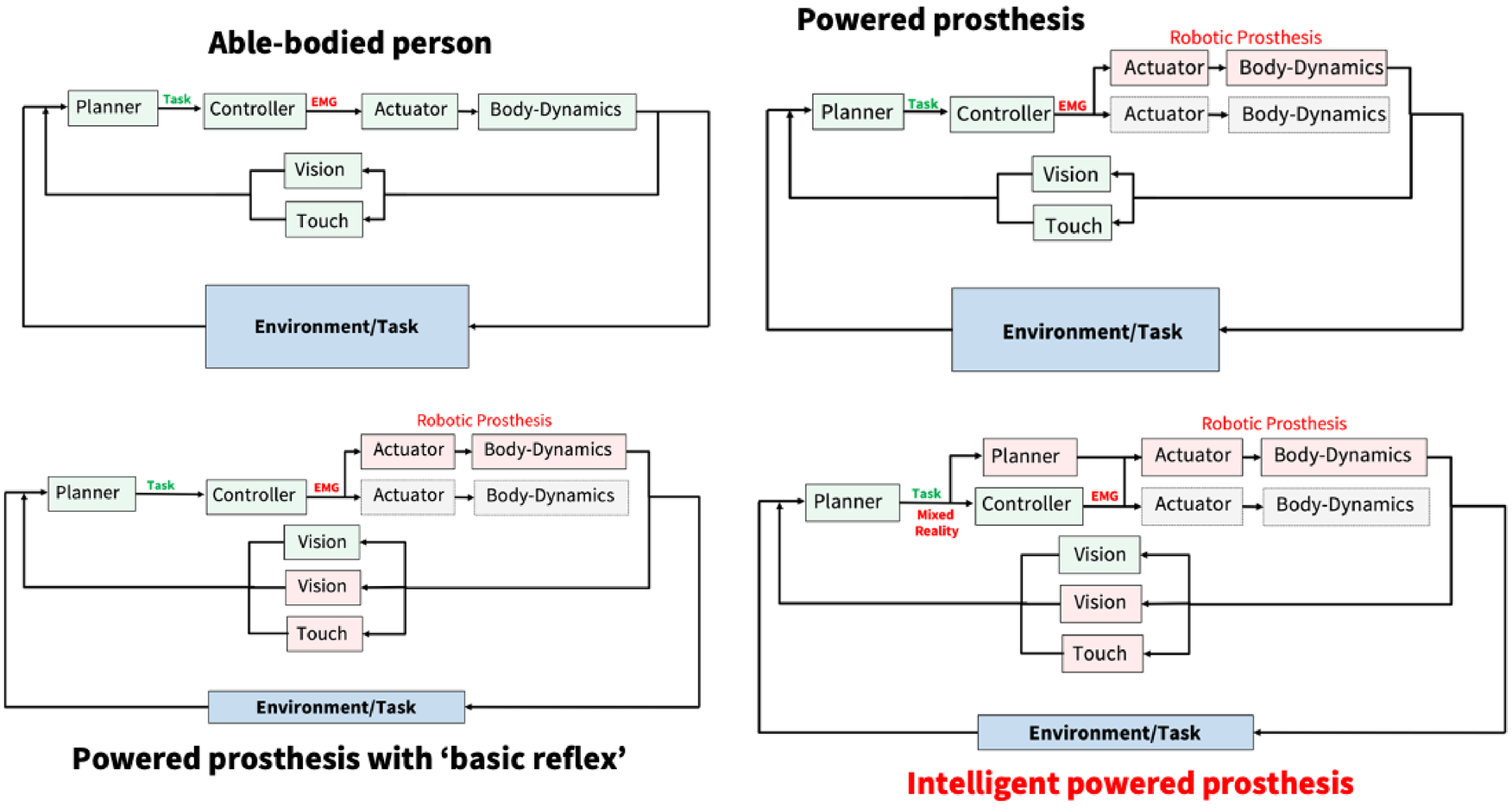
# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Intelligent Prosthetic Arm

| Name | Purpose | Virtual arm type | Control method | Display | Environment | Access |
|---|---|---|---|---|---|---|
| JHU/APL VIE [25] | Research | MPL | EMG | 3D goggles | ODE, MATLAB | not available |
| JHU/APL miniVIE [26] | User training | MPL | EMG | Screen | MATLAB | open |
| MPI ArmSym [27] | Research | Barrett WAM | HTC Vive | Immersive VR | Unity/C# | open |
| HoloPHAM [28] | User training | MPL | EMG | Immersive AR | Unity | not available |
| Virtual BBT [29] | User training | Human avatar | EMG | Immersive VR | Unity | not available |
| ProACT (this work) | Research | MPL | EMG, gaze, motion planning | Immersive AR | ROS base, Unity interface | open |

# Assistive Robotics and Manipulation Laboratory

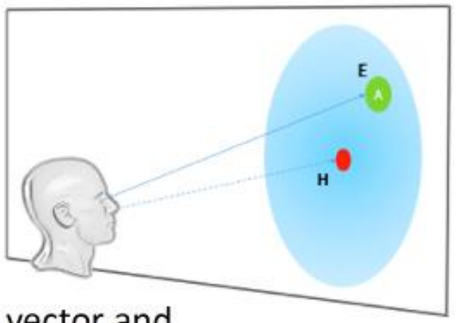
## Intelligent Wearables - Intelligent Prosthetic Arm



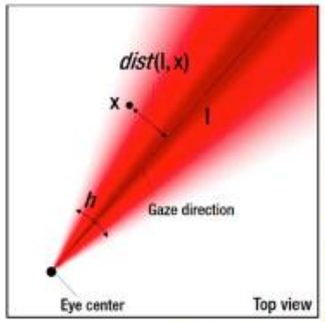
# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Intelligent Prosthetic Arm

Augmented reality (AR) is a powerful tool allowing the robot to both **extract** and **present information** *to the wearer*




Eye gaze vector and head gaze cone






Object affordances



Pose, motion of other limb(s)




Scene understanding

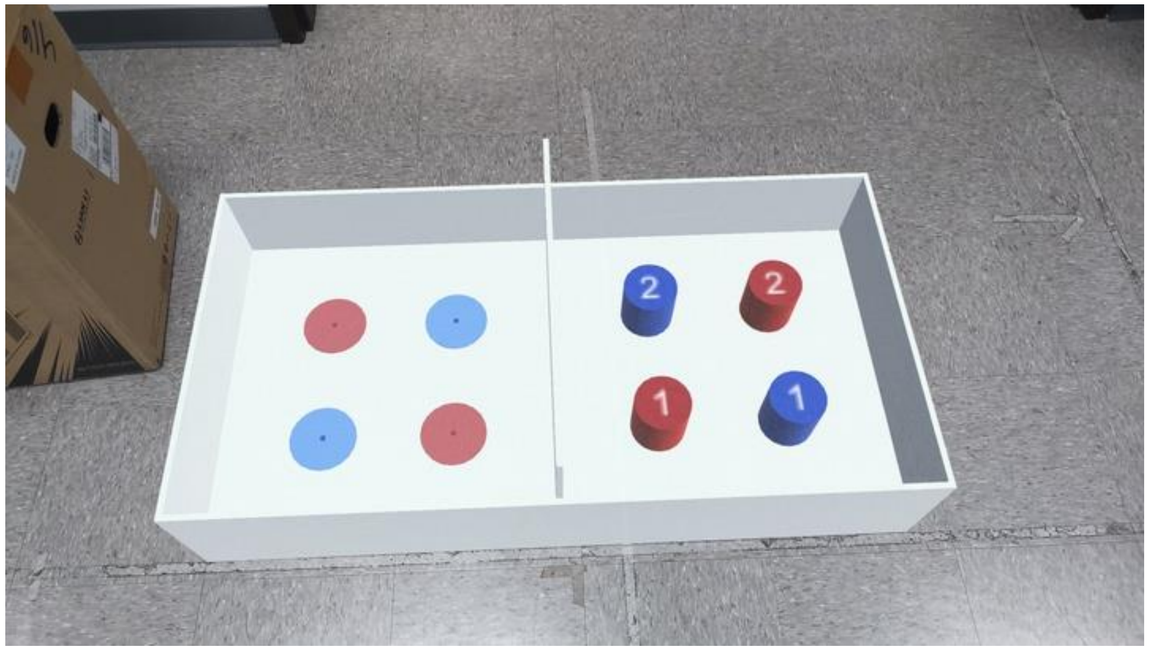


Pose, motion of other agents

# Intelligent Wearables - Intelligent Prosthetic Arm

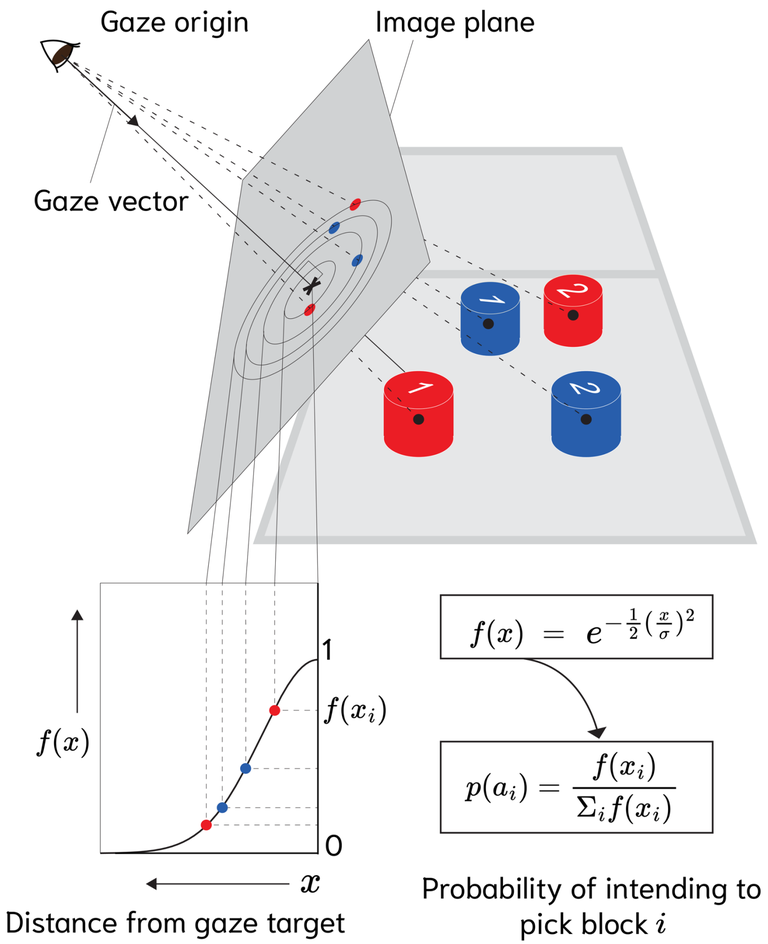
## Box-and-blocks test of dexterity

| Task type | Initial configuration | Task description |
|---|---|---|
| sBBT |  | • Transport as many blocks as possible in 60 seconds over the partition using only the dominant hand<br>• At a minimum, the fingertips of the dominant hand are required to cross the plane of the partition<br>• Score defined by the number of blocks transported within the time limit |
| mBBT |  | • Transport each block over the partition as quickly as possible, starting the with innermost left block and moving across the row.<br>• At a minimum, the fingertips of the dominant hand are required to cross the plane of the partition<br>• Score defined by the time required to transport all 16 blocks. |
| tBBT |  | • Transport each block over the partition using only the dominant hand, starting the with innermost left block and moving across the row, and place it in its mirrored position as quickly and accurately as possible<br>• Score defined by the time required to transport all 16 blocks. |




Source: Kontson K, Marcus I, Myklebust B, Civillico E. Targeted box and blocks test: Normative data and comparison to standard tests. PLoS One. 2017 May 19;12(5):e0177965. doi: 10.1371/journal.pone.0177965. PMID: 28542374; PMCID: PMC5438168.

# Intelligent Wearables - Intelligent Prosthetic Arm

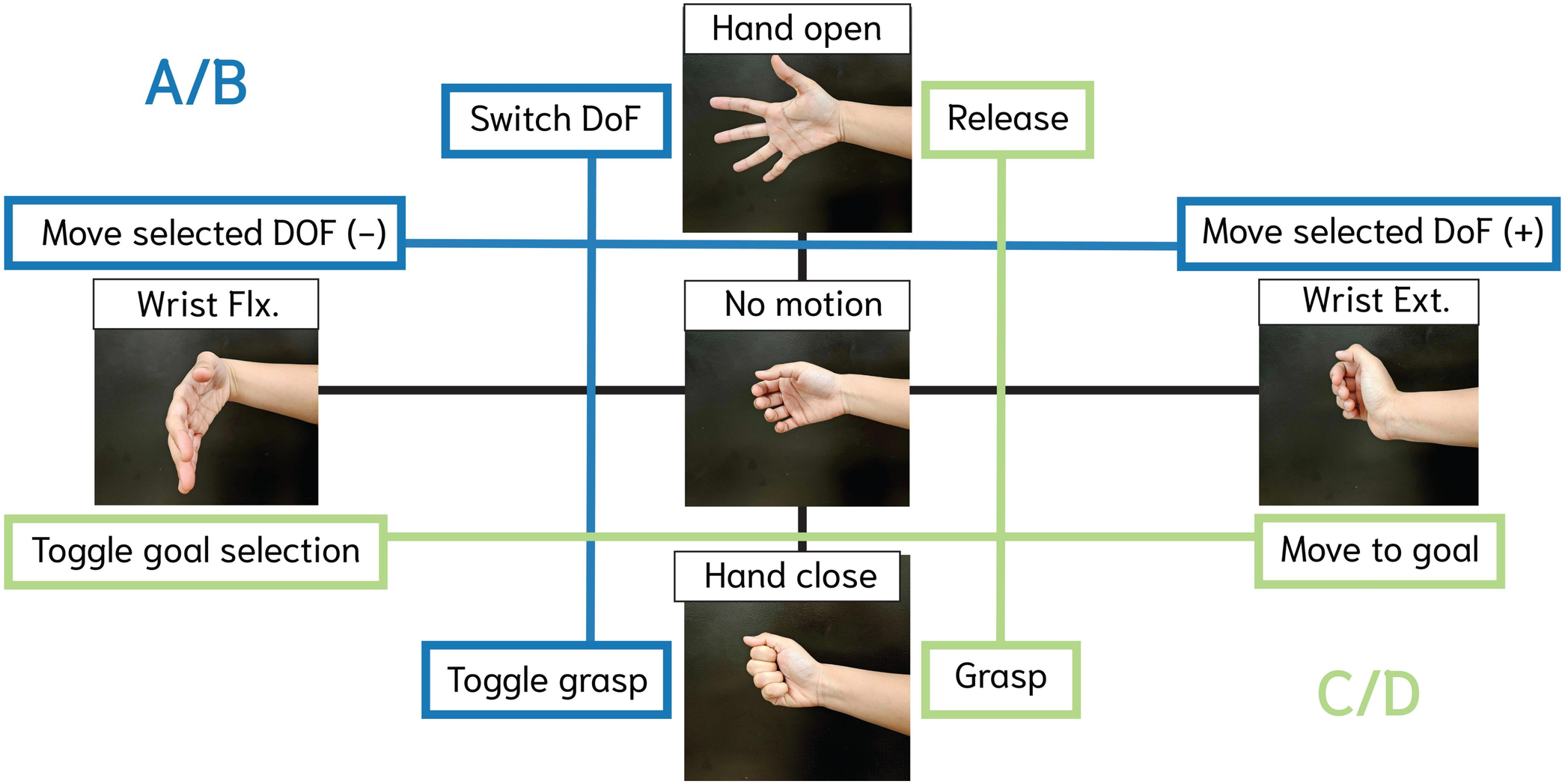



$$p(a_i|g,s) = \frac{p(g|a_i,s)p(a_i|s)}{p(g|s)}$$

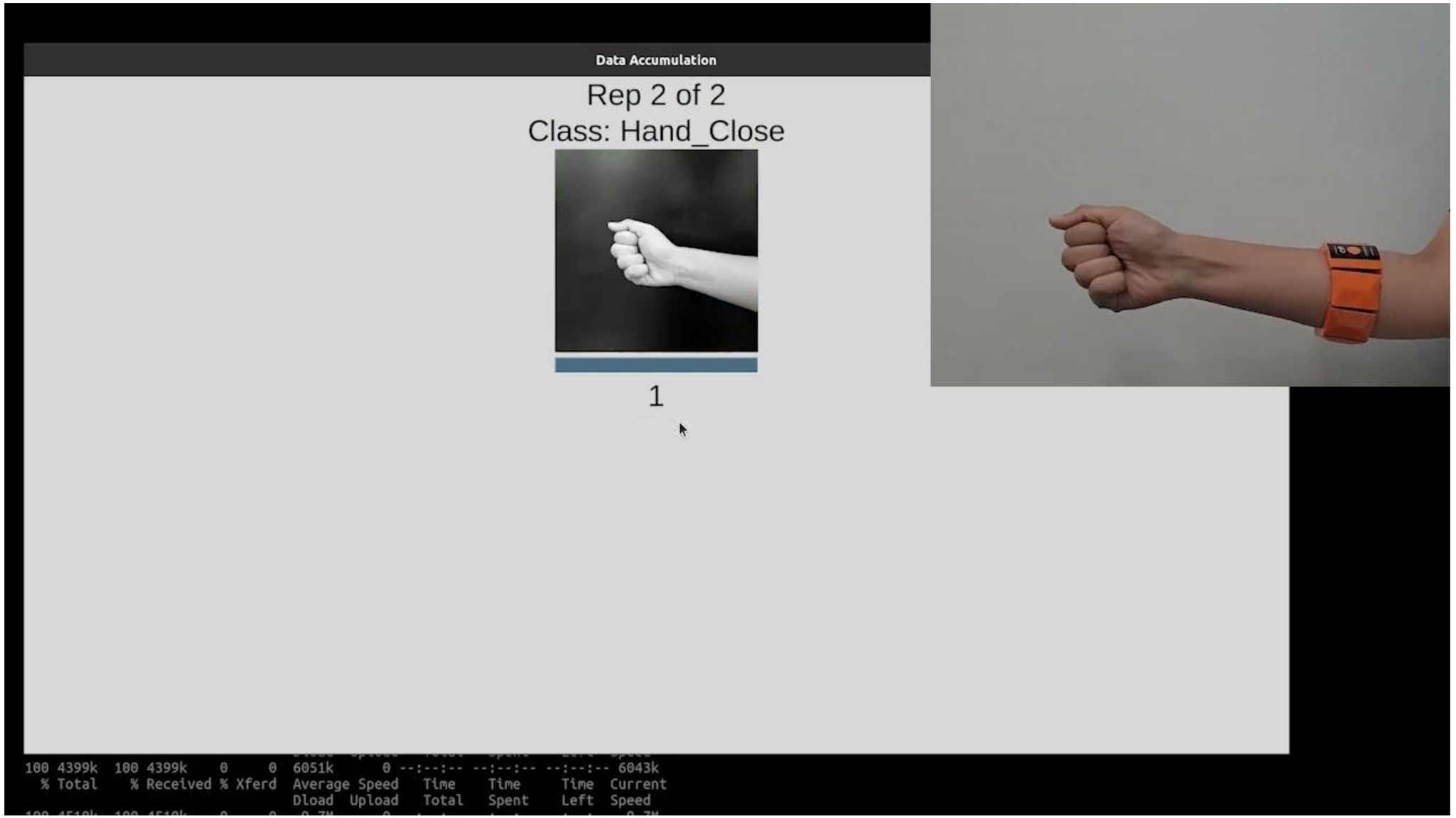
TABLE II: Probability weighting $p(a_i|s)$ for each block in Method D, conditioned on previous block color. The columns, left to right, are in the sequence specified for the task.

| Previous block color | Red #1 | Blue #1 | Red #2 | Blue #2 |
|---|---|---|---|---|
| Red | 0.125 | 0.375 | 0.125 | 0.375 |
| Blue | 0.375 | 0.125 | 0.375 | 0.125 |

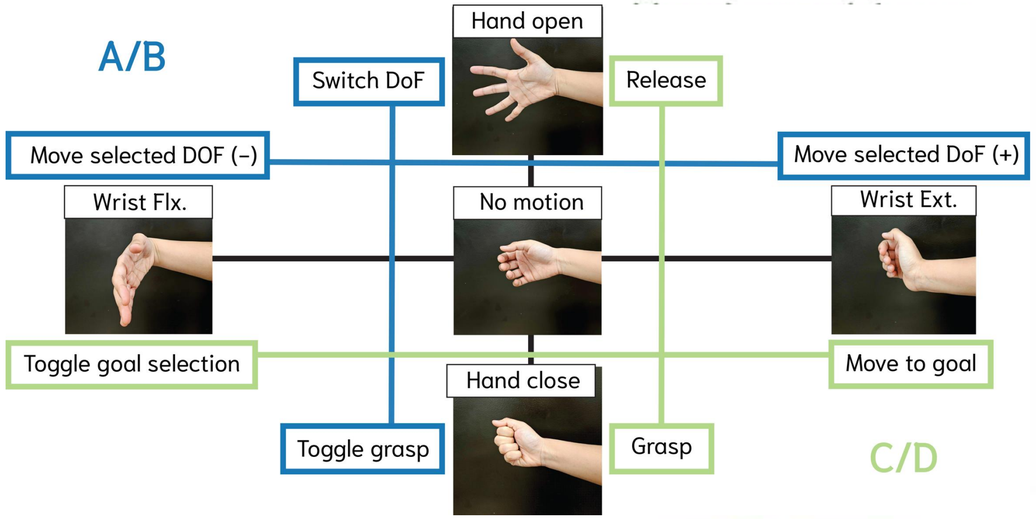
# Intelligent Wearables - Intelligent Prosthetic Arm



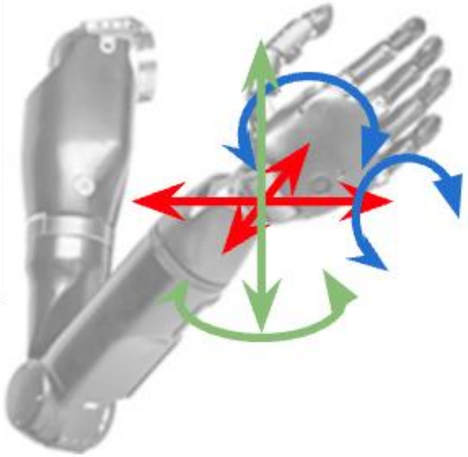
# Intelligent Wearables - Intelligent Prosthetic Arm



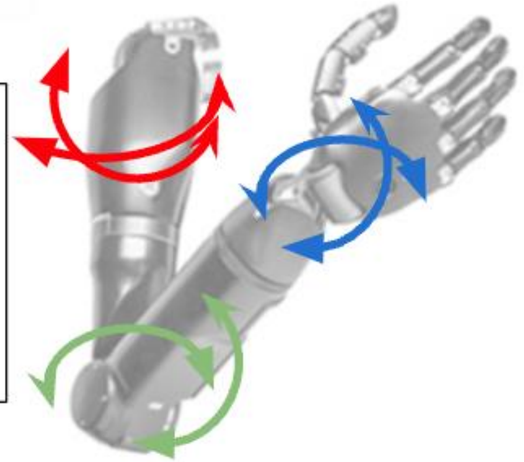
# Intelligent Wearables - Intelligent Prosthetic Arm




**B (task space)**
Mode 1:
Wrist translation forward, back, left, right
Mode 2:
Wrist translation up, down; rotation clockwise/counterclockwise about vertical
Mode 3:
Wrist rotation positive and negative about horizontal axes

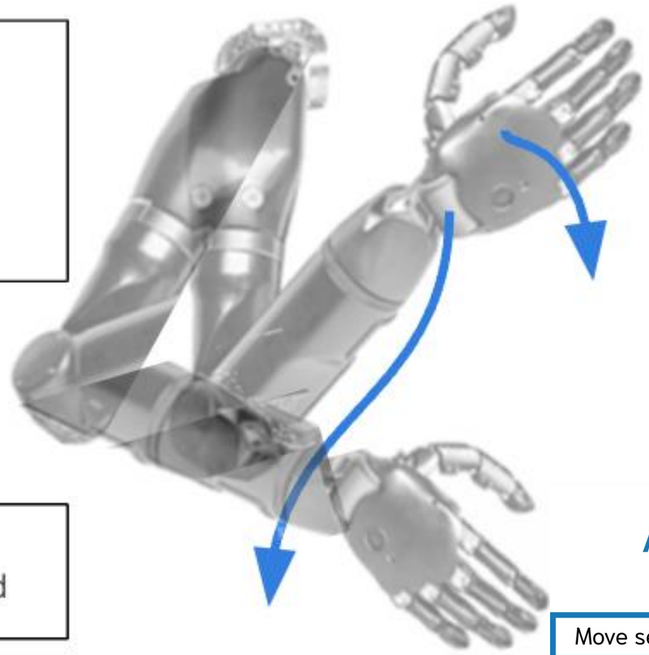


**A (joint space)**
Mode 1:
Shoulder abduction, adduction, flexion, extension
Mode 2:
Elbow flexion, extension, internal, external rotation
Mode 3:
Wrist flexion, extension, internal, external deviation



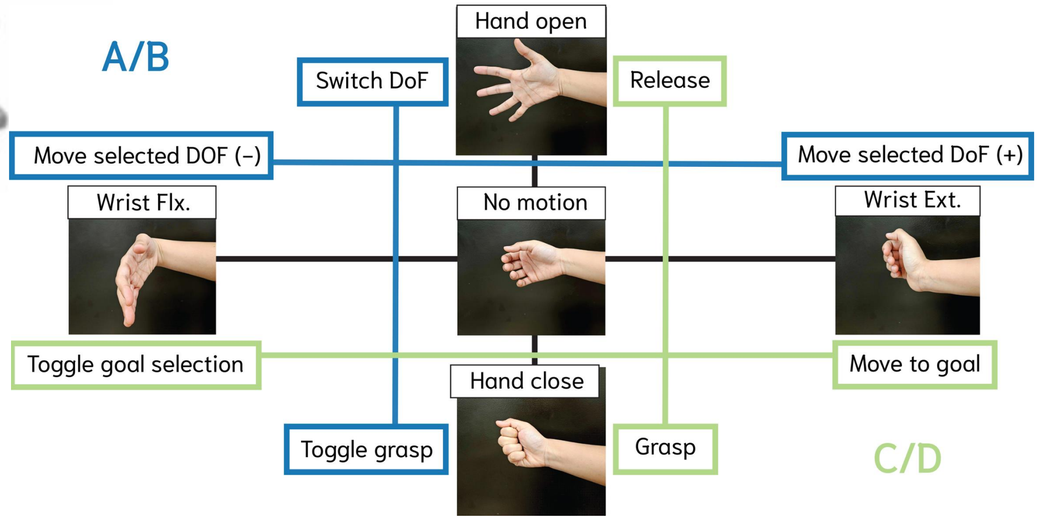
# Intelligent Wearables - Intelligent Prosthetic Arm

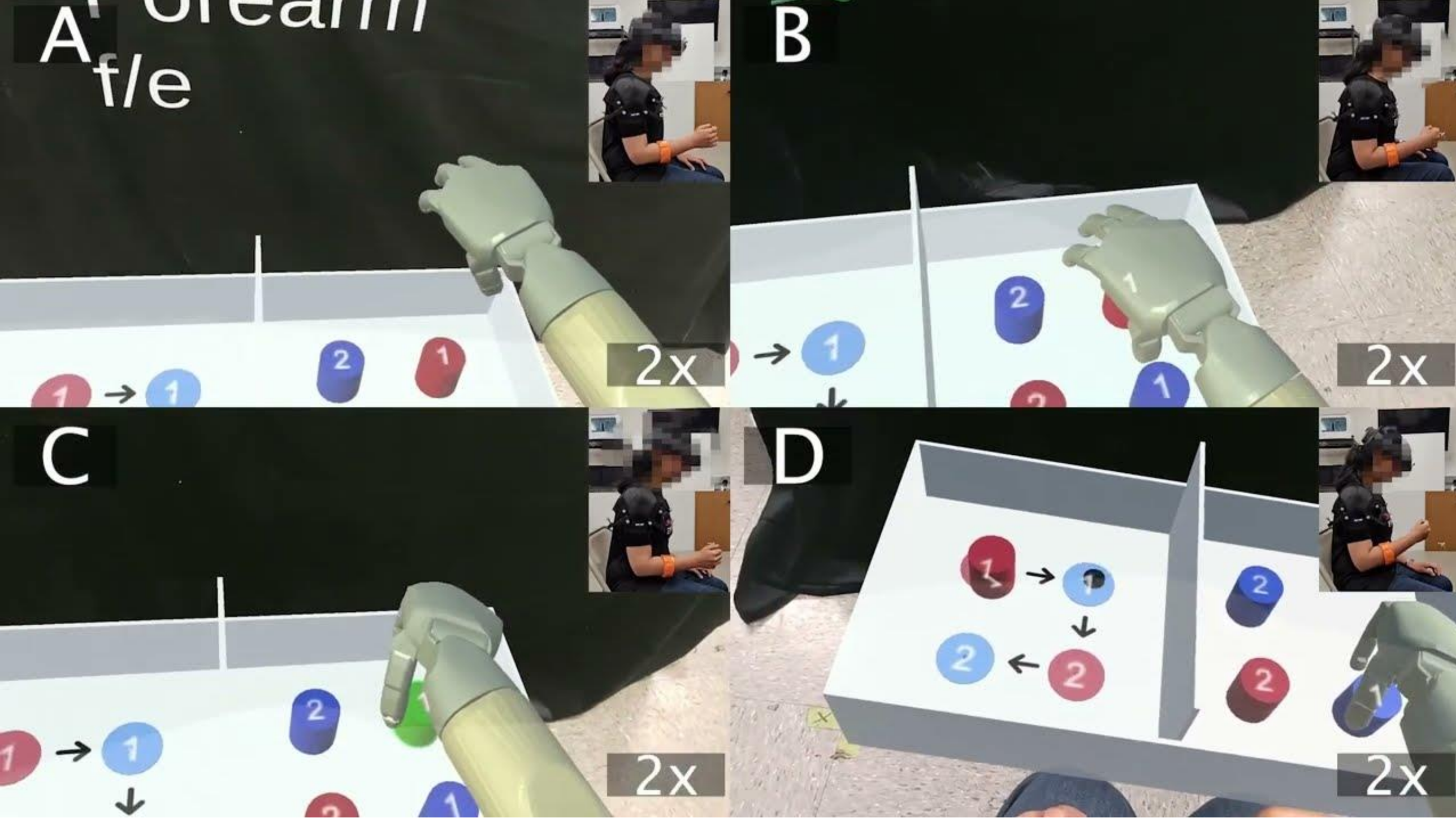
**C and D**
Gazing at block/target spot highlights it
MoveIt! plans collision-free path
Touching joystick in any direction moves along path
Releasing joystick stops motion



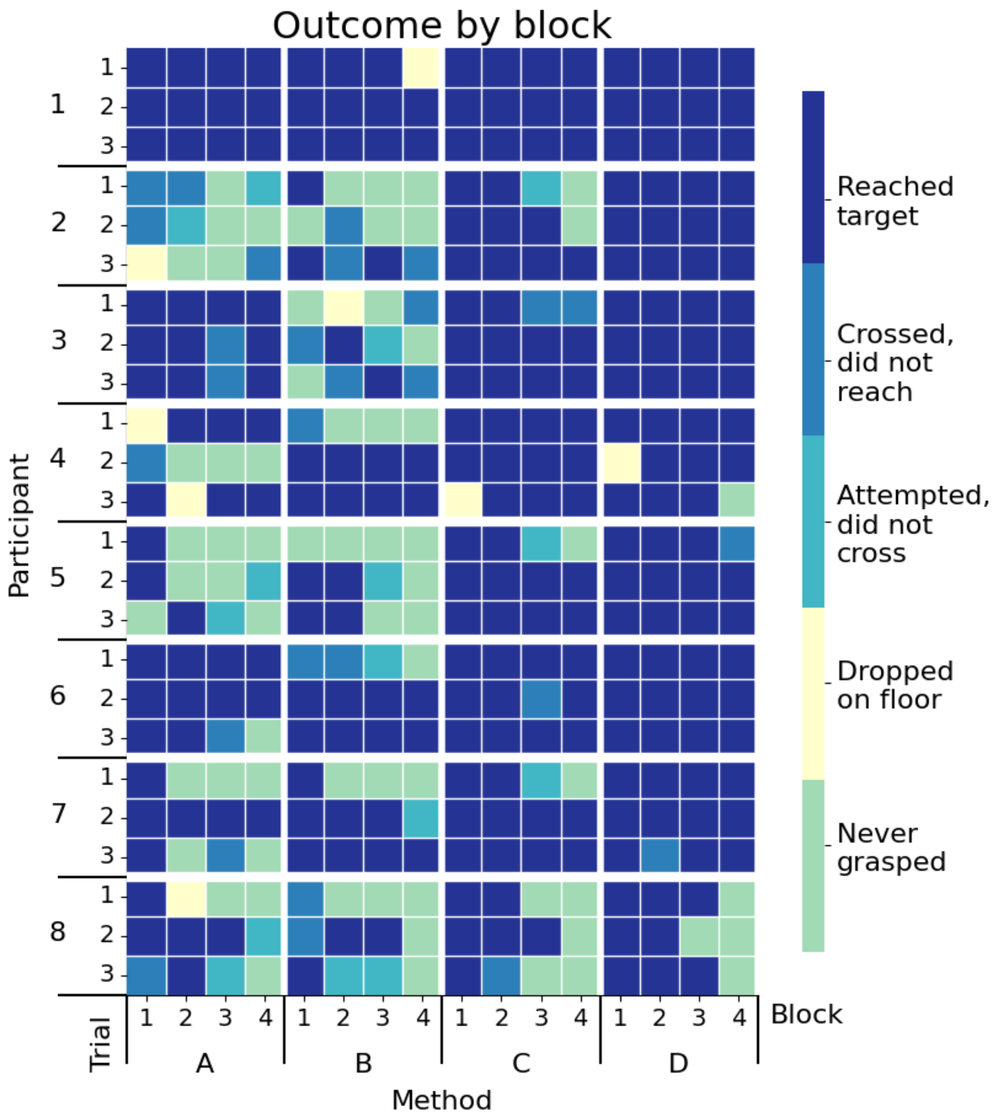
**C**
Block closest to gaze in the image plane is highlighted

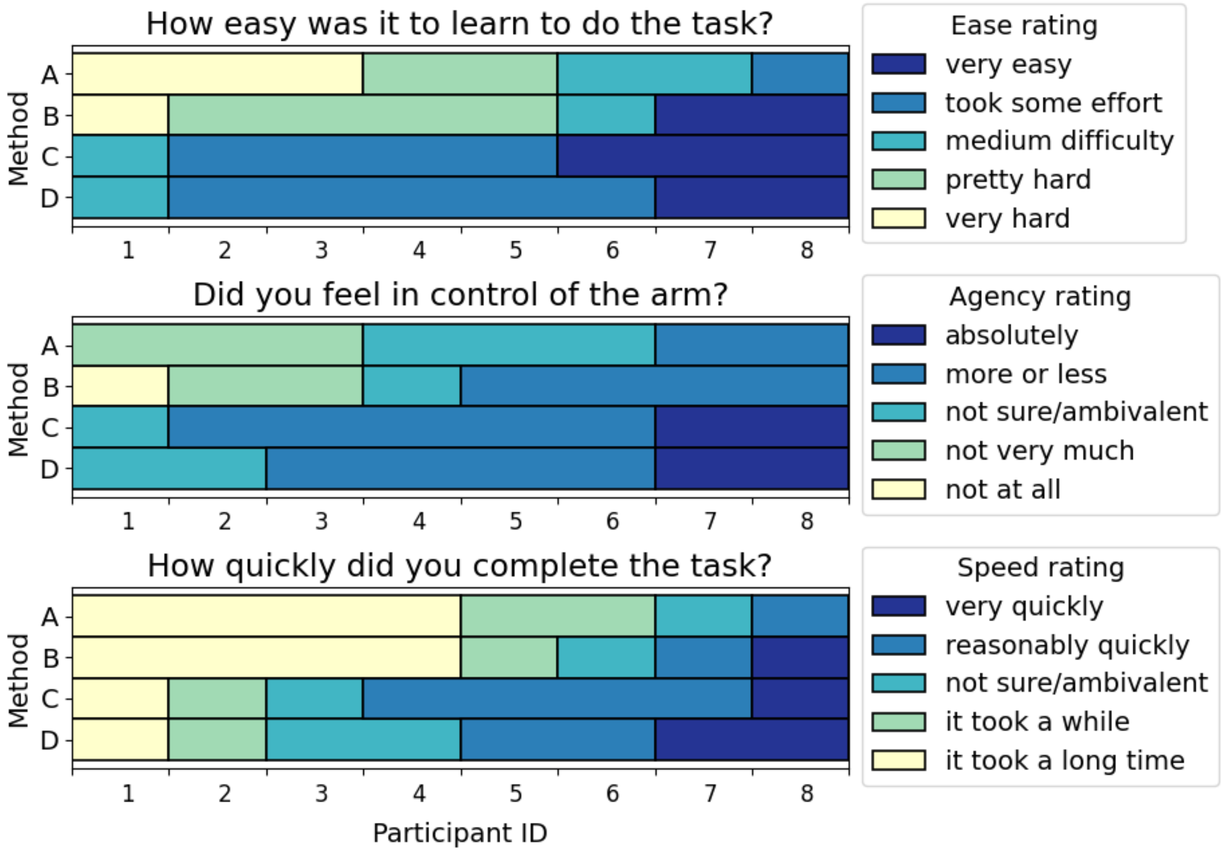
**D**
The probability of a block being highlighted is more if the block color matches the known instruction, than if not



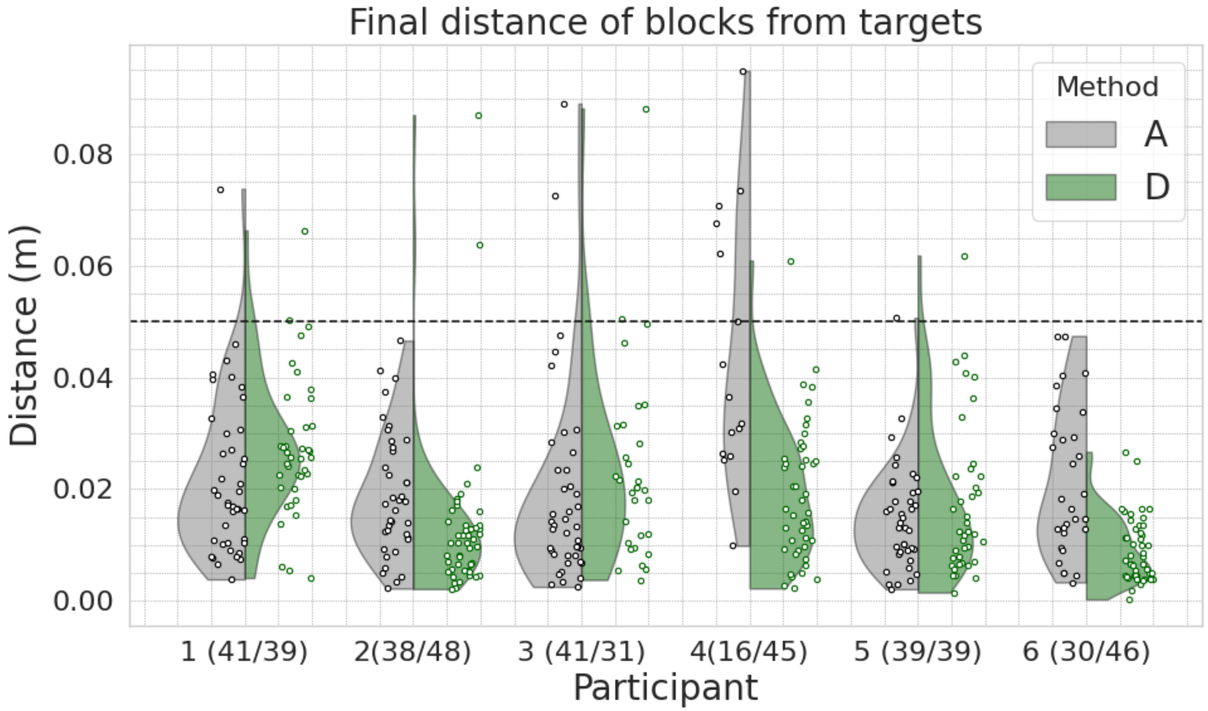

A
B
C
D
2x
2x
2x
2x

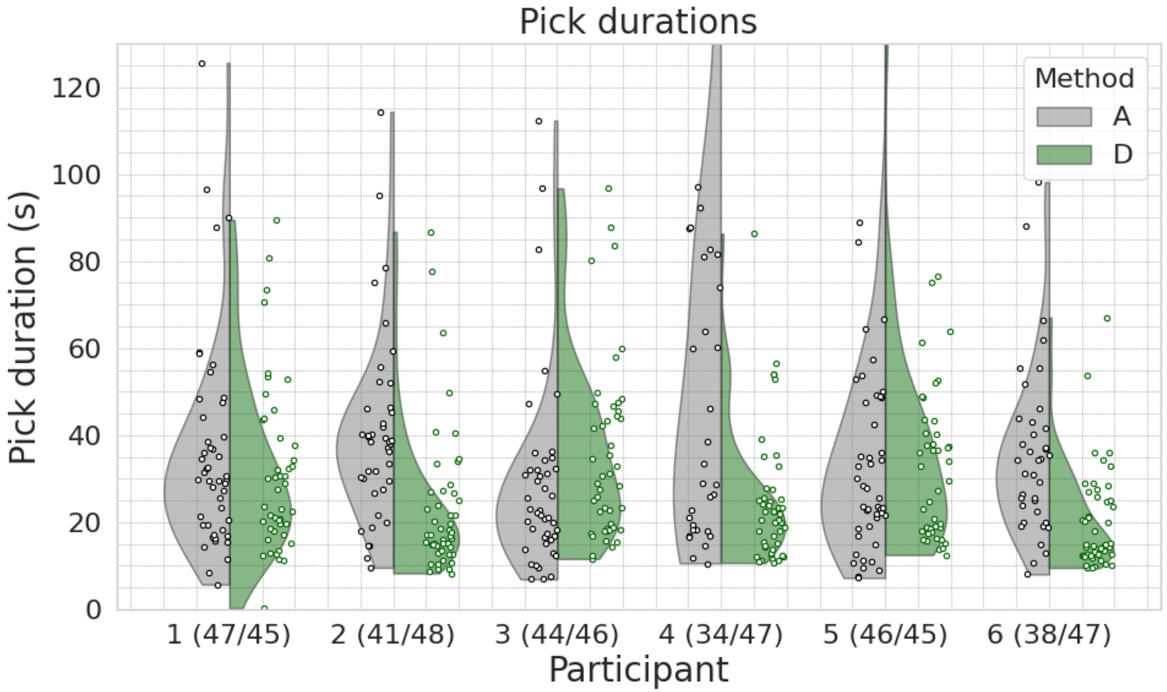
# Intelligent Wearables - Intelligent Prosthetic Arm



# Intelligent Wearables - Intelligent Prosthetic Arm



# Face Haptics

# Motivation

- Haptic feedback is useful in manipulation tasks
- In prosthetic limbs, it improves embodiment
- In BCIs, as in video games, it improves control

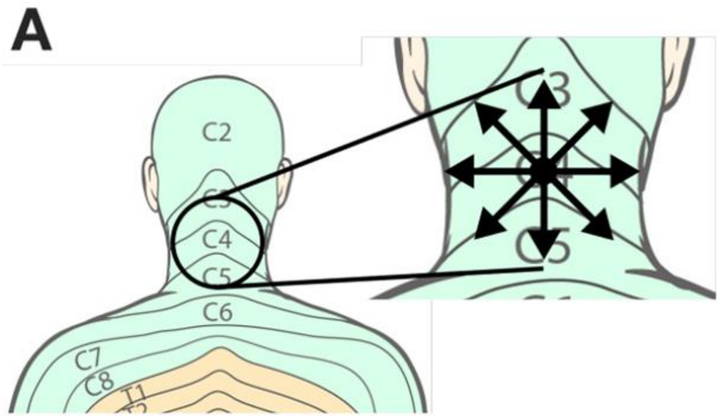


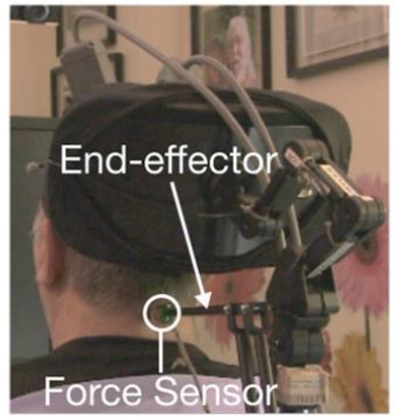

Roland Johansson Lab - Department of Integrative Medical Biology. Umea University, Sweden

# Motivation

- Sometimes we cannot give haptic feedback on the hand or arm
  - Lost limb
  - Lost sensation
- Other options are toes, back, chest, or neck – but not very sensitive



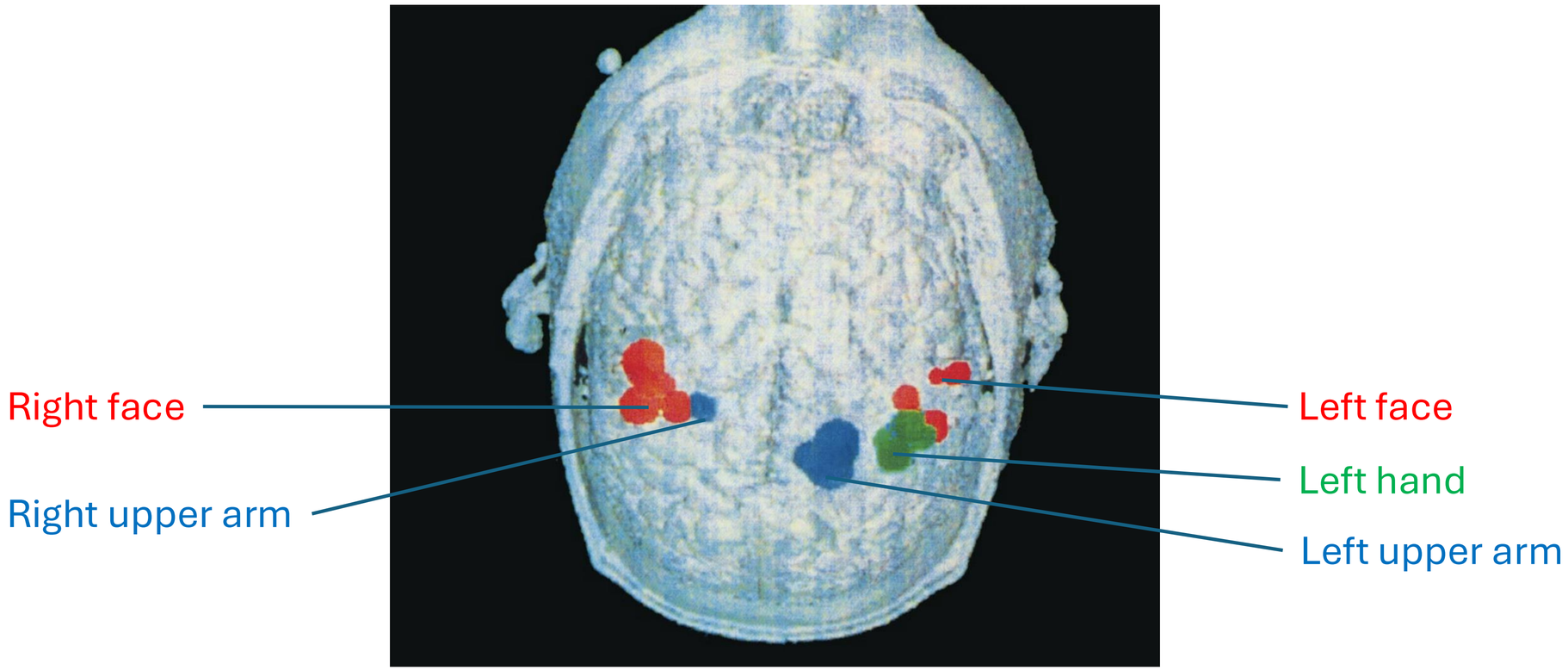




Deo DR, Rezaii P, Hochberg LR, M Okamura A, Shenoy KV, Henderson JM. Effects of Peripheral Haptic Feedback on Intracortical Brain-Computer Interface Control and Associated Sensory Responses in Motor Cortex. IEEE Trans Haptics. 2021 Oct-Dec;14(4):762-775. doi: 10.1109/TOH.2021.3072615. Epub 2021 Dec 17. PMID: 33844633; PMCID: PMC8745032.

Morand R, Brusa T, Schnüriger N, Catanzaro S, Berli M and Koch VM (2022) FeetBack–Redirecting touch sensation from a prosthetic hand to the human foot. *Front. Neurosci.* 16:1019880. doi: 10.3389/fnins.2022.1019880

# What if we could use the face?

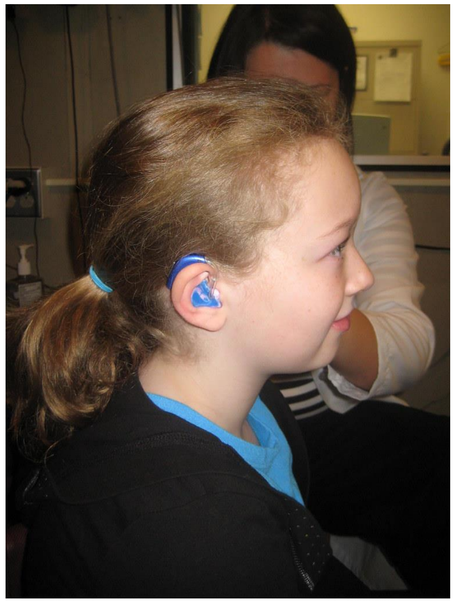
- Brain regions for hand and face are close, can be remapped
- Face skin is much more sensitive other regions (though not as much as fingertips)

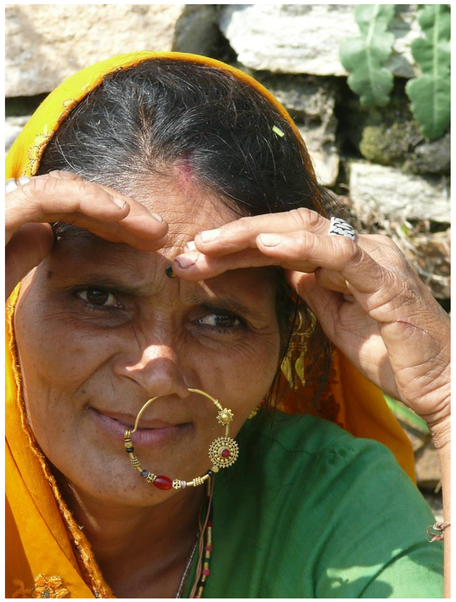



V. S. Ramachandran and W. Hirstein, “The perception of phantom limbs. the D. O. Hebb lecture.” *Brain : A Journal of Neurology*, vol. 121 ( Pt 9), pp. 1603–30, 1998. [Online]. Available: https: //api.semanticscholar.org/CorpusID:11764495

# Should we even use the face?

- Any occlusion is terrible
  - Face is very important for communication and social connection
  - Eyes, ears, nose, jaw, eyebrows, lips must be free
- More than many other body parts, assistive technology on the face must be socially acceptable and look good
- But we do wear things on the face already

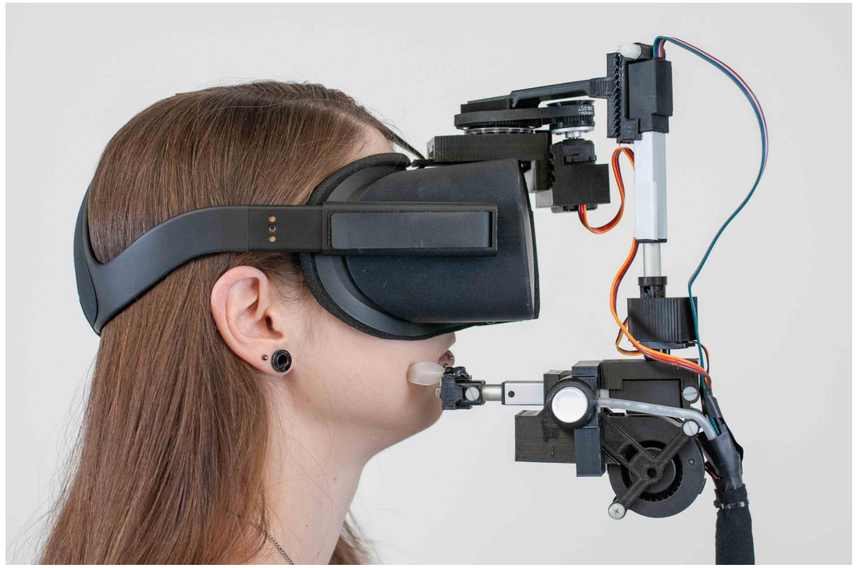





# A face haptic device for assistive applications

- Must be lightweight and compact
- Must not block any function of the face, including expressions
- Must give information in  ways people can interpret easily

We cannot repurpose VR face haptic devices for this!



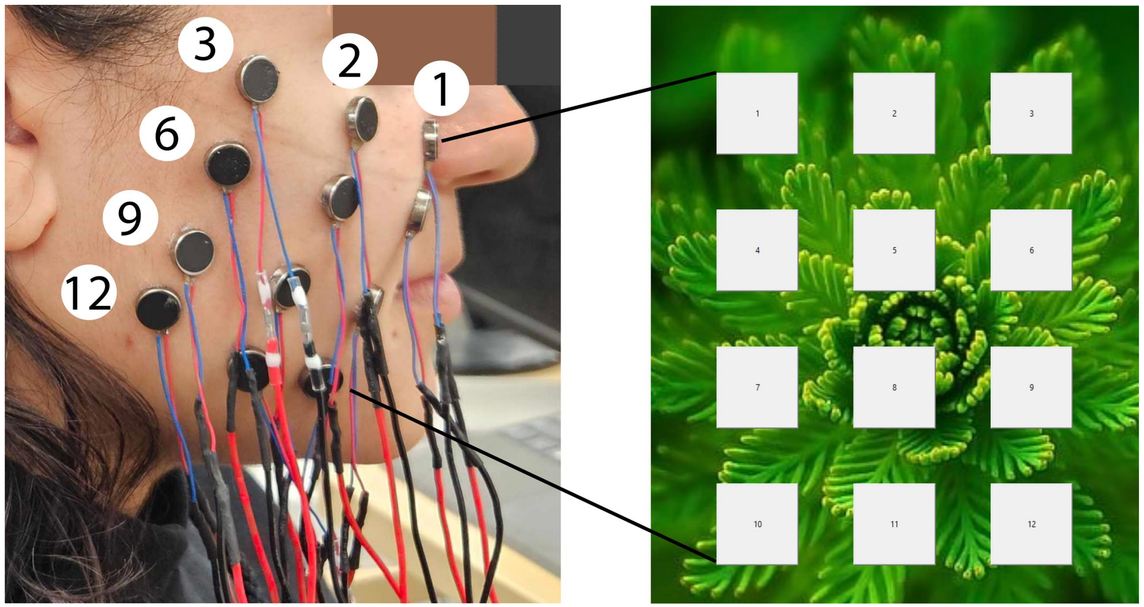
Wilberz, A., Leschtschow, D., Trepkowski, C., Maiero, J., Kruijff, E., & Riecke, B. E. (2020). FaceHaptics: Robot Arm based Versatile Facial Haptics for Immersive Environments. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3313831.3376481



Vivian Shen, Craig Shultz, and Chris Harrison. 2022. Mouth Haptics in VR using a Headset Ultrasound Phased Array. In CHI Conference on Human Factors in Computing Systems (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA. ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3491102.3501960

# Small vibration motors are compact and easy to find

- We did a first experiment with 200ms buzzes at 12 locations
- Participants liked the feeling of short vibrations on the cheek
- People perceive ambiguous vibrations to be further out than they are



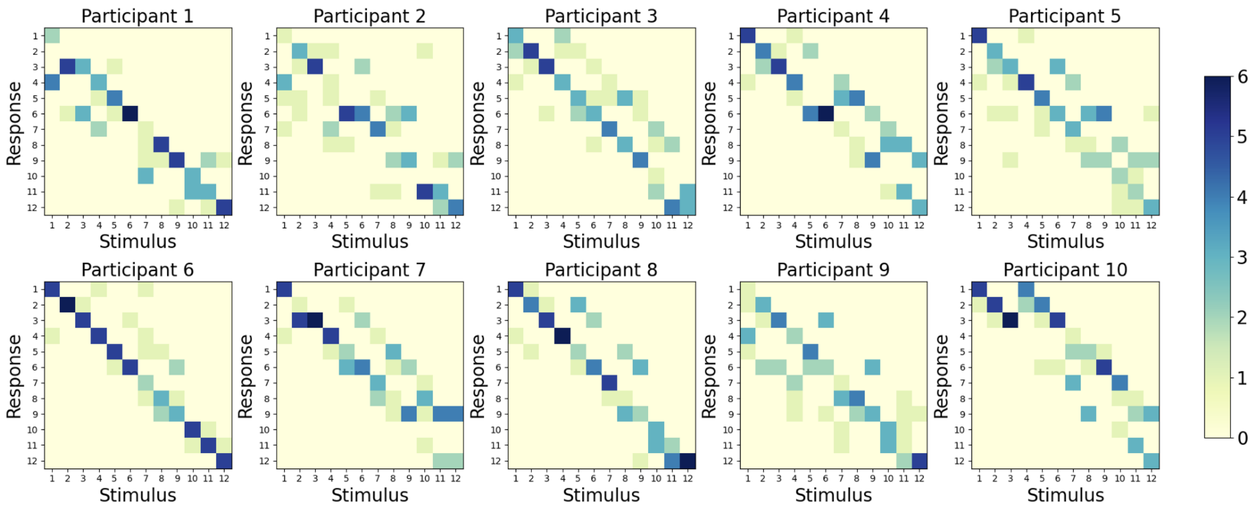
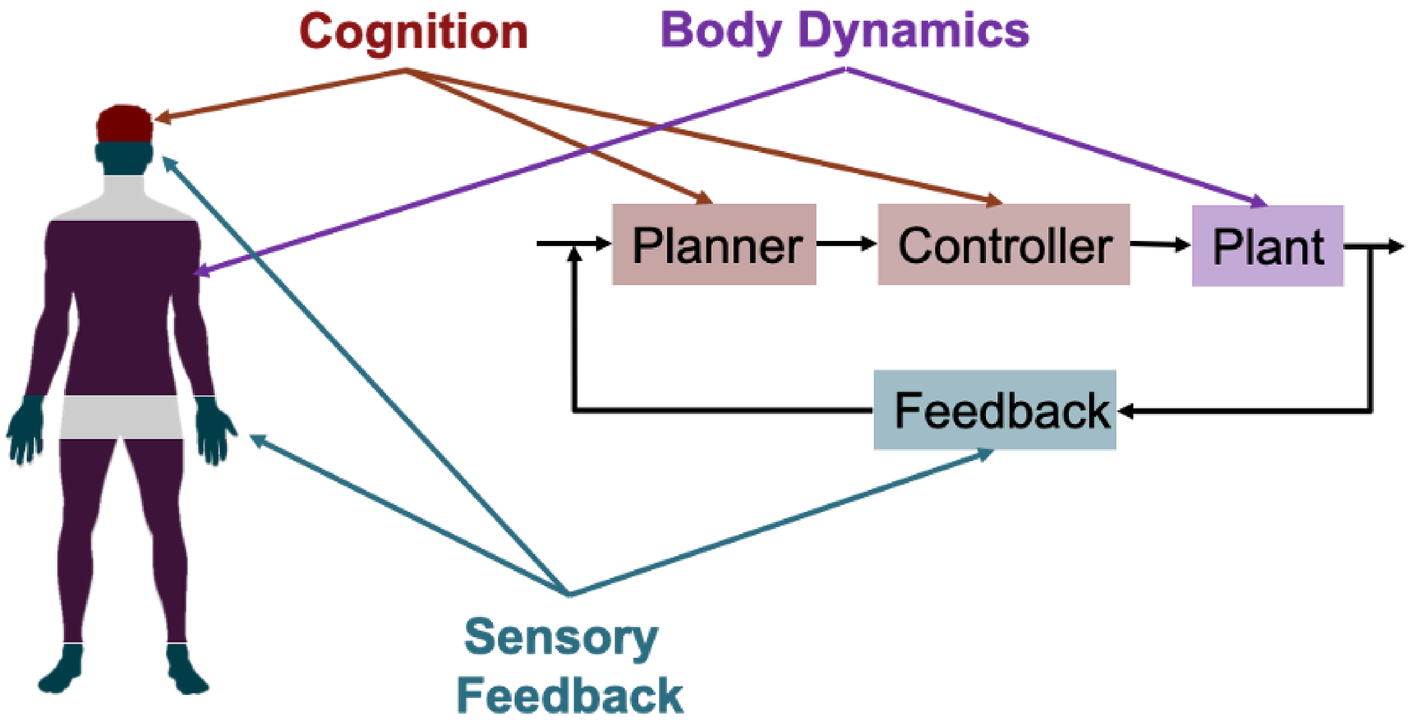




Fig. 2. Confusion matrices showing correct responses along the diagonal, and misclassifications off the diagonal.

# Intelligent Wearables - Fall Prevention Sensor




Ability enhancing device usually **improves sensory feedback** concerning the world

# Assistive Robotics and Manipulation Laboratory

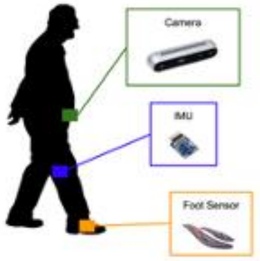
## Intelligent Wearables - Fall Prevention Sensor

**Motivation**:
Falls are the leading cause of fatal and non-fatal injuries in older adults (ages 65+). Can falls be predicted and mitigated using a wearable sensor that observes the person and the environment?

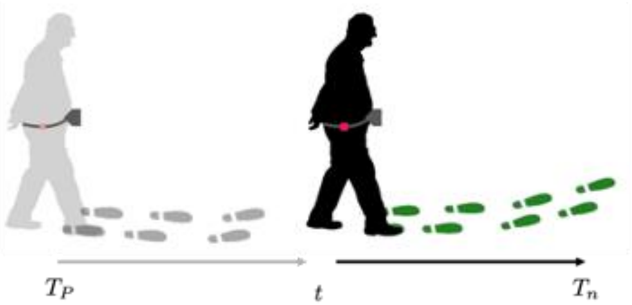
**Related work**:
**"The elderly fall risk assessment and prediction based on gait analysis"** by Jiang, Zhang, Wei.
Used wearable accelerometer to sense gait cycle and correlate to wearer fall risk (conditioned only on gait)

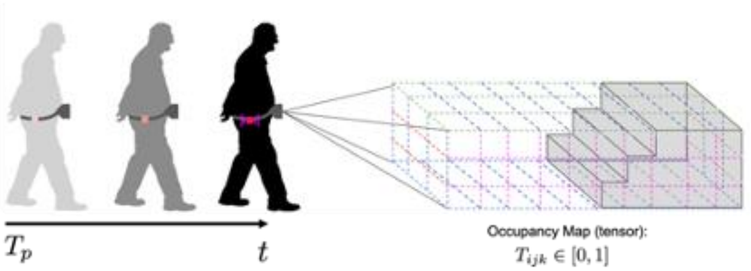
**Approach**:
We observe the persons gait and the surroundings to **predict** the path the wearer will take, their gait over that path and the associated risk of falling given that path and gait.

**Expected outcomes**:
Wearable sensor (with iterative user informed design) capable of predicting wearers path, gait and stability and warning user when risk of falling is significant.



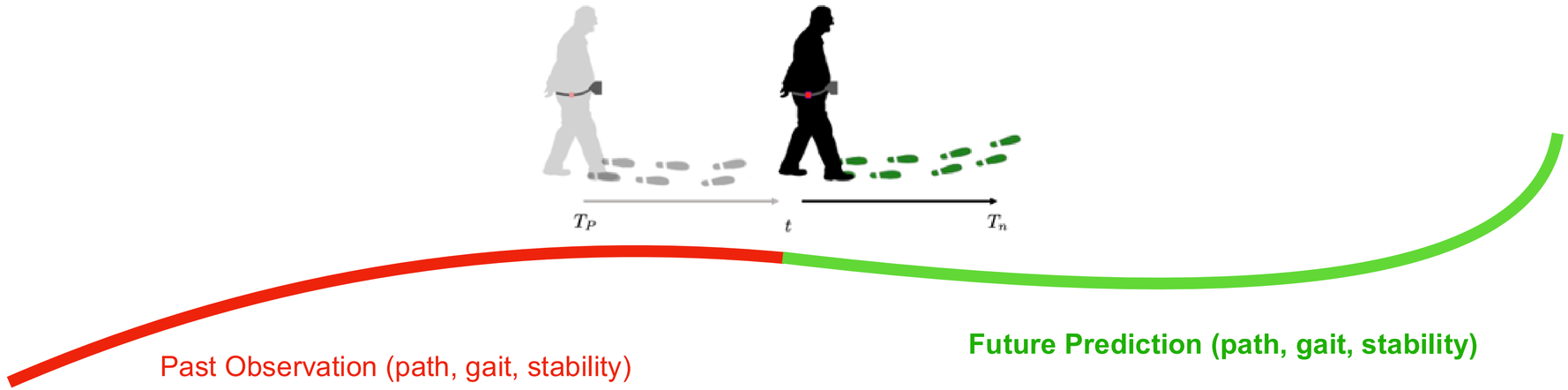

| Sensory Measurement | Model Training | Model Deployment |
|---|---|---|
| Torso Odometry (pose/twist) | ✓ | ✓ |
| Occupancy Map (obstacles) | ✓ | ✓ |
| Gait Cycle (scalar) | ✓ | ✓ |
| Leg Joint Angles (hip, knee, ankle) | ✓ | |
| Foot Pressure Map | ✓ | |



# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Fall Prevention Sensor




**Inputs**

Camera, depth image

Inertial Measurement Unit (Acceleration, angular velocity)

**Machine Learning Modeling and Prediction**

Use time series data (state history) and obstacles to predict the future states. (AutoEncoder and Recurrent Neural Networks)

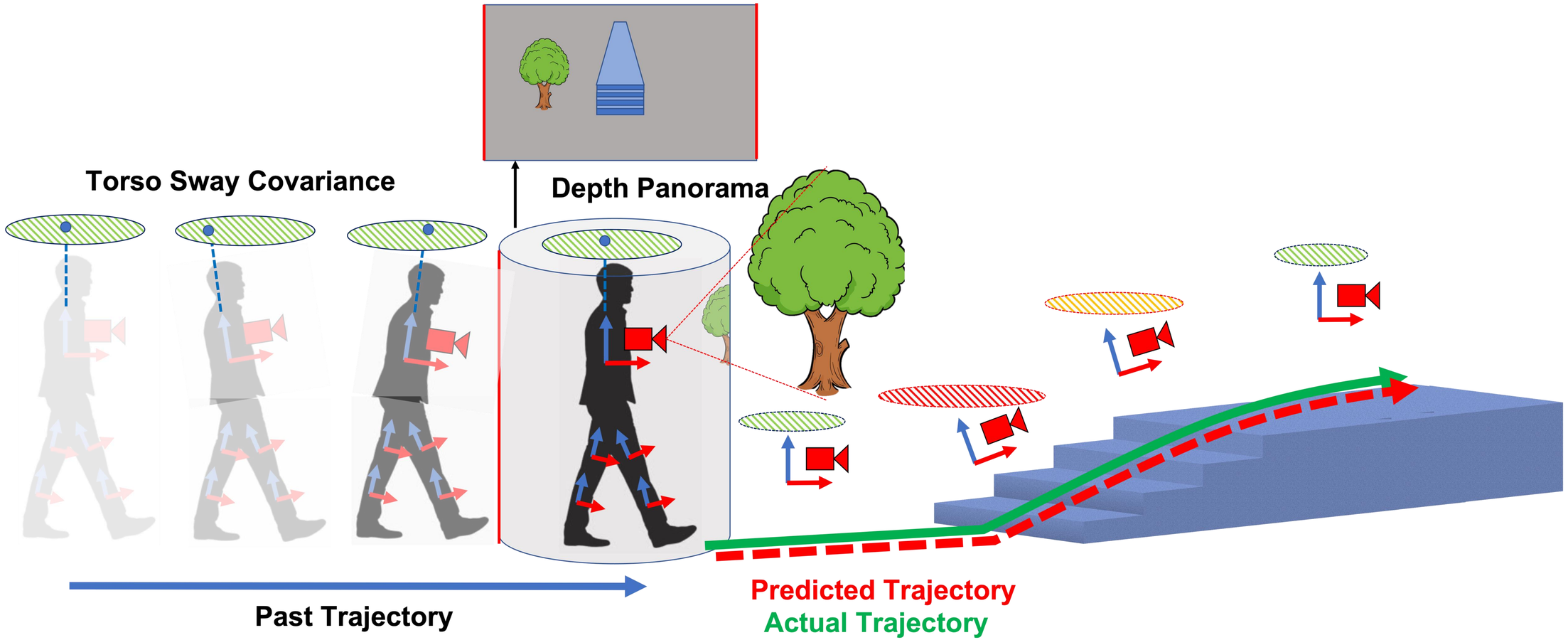
**Outputs**

Expected path, gait, stability

Alert user if instability is predicted

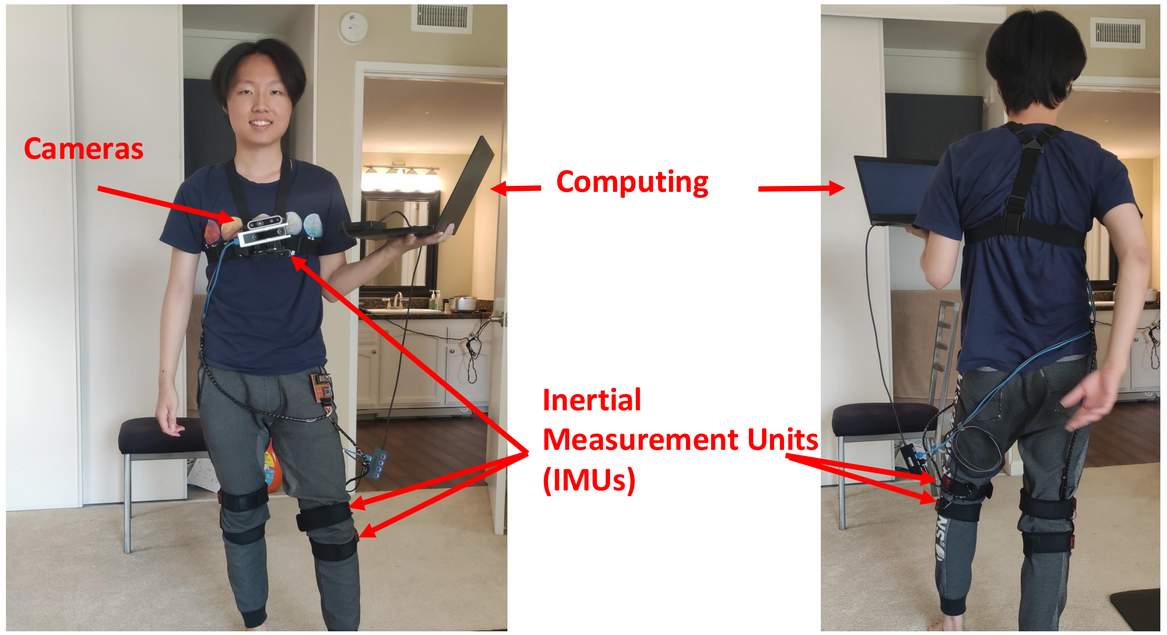
# Assistive Robotics and Manipulation Laboratory

## Intelligent Wearables - Fall Prevention Sensor




Wang, W., Raitor, M. ., Collins, S., Liu, K. ., & Kennedy, M. Trajectory and Sway Prediction Towards Fall Prevention ICRA 2023 accepted.

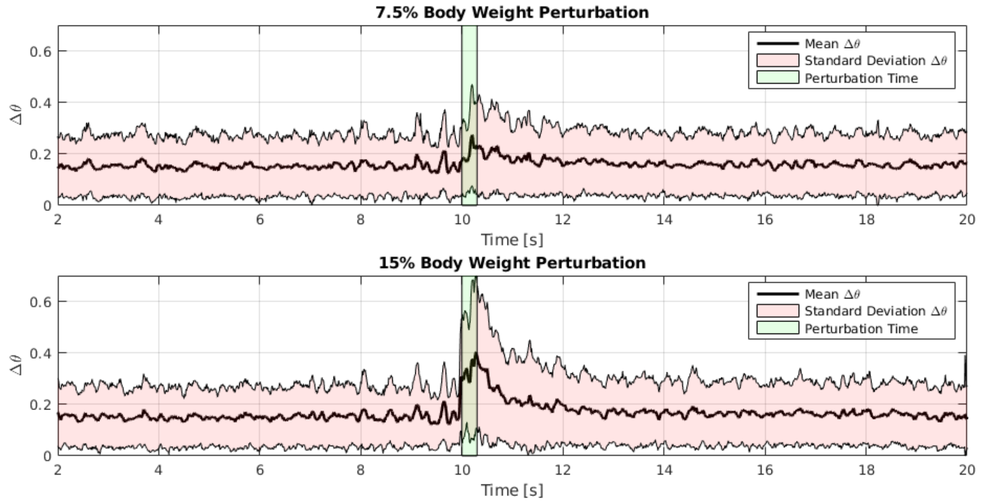
# Experimental Setup for Data Collection



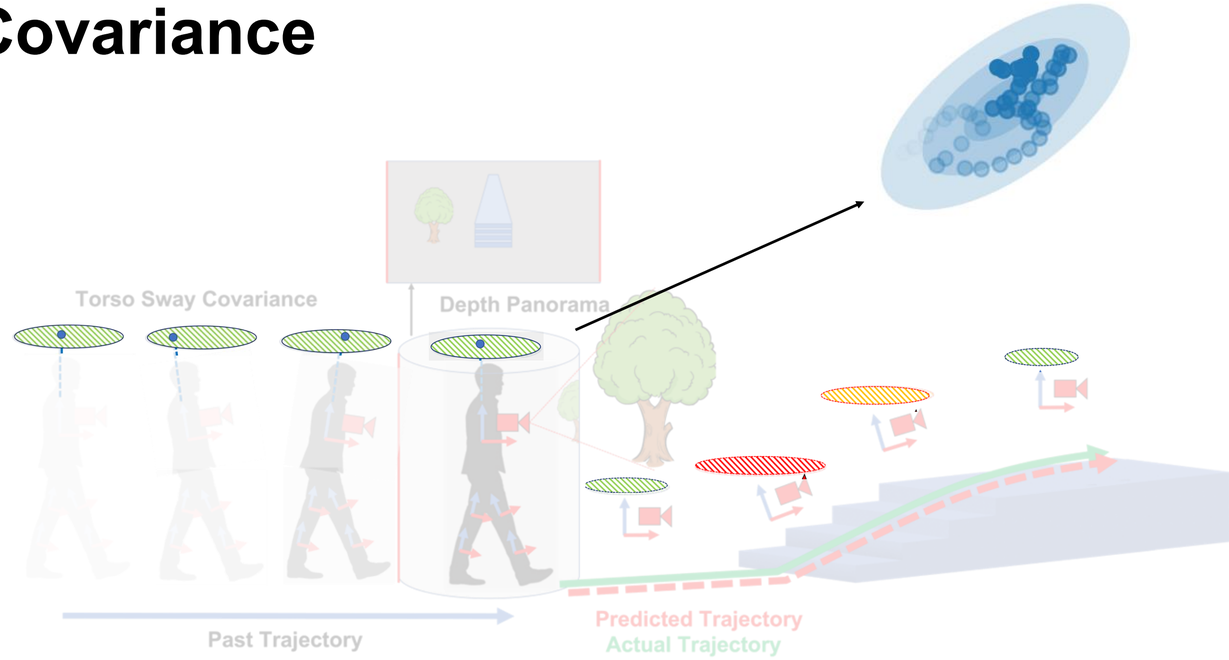
# Sway Covariance

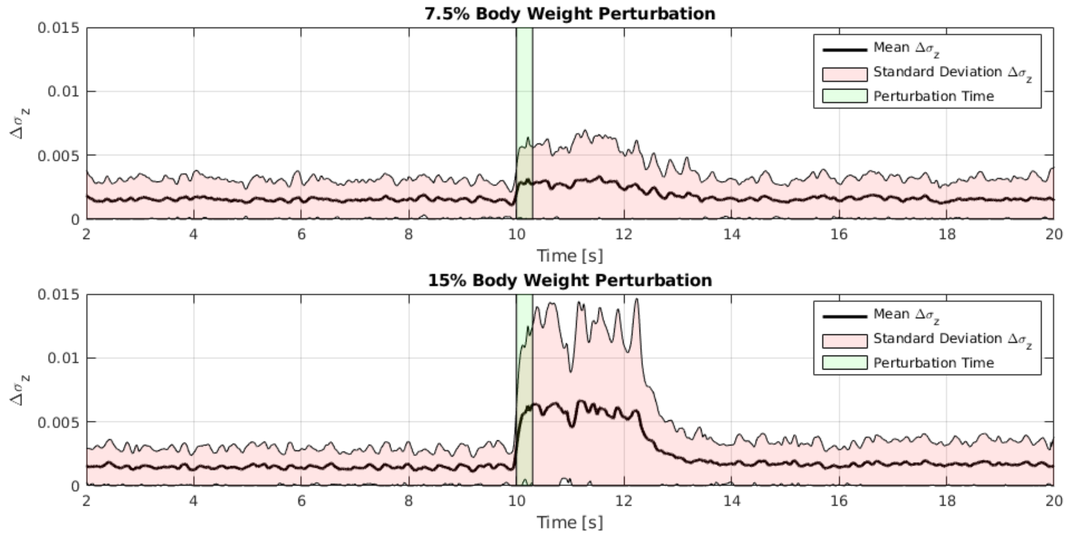
Prof. Steve Collins, Michael Raitor https://youtu.be/IZdGe3KkvkU



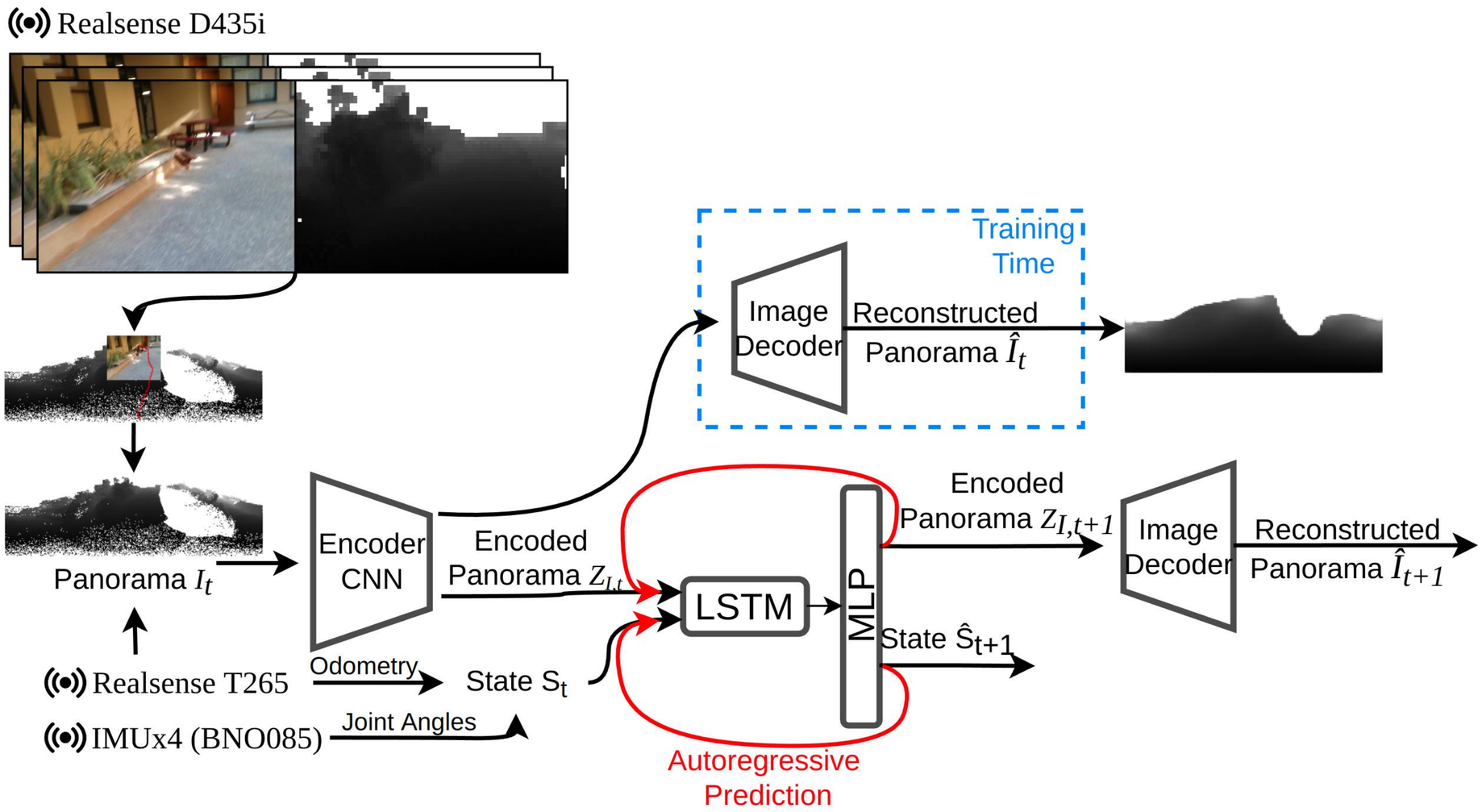

Actual variance data



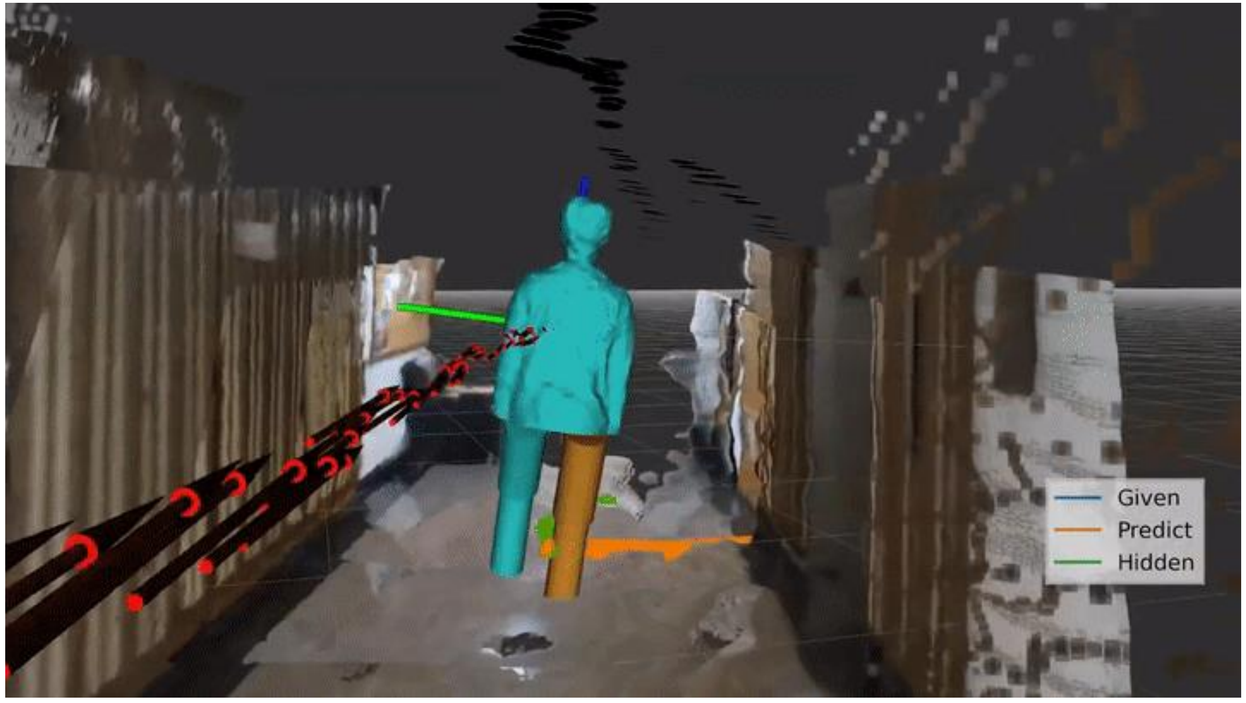



# Assistive Robotics and Manipulation Laboratory

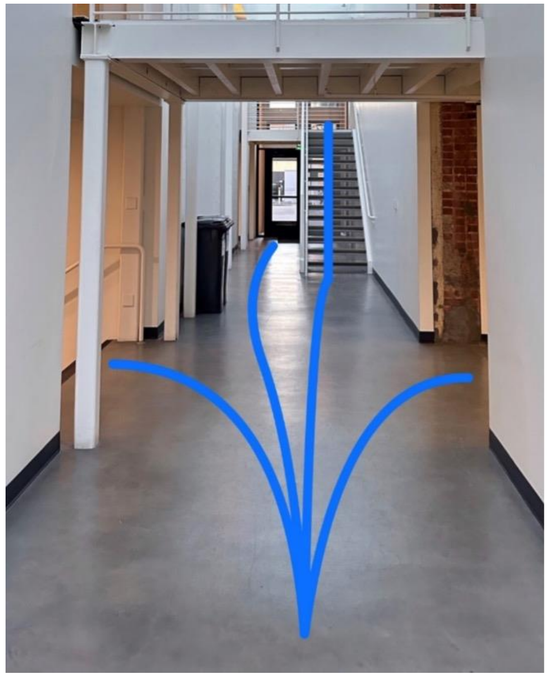
## Intelligent Wearables - Fall Prevention Sensor



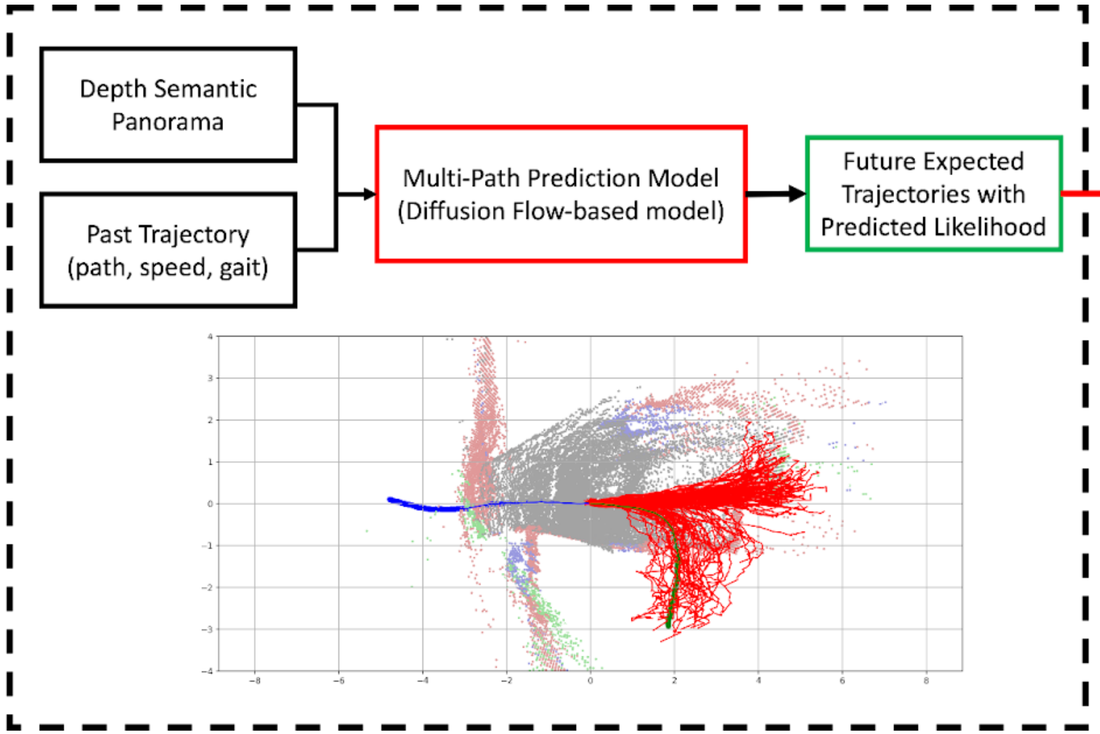

The sway covariance ellipse is a key component in detecting external perturbations.

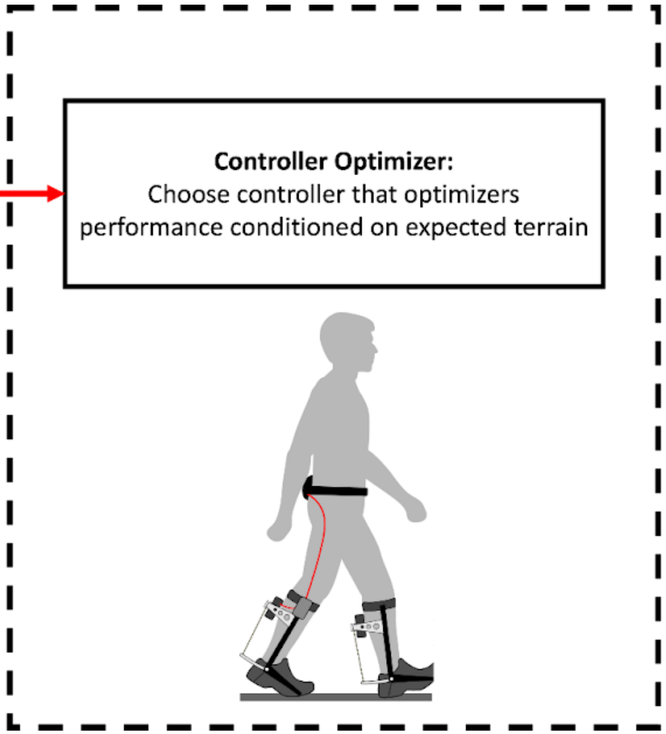

Given
Predict
Hidden

# What's Next?



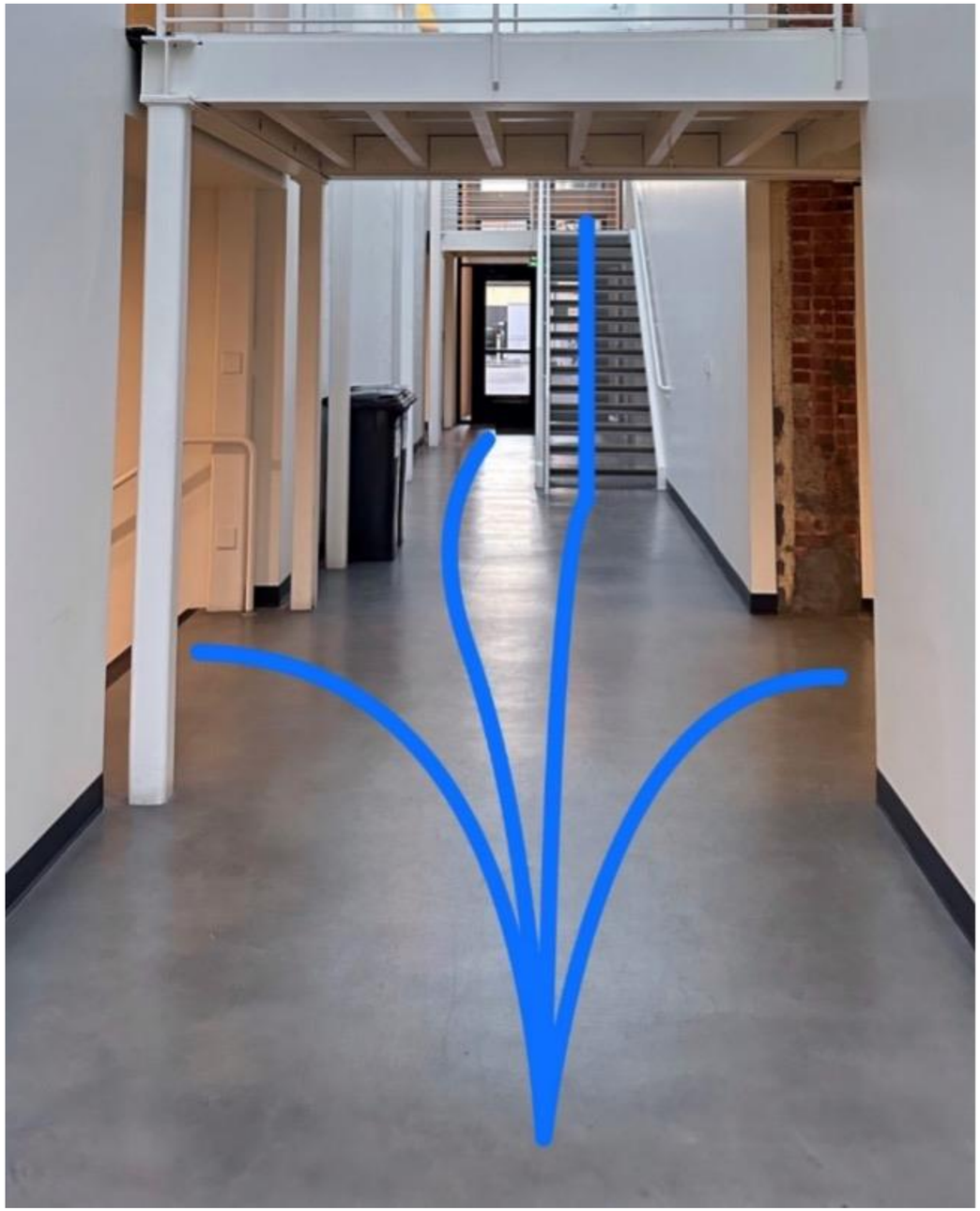
Predicting multi-path hypothesis



# Multi-Modal Path Prediction

Wang, W., Liu, C. K., & Kennedy III, M. (2024). **Egocentric Scene-aware Human Trajectory Prediction**. *arXiv preprint arXiv:2403.19026*.

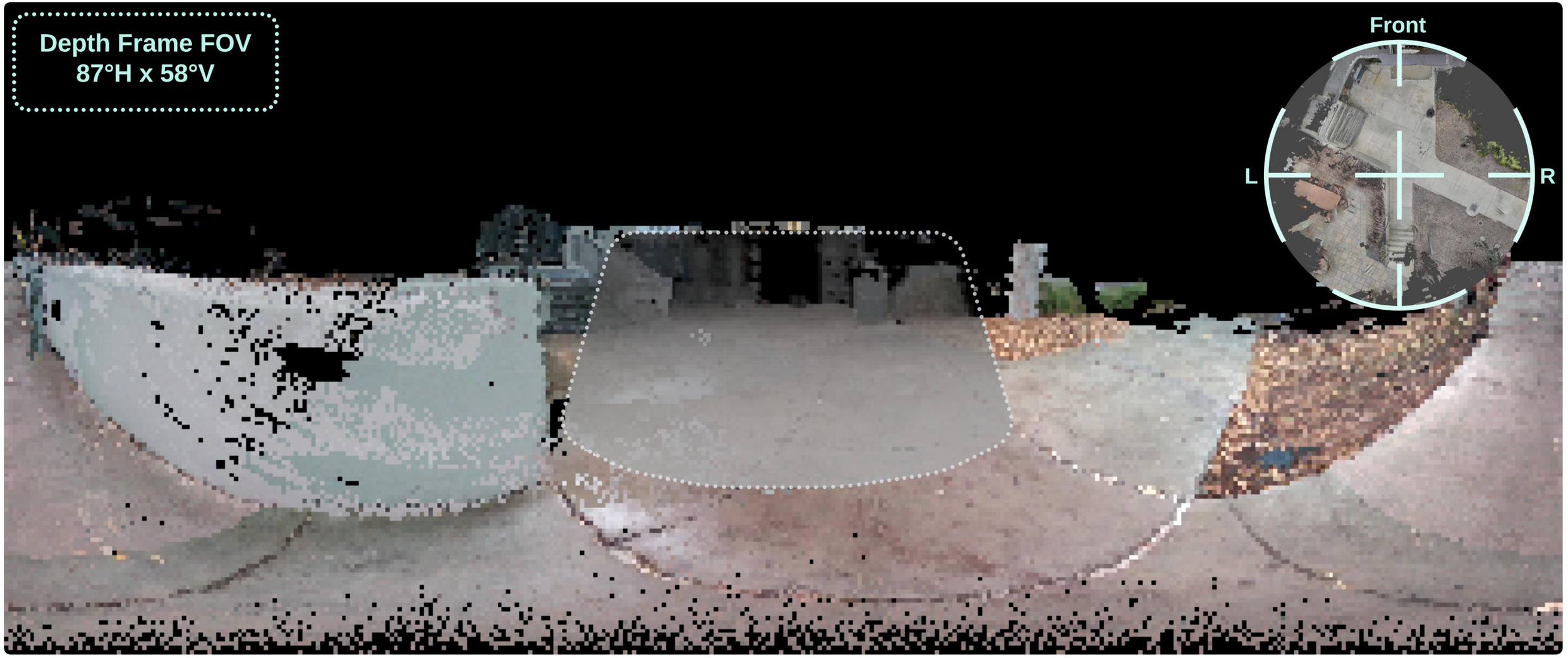


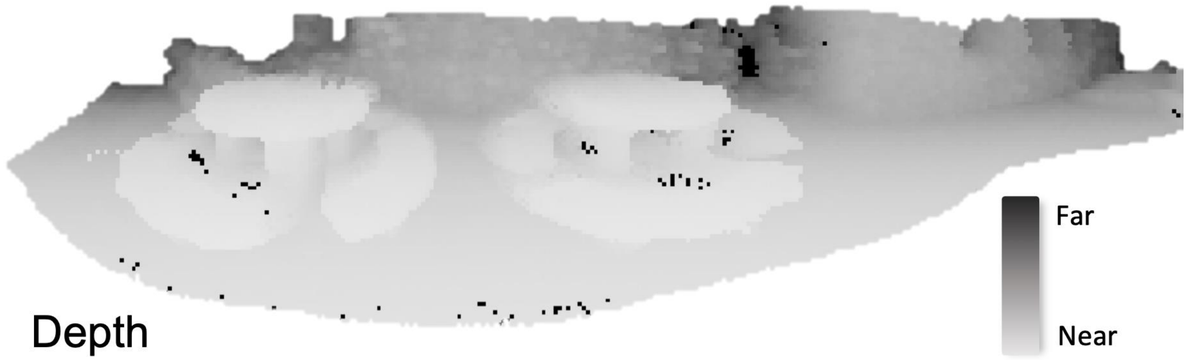
Predicting multi-path hypothesis


D455 - RGBD
T265 - 6 DoF Pose
Panorama
Semantics




Prediction
GT
Past


Depth Frame FOV
87°H x 58°V
Front
L
R



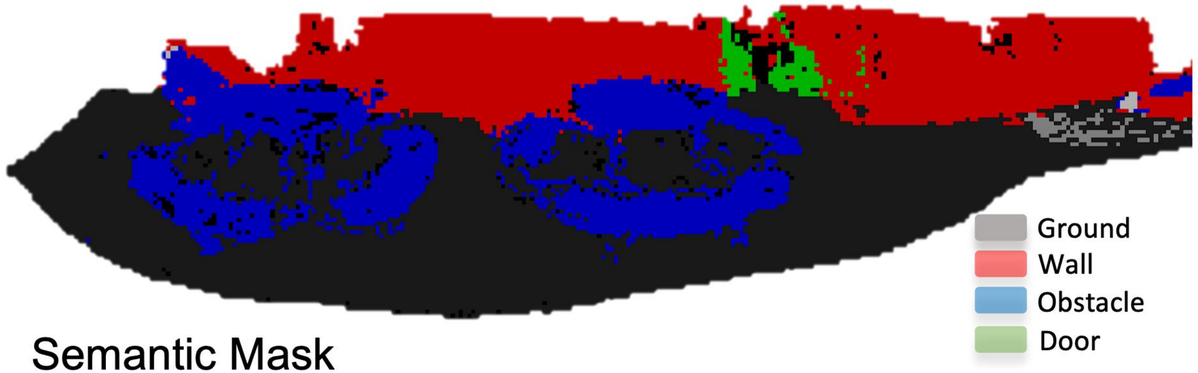

Depth

+



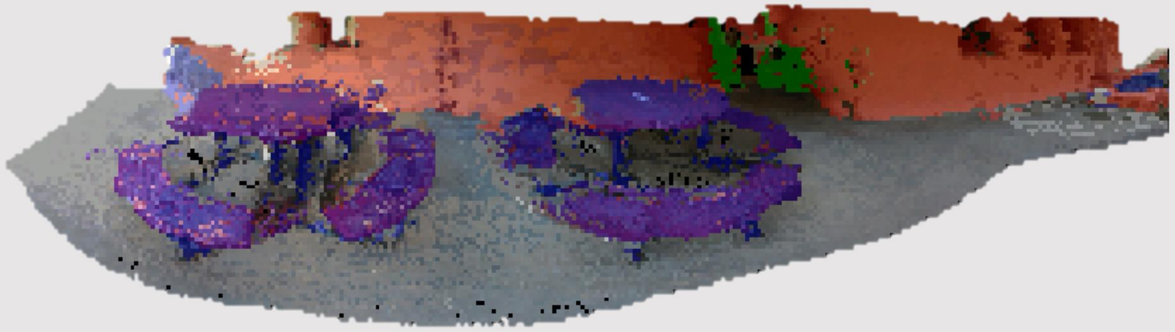
RGB

+

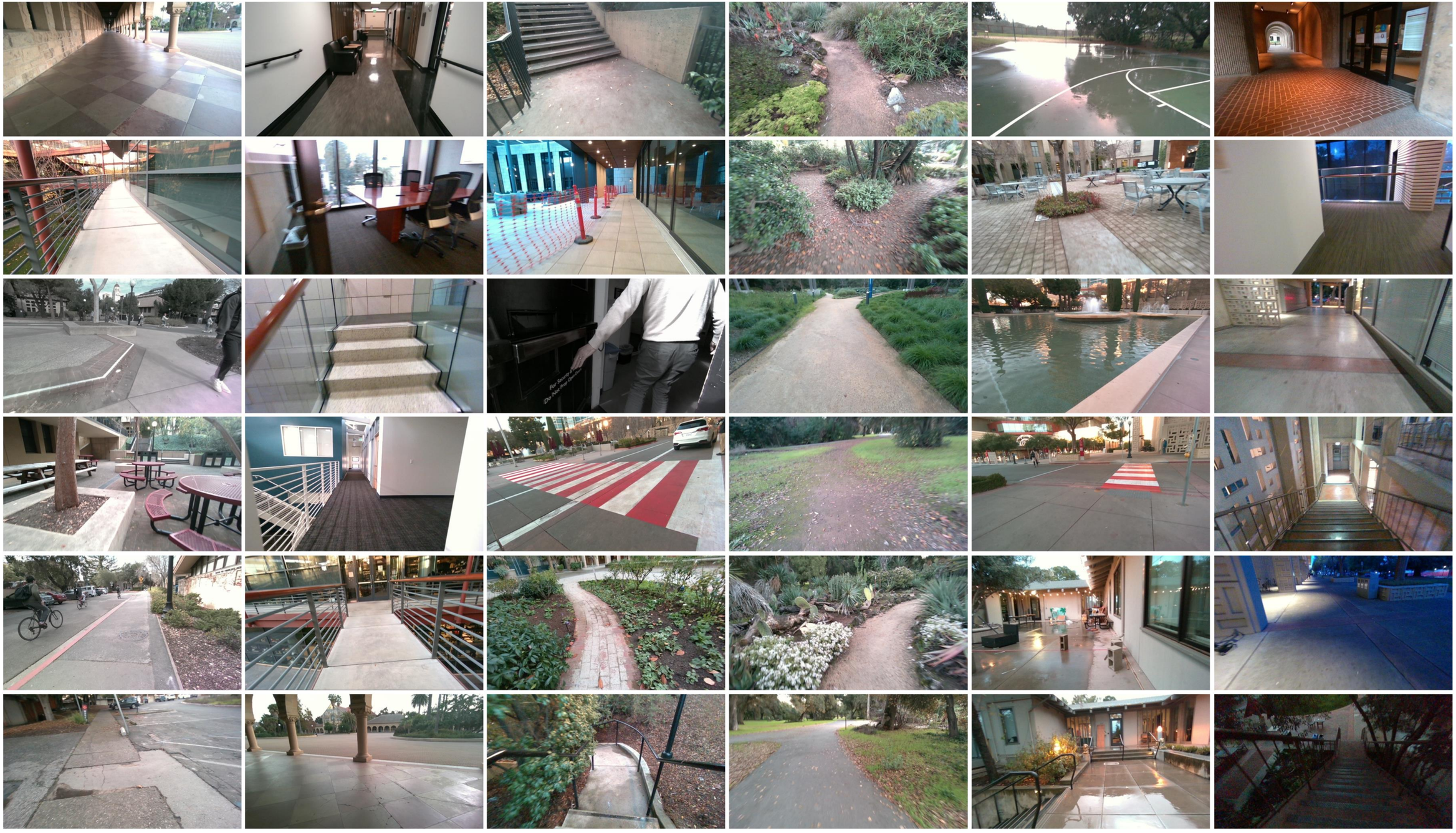



Semantic Mask

=

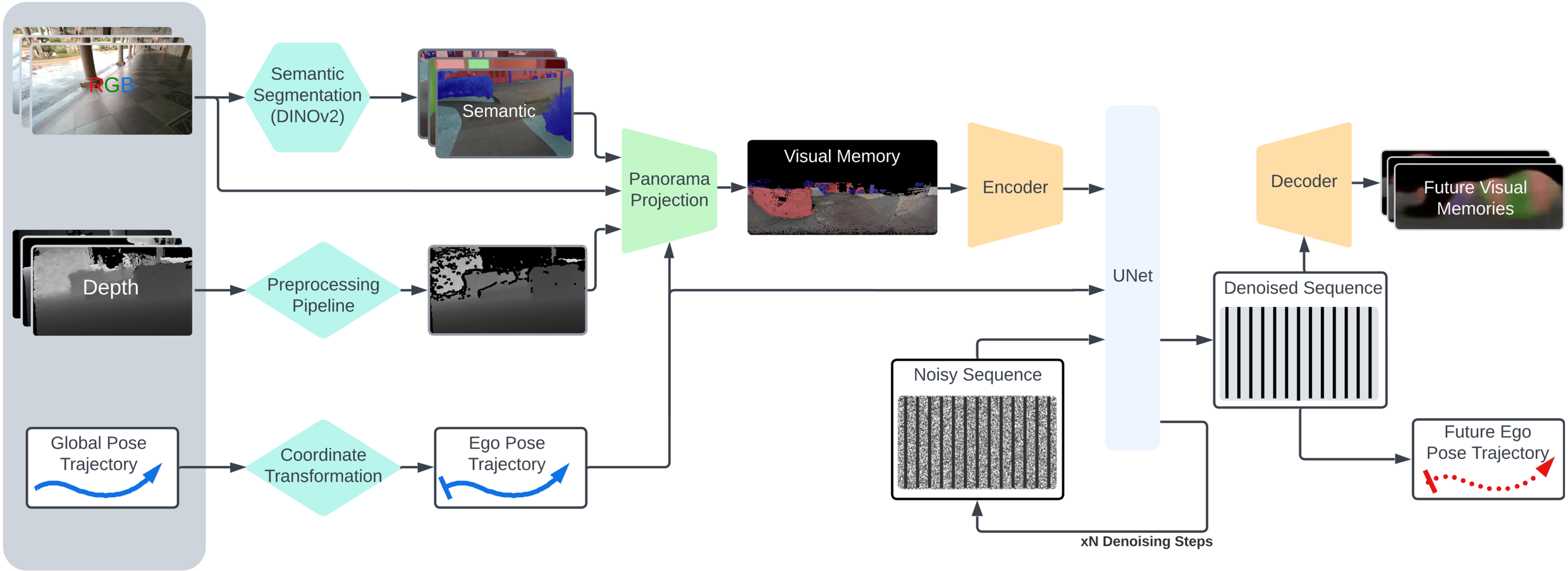


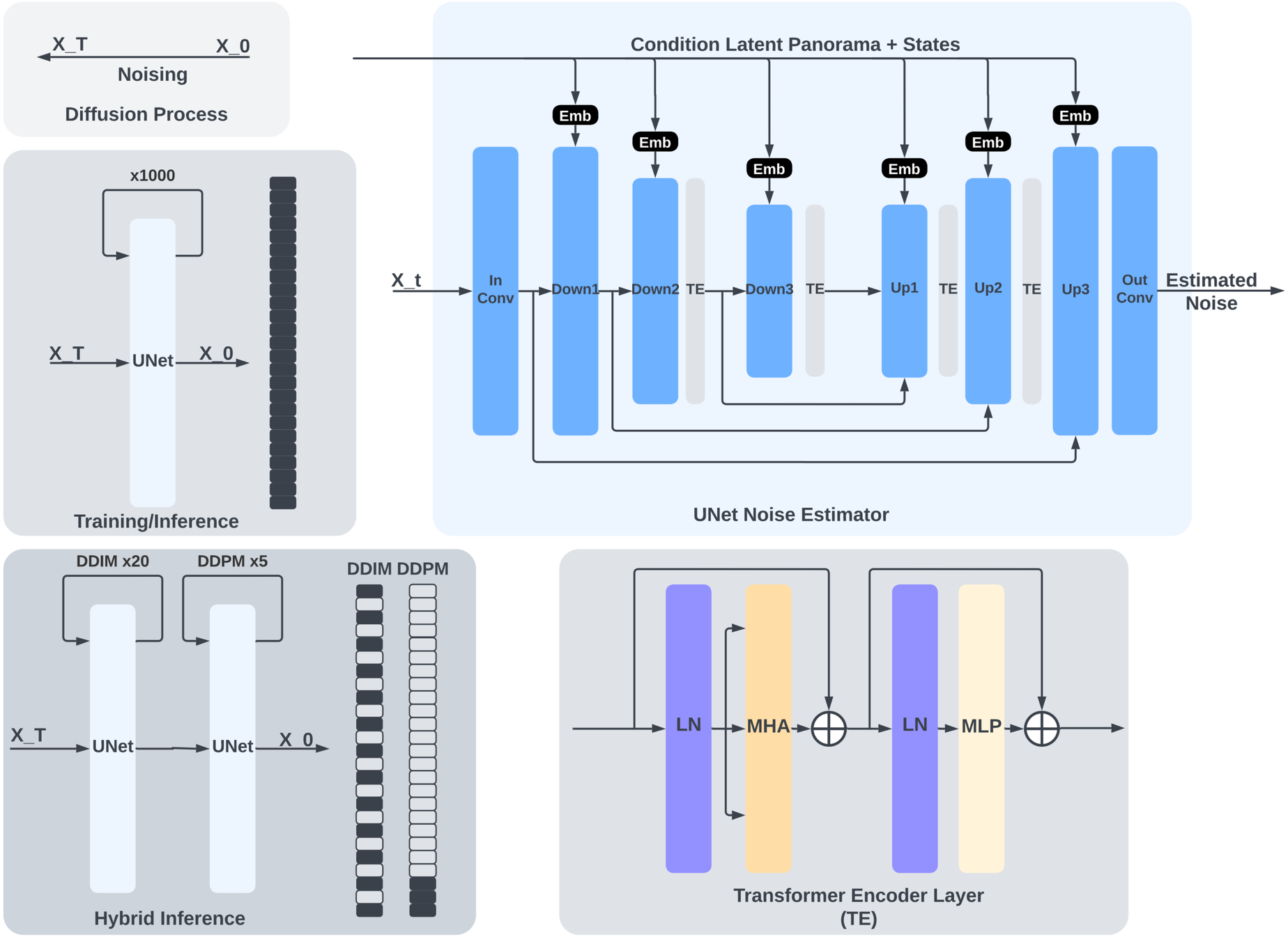
Combined

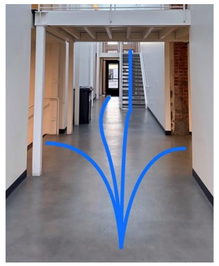


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Stanford University

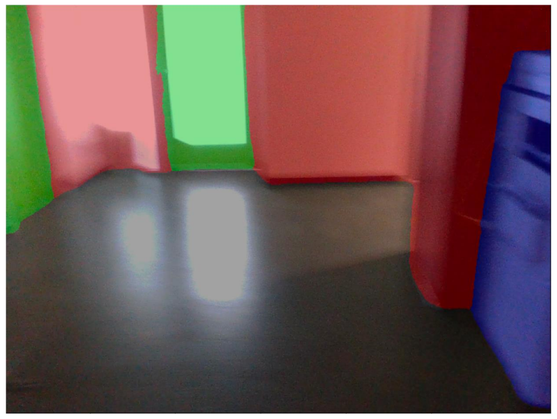

RGB
Semantic Segmentation (DINOv2)
Semantic
Depth
Preprocessing Pipeline
Global Pose Trajectory
Coordinate Transformation
Ego Pose Trajectory
Panorama Projection
Visual Memory
Encoder
UNet
Noisy Sequence
xN Denoising Steps
Denoised Sequence
Decoder
Future Visual Memories
Future Ego Pose Trajectory


X_T
X_0
Noising
Diffusion Process
x1000
X_T
UNet
X_0
Training/Inference
Condition Latent Panorama + States
Emb
Emb
Emb
Emb
Emb
Emb
X_t
In Conv
Down1
Down2
TE
Down3
TE
Up1
TE
Up2
TE
Up3
Out Conv
Estimated Noise
UNet Noise Estimator
DDIM x20
DDPM x5
DDIM DDPM
X_T
UNet
UNet
X_0
Hybrid Inference
LN
MHA
LN
MLP
Transformer Encoder Layer (TE)

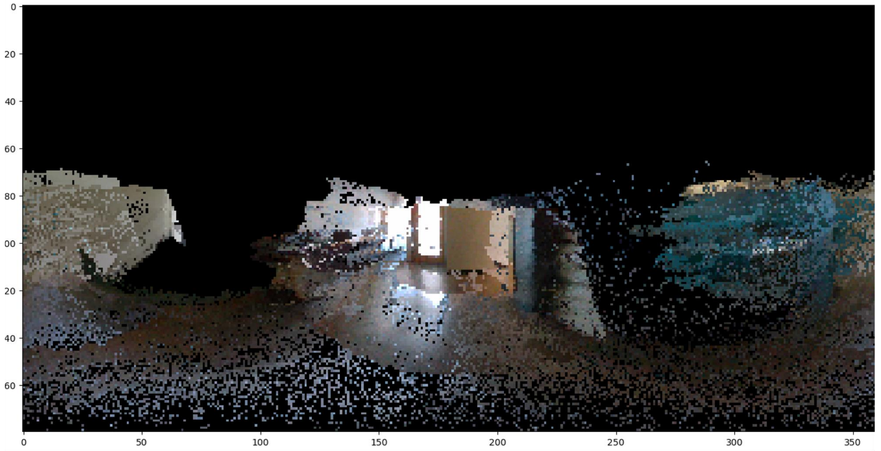




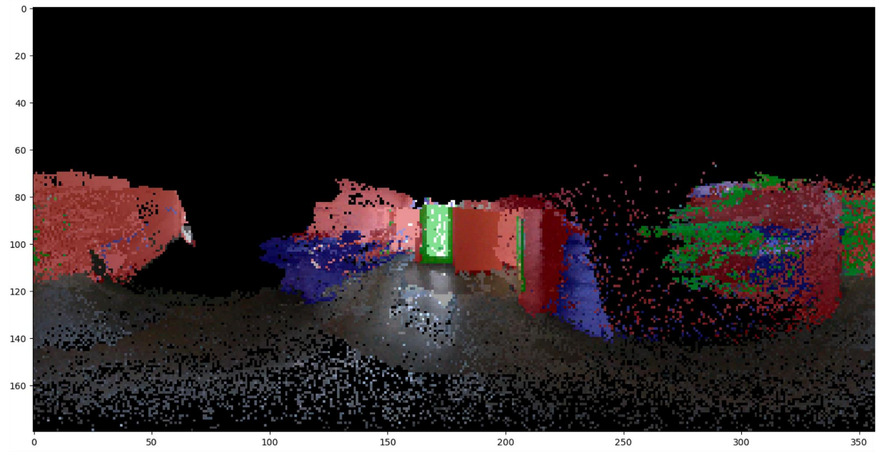
(a)



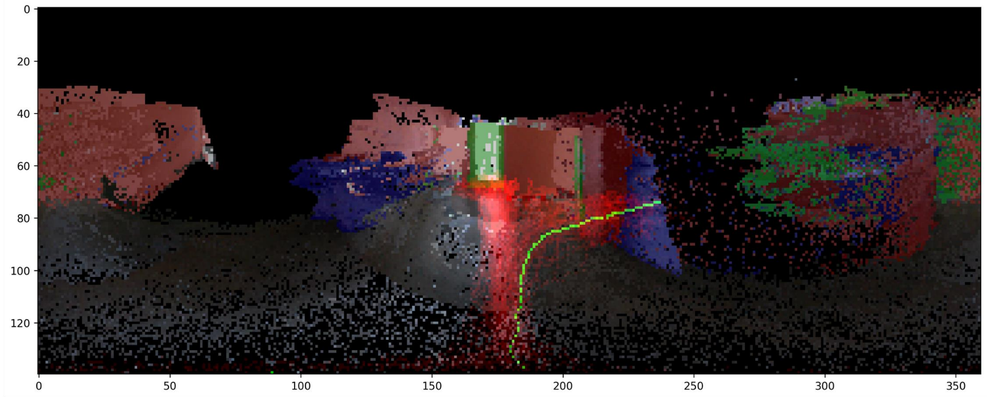
(b)


0
20
40
60
80
00
20
40
60
0
50
100
150
200
250
300
350

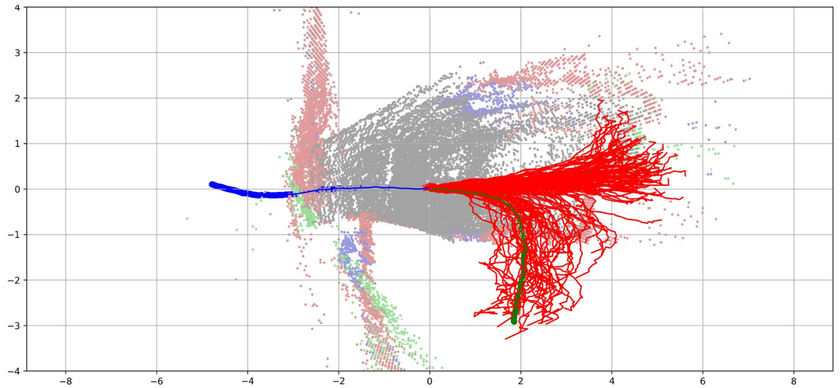
(c)


0
20
40
60
80
100
120
140
160
0
50
100
150
200
250
300
350

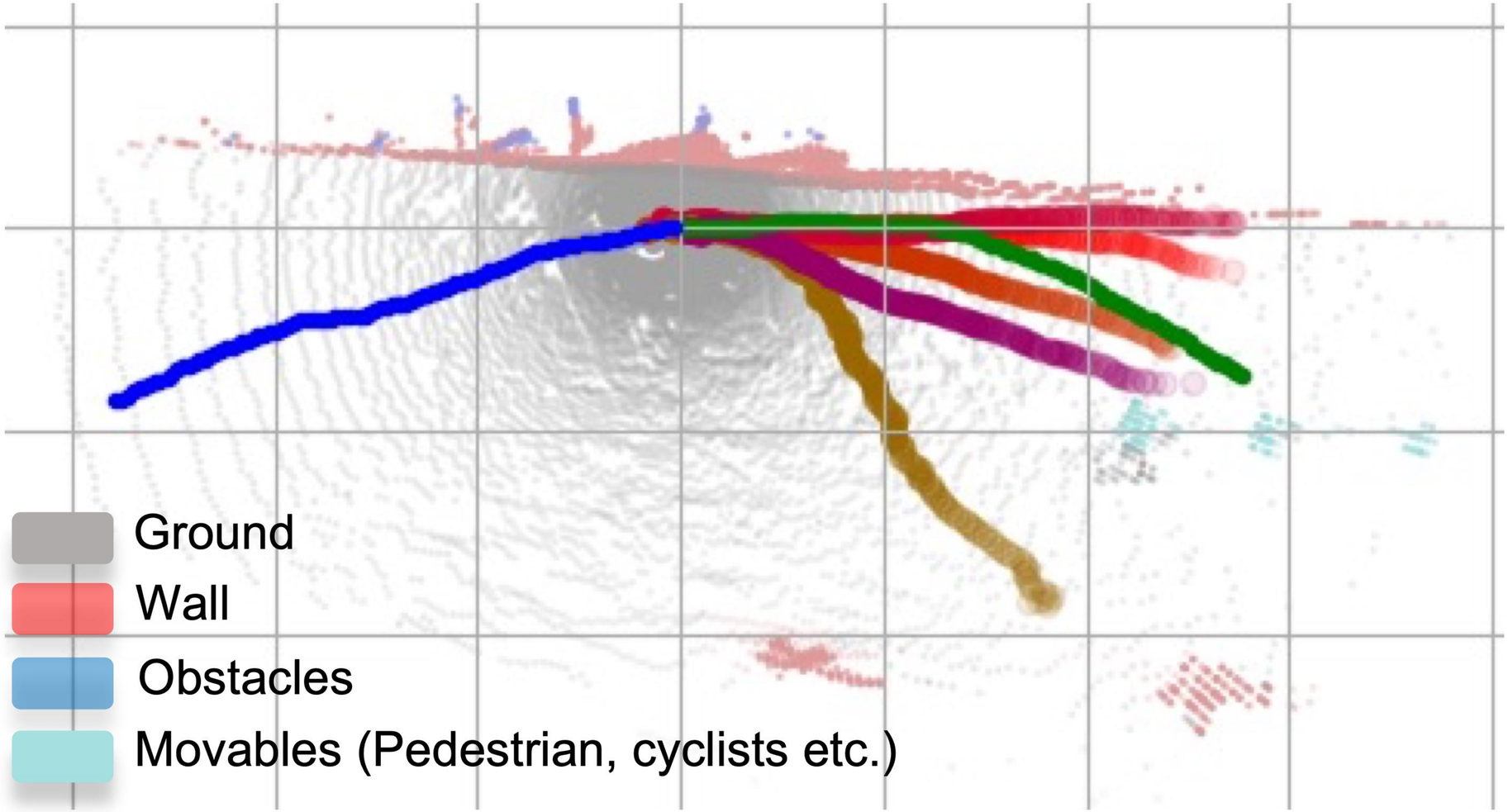
(d)


0
20
40
60
80
100
120
0
50
100
150
200
250
300
350

(e)


4
3
2
1
0
−1
−2
−3
−4
−8
−6
−4
−2
0
2
4
6
8

(f)

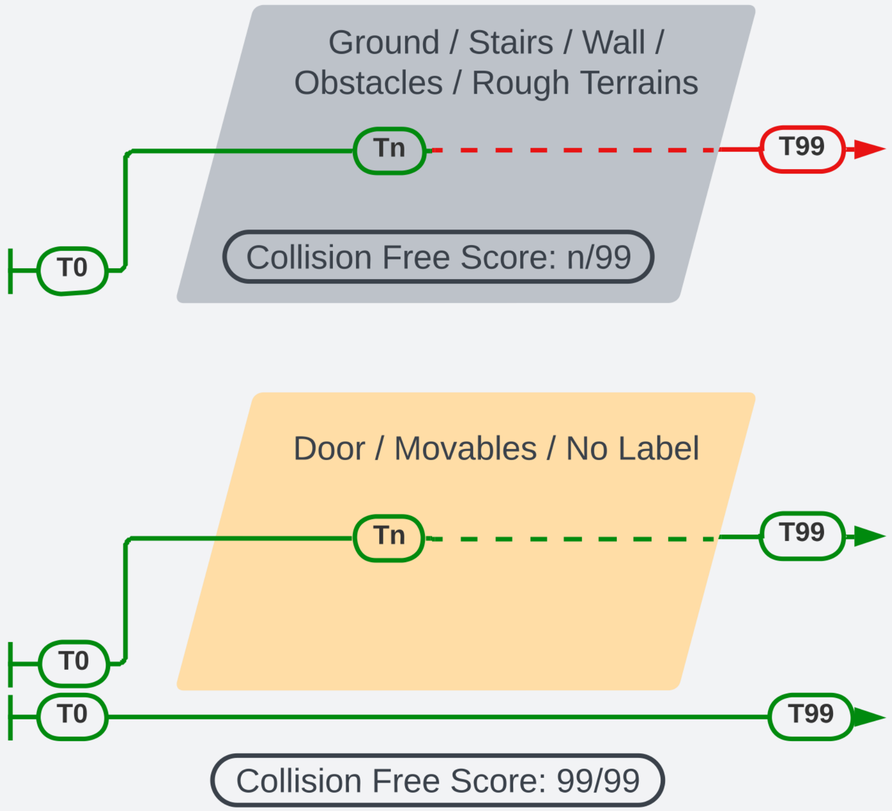



Past trajectory

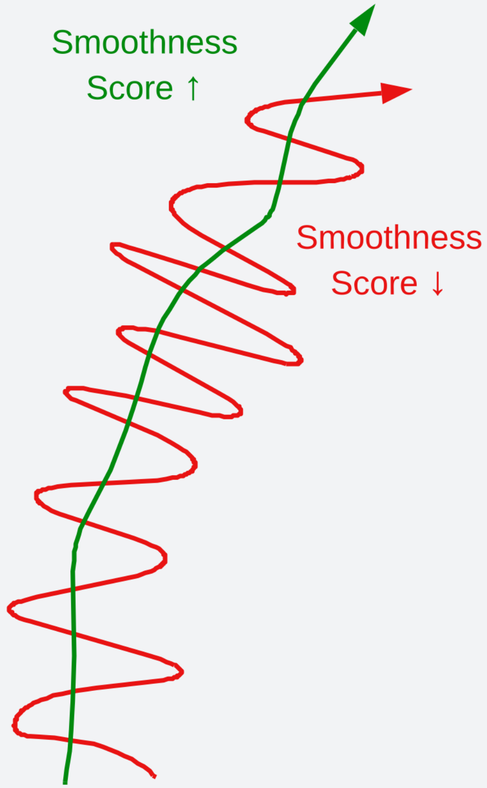
GT future trajectory

Sampled trajectory x 5

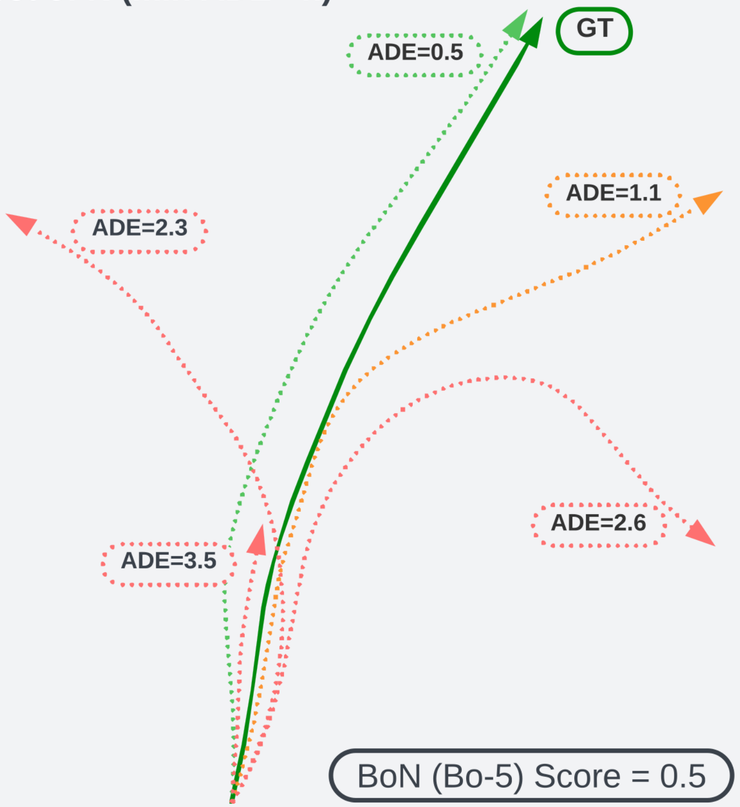
## Collision Free Score




## Smoothness Score




## Best of N (min ADE - n)

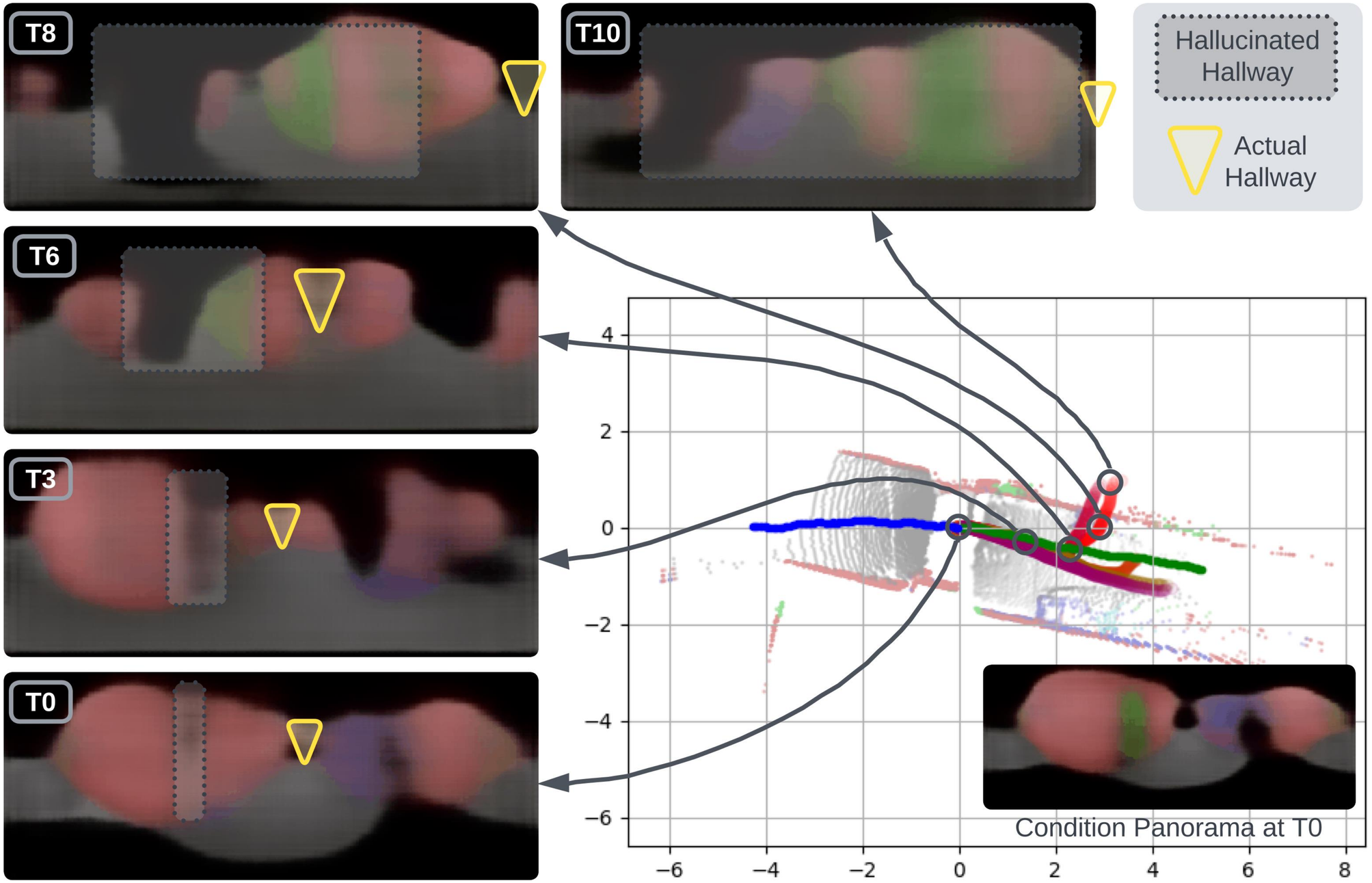


| Ablation | Collision ↑ | Smoothness ↑ | Best of 1 ↓ | Best of 15 ↓ |
|---|---|---|---|---|
| Ground Truth | 97.6 | - | - | - |
| Ours (Full dataset) | **90.6** | **4.76** | **0.81** | **0.41** |
| w/o visual memory prediction | *89.3* | 3.13 | 0.91 | 0.50 |
| Ours (Pilot Dataset) | 89.2 | 2.04 | *0.87* | *0.47* |
| w/ Markovian past state | 88.8 | 1.56 | 1.04 | 0.52 |
| w/ Hybrid generation (I20 P10) | 88.7 | 2.17 | 0.89 | 0.49 |
| w/o attention | 86.6 | 2.78 | 1.00 | 0.49 |
| w/ DDIM generation (n=30) | 85.3 | 0.46 | 0.92 | 0.52 |
| w/o semantic (RGBD only) | 84.1 | *4.17* | 0.91 | 0.53 |
| w/o visual input (Traj only) | 82.5 | 2.04 | 1.19 | 0.48 |

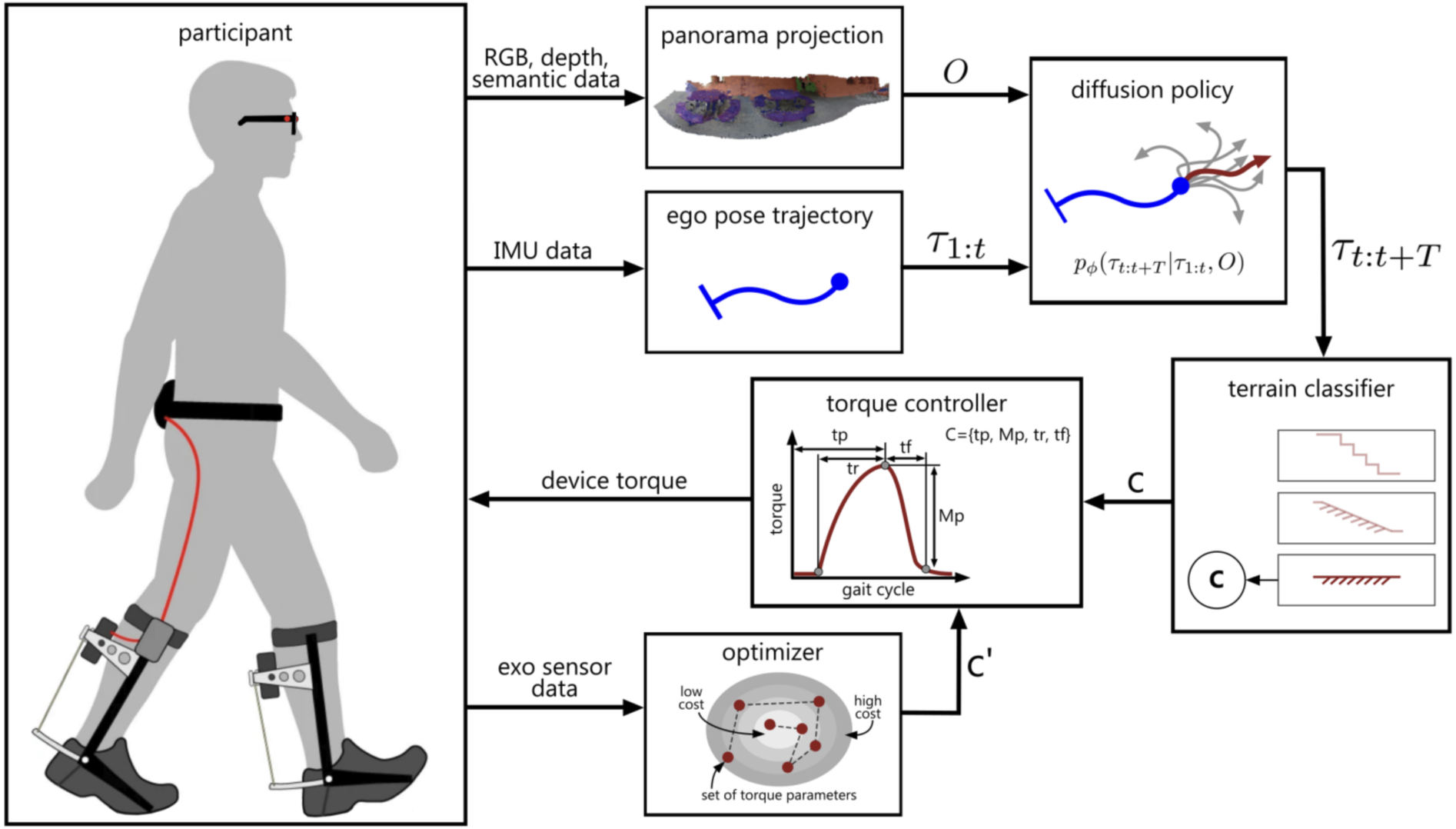
**Metric comparison table across ablations:**
**5 second prediction horizon**

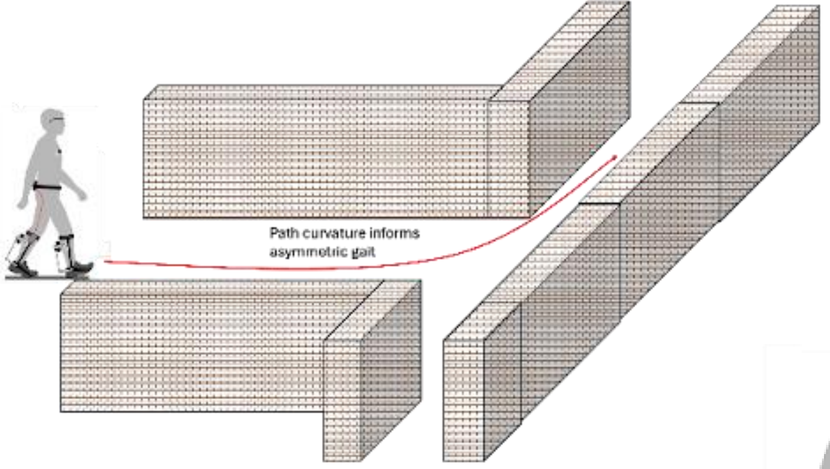
| Model | Collision ↑ | Smoothness ↑ | Best of 1 ↓ | Best of 15 ↓ |
|---|---|---|---|---|
| CXA Transformer | 80.3 | 3.70 | 1.25 | N/A |
| LSTM-VAE | 84.5 | **0.09** | 1.01 | N/A |
| Ours | **89.2** | 2.04 | **0.87** | **0.472** |

**Metric comparison across baselines**
**(5 second prediction horizon)**

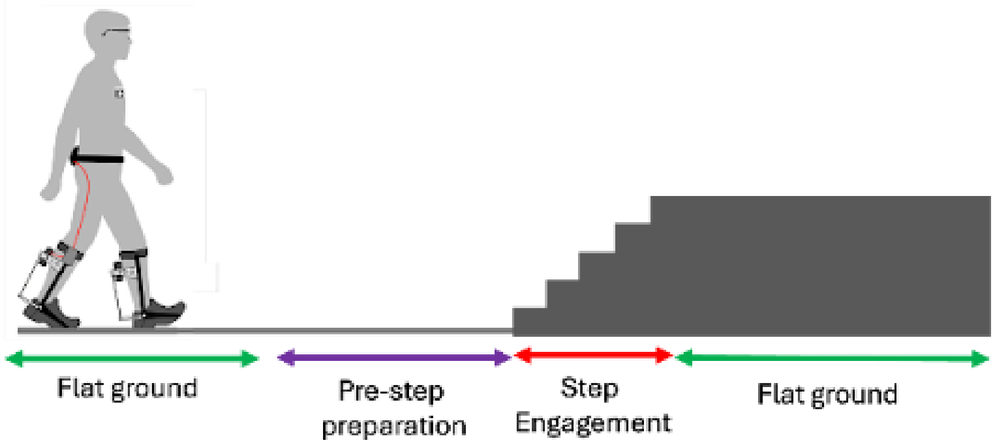

T8
T10
Hallucinated Hallway
Actual Hallway
T6
T3
T0
4
2
0
−2
−4
−6
−6
−4
−2
0
2
4
6
8
Condition Panorama at T0


Motivation
Approach
Results

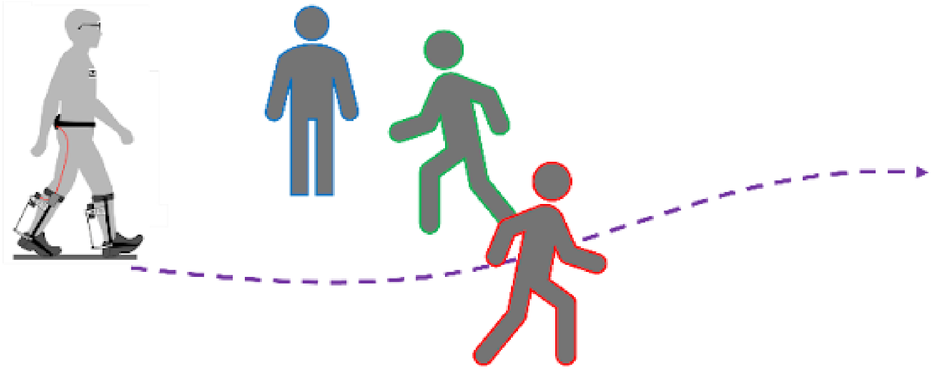

participant
RGB, depth, semantic data
panorama projection
$O$
diffusion policy
IMU data
ego pose trajectory
$\tau_{1:t}$
$p_\phi(\tau_{t:t+T}|\tau_{1:t}, O)$
$\tau_{t:t+T}$
terrain classifier
torque controller
C={tp, Mp, tr, tf}
tp
tf
tr
Mp
torque
gait cycle
C
device torque
C
exo sensor data
optimizer
low cost
high cost
set of torque parameters
C'




Turning Corners




Traversing Steps



Navigating Crowds

# Summary and Takeaways

- Prosthesis and assistive technology has made many advances over the years, but many problems exist that are still extremely burdensome for those who use this technology
- Often there is a tradeoff between performance of traditional assistive technology and the invasive requirements needed in order to afford the person a high degree of control
- **Robotics** (thinking machines) provides a unique opportunity to *bridge the gap* between the limitations of non-invasive assistive technology and the complex tasks through their ability to ***see, think and act***

# Thank you!