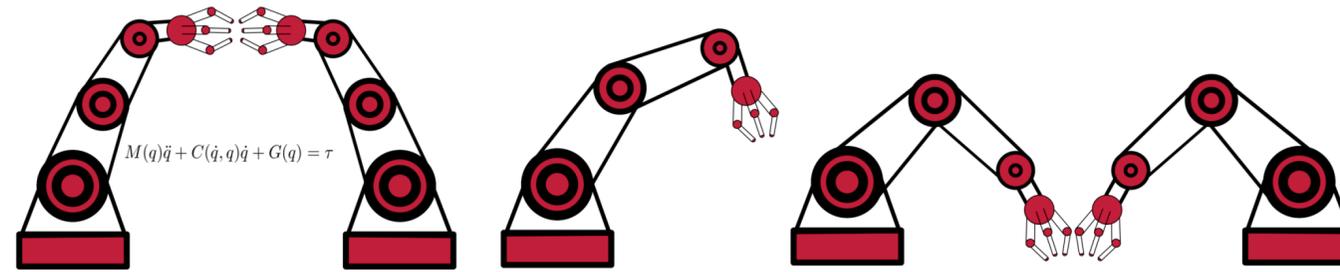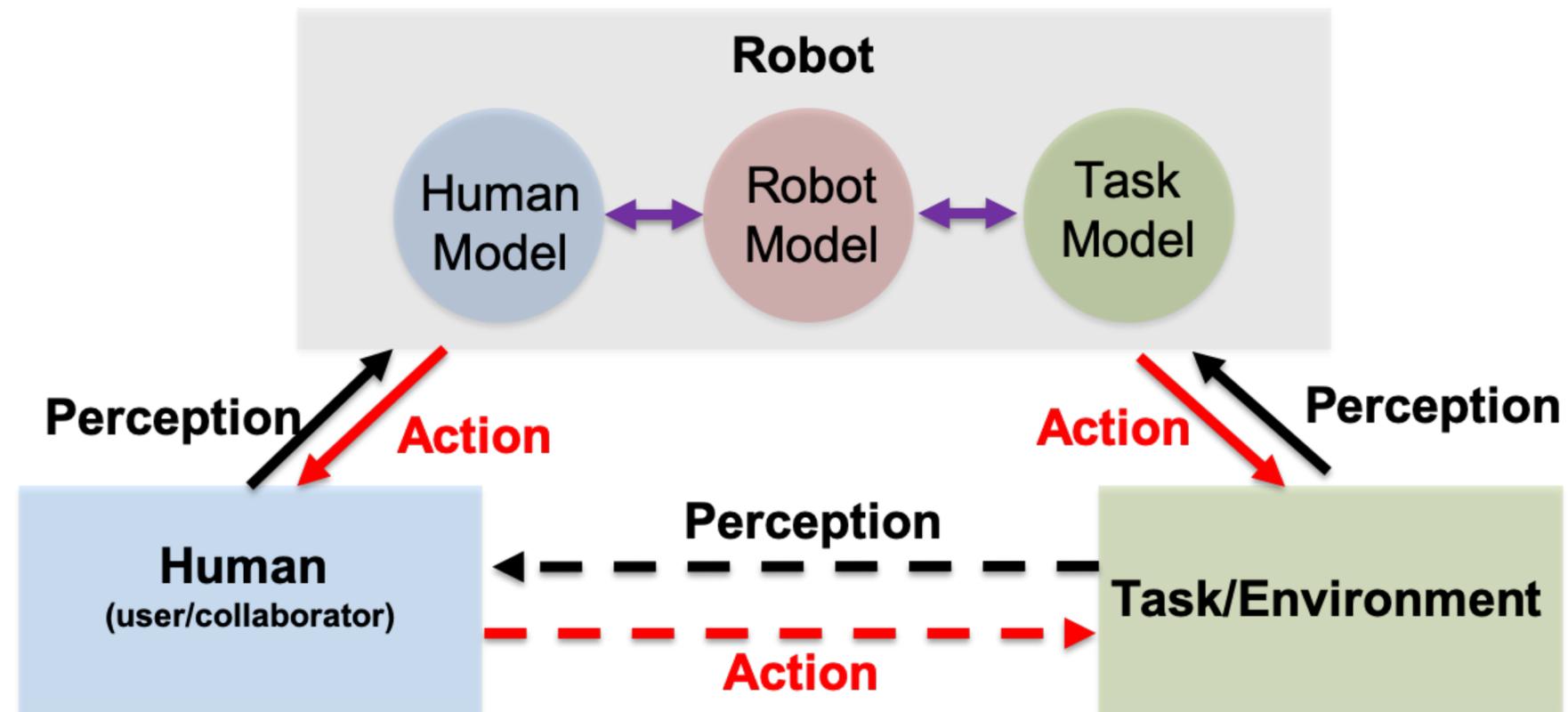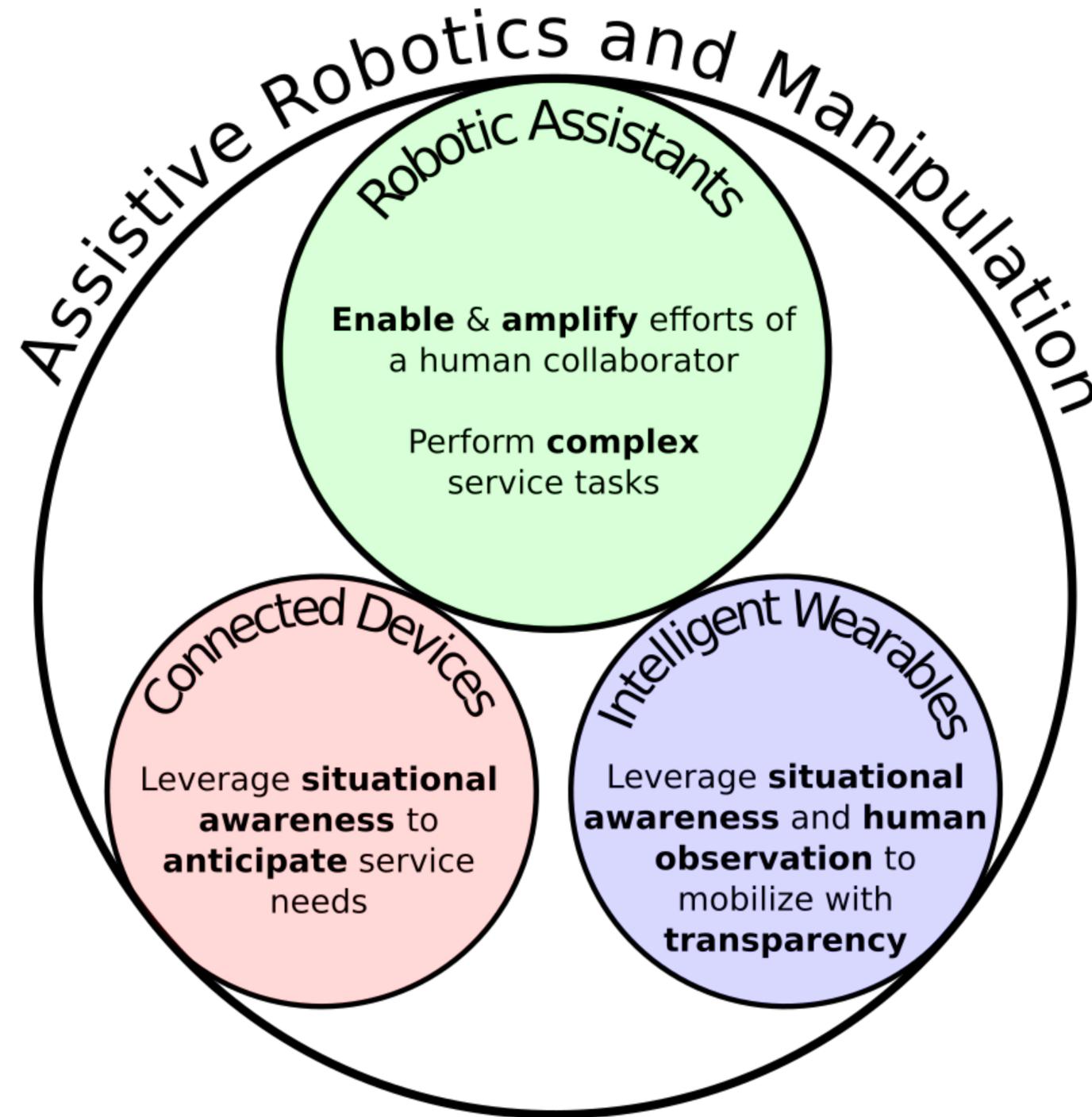# Assistive Robotics

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

Assistive Robotics and Manipulation Laboratory
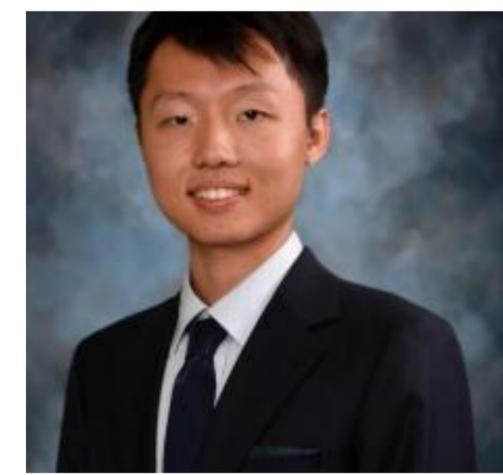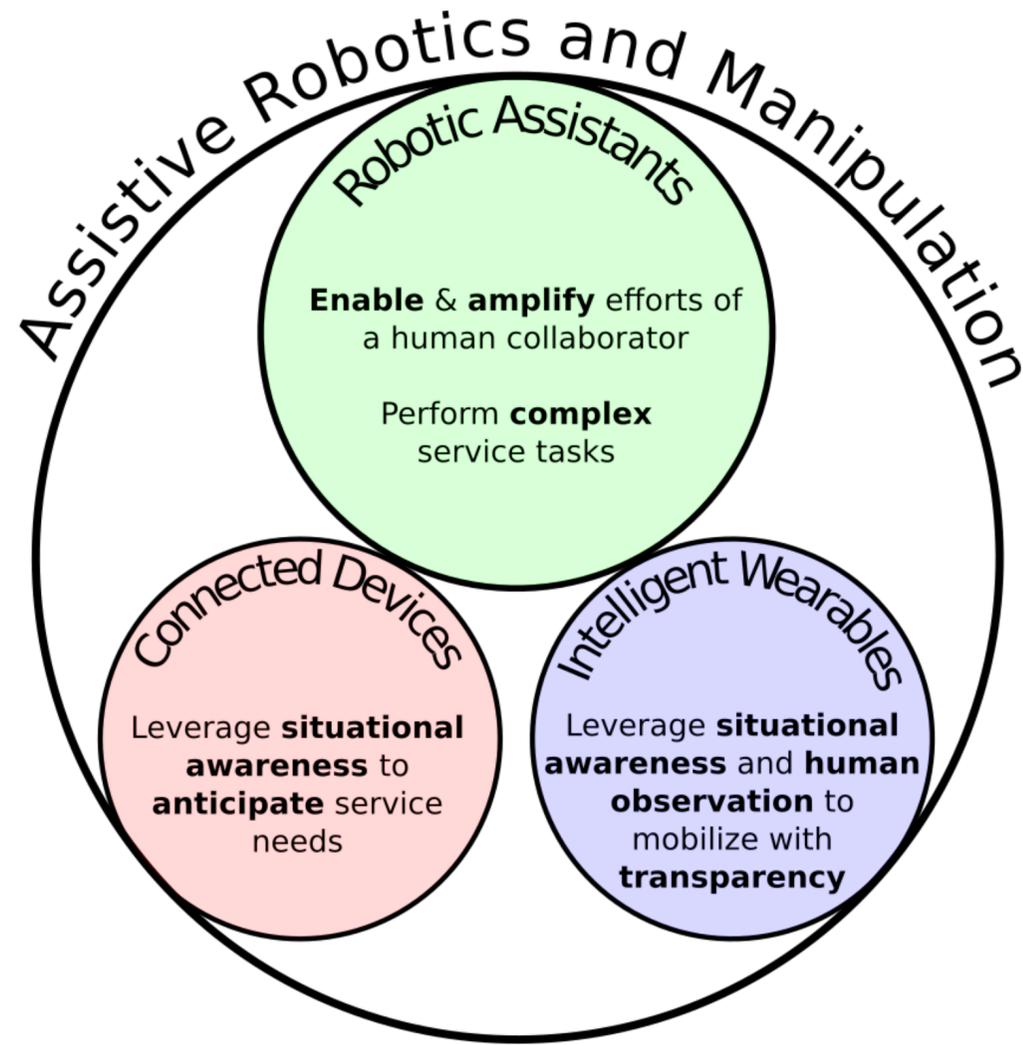
Assistive Robotics and Manipulation Laboratory

Assistive Robotics and Manipulation

Robotic Assistants
Enable & **amplify** efforts of a human collaborator

Perform **complex** service tasks

Connected Devices
Leverage **situational awareness** to **anticipate** service needs

Intelligent Wearables
Leverage **situational awareness** and **human observation** to mobilize with **transparency**
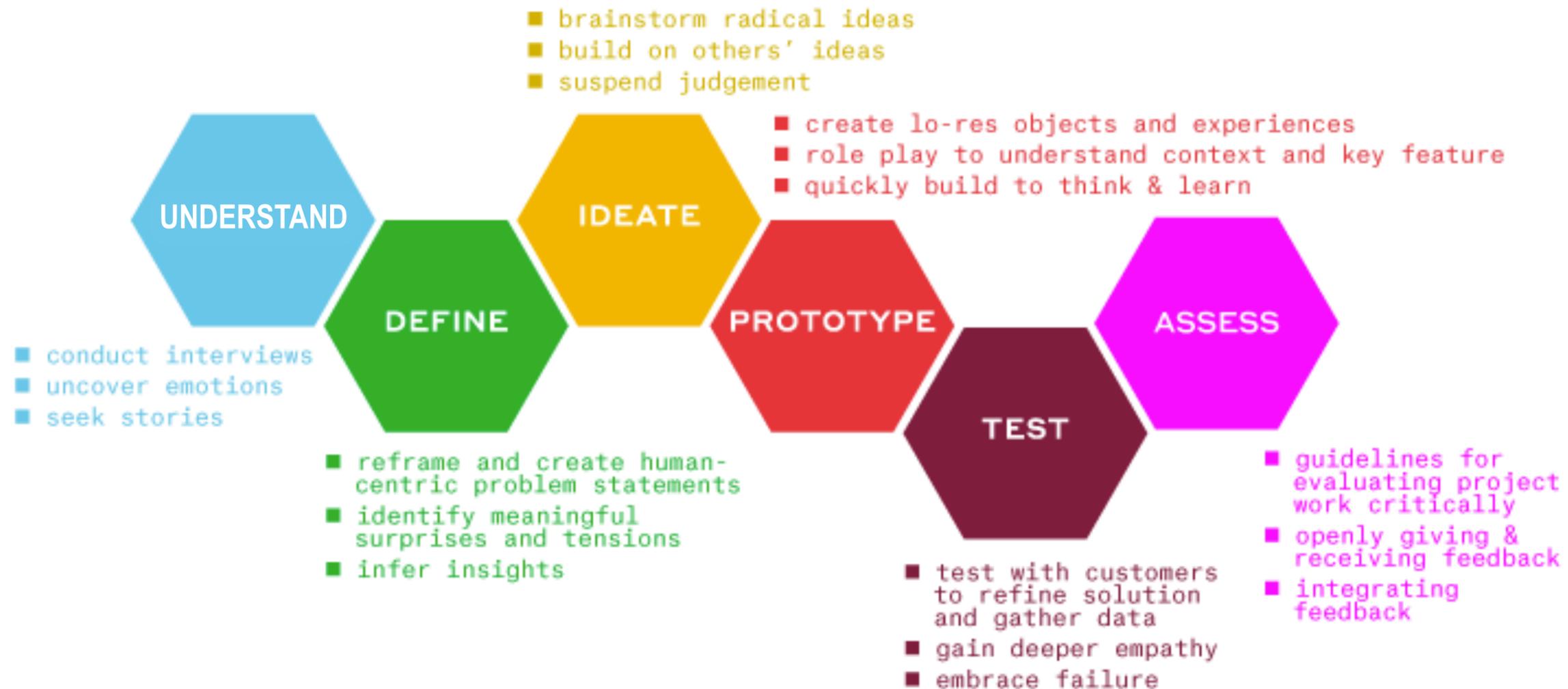
<u>Mission</u>
The mission of the **A**ssistive **R**obotics and **M**anipulation Lab is to develop **intelligent**, **assistive** technology that **improves** human life

Assistive Robotics and Manipulation Laboratory

Stanford University

Assistive Robotics and Manipulation Laboratory (ARMLab)

Passive versus Active Assistive Devices

Assistive Technology Design Process

brainstorm radical ideas
build on others' ideas
suspend judgement

create lo-res objects and experiences
role play to understand context and key feature
quickly build to think & learn

UNDERSTAND

IDEATE

DEFINE

PROTOTYPE

ASSESS

conduct interviews
uncover emotions
seek stories

reframe and create human-centric problem statements
identify meaningful surprises and tensions
infer insights

TEST

guidelines for evaluating project work critically
openly giving & receiving feedback
integrating feedback

test with customers to refine solution and gather data
gain deeper empathy
embrace failure

d.school Executive Education
Hasso Plattner Institute of Design at Stanford University

*not necessarily linear, apply as needed ©2019

6

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Assistive Technology

Passive Devices - Body Powered

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

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Assistive Technology
Passive Devices - Body Powered

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Assistive Robotics and Manipulation
Laboratory

Assistive Technology
Passive Devices - Body Powered

Carbon Fiber Reinforced polymer for running prosthesis

https://youtu.be/42mI6kDvPeE (0-30s)

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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

What is the
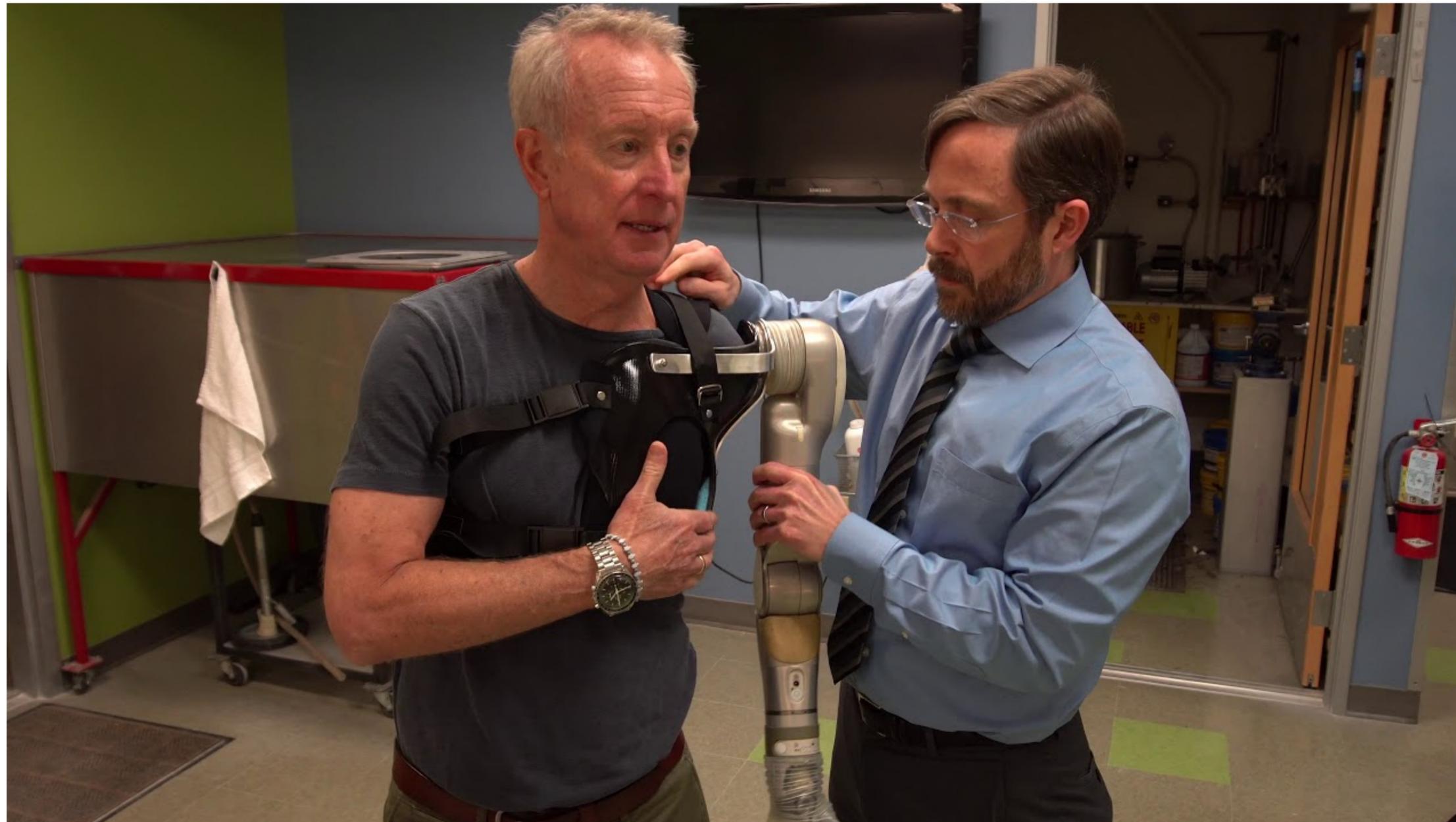person's **Goal**?

What **action** should the
active device take?

How does the device **detect** how
things have changed?

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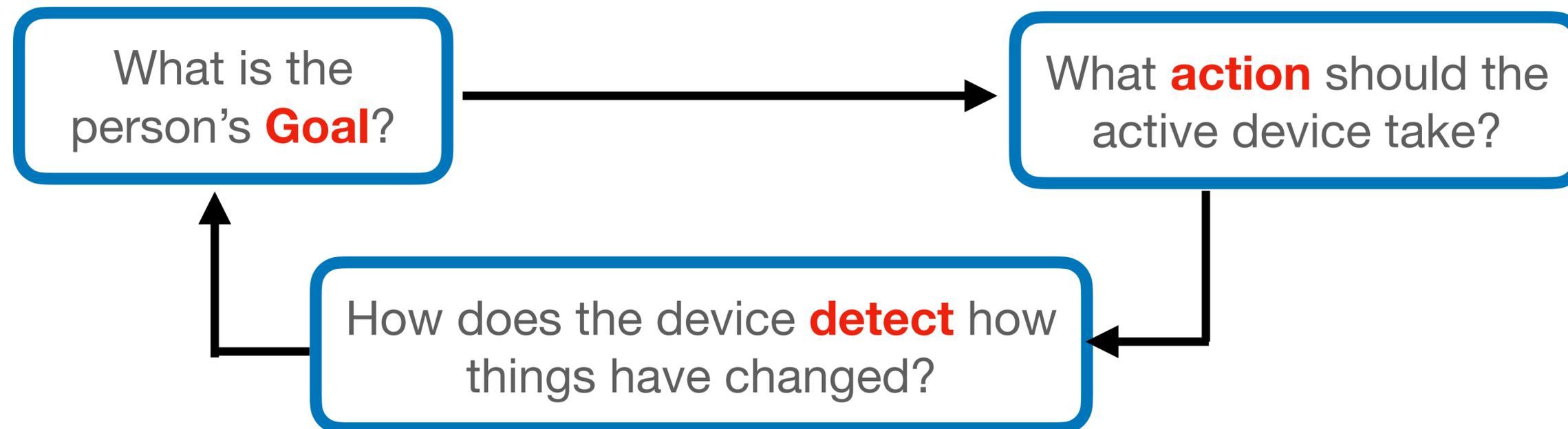
Assistive Technology

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

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Assistive Technology
Active Devices - Luke Arm (Mobius Bionics)

Shoulder Abduction and Adduction

Shoulder Flexion and Extension
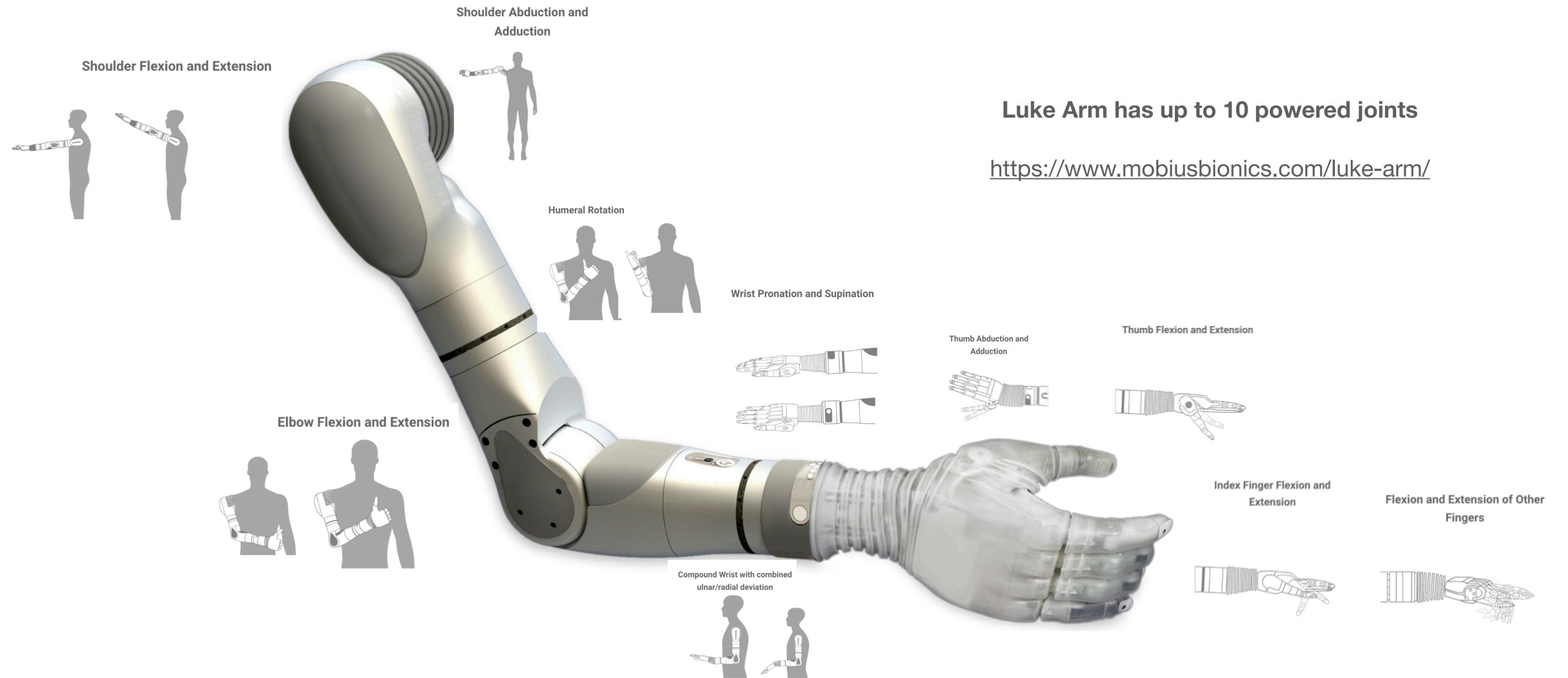
Luke Arm has up to 10 powered joints

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

Humeral Rotation

Wrist Pronation and Supination

Thumb Abduction and Adduction

Thumb Flexion and Extension

Elbow Flexion and Extension

Index Finger Flexion and Extension

Flexion and Extension of Other Fingers

Compound Wrist with combined ulnar/radial deviation

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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

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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)

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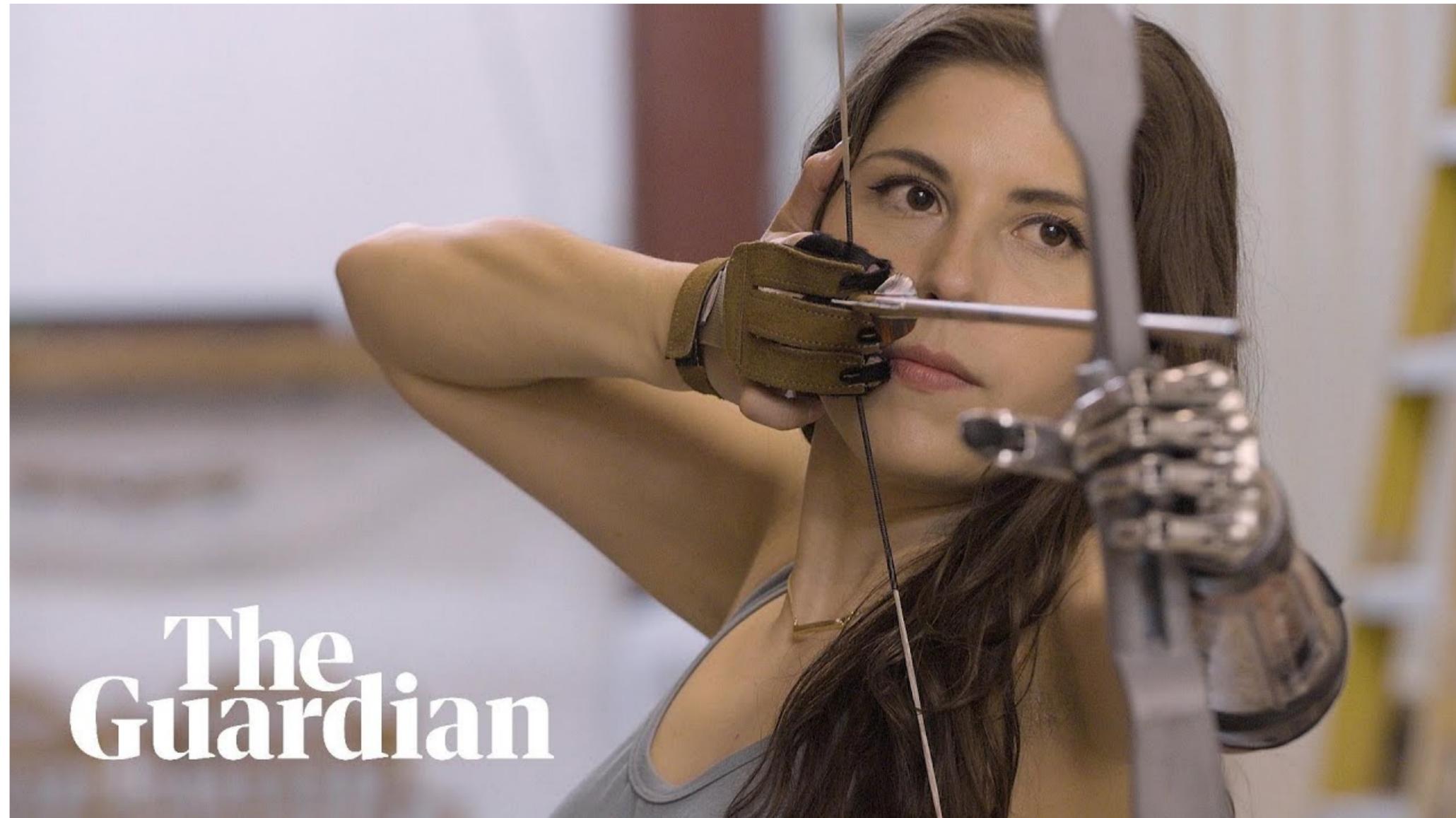
Limitations of Existing Assistive Technology

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?

Functionality
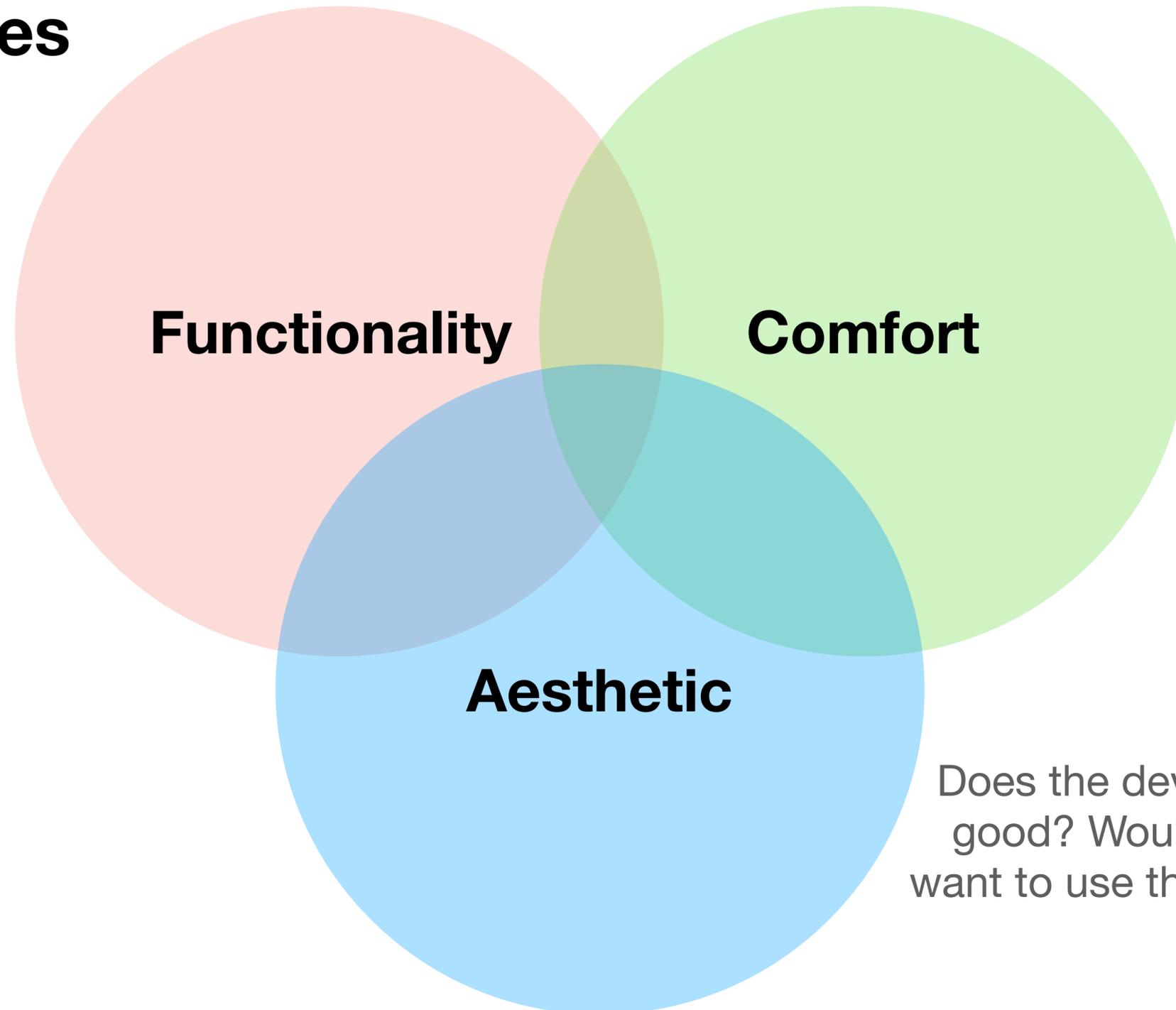
Comfort

Is it comfortable for users?

Aesthetic

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

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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%

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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) Decreased task difficulty and more frequent bilateral use (Weaver et al. 1988) Better grasp of heavy objects (Kruger and Fishman 1993)	Better manipulative function (van Lunteren et al. 1983) Better overall function (voluntary closing mechanism) (Crandall and Tomhave 2002) 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) 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). 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) Active users preferred BP while passive users of active prostheses preferred ME (Kruger and Fishman 1993) Only 30% of children used ME for active prehension and none under the age of 5. (Kruger and Fishman 1993) Full-time use of ME rare before adolescence (Menkveld et al. 1987) 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). 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) Reduced noise levels (Kruger and Fishman 1993) 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

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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

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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

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

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.

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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
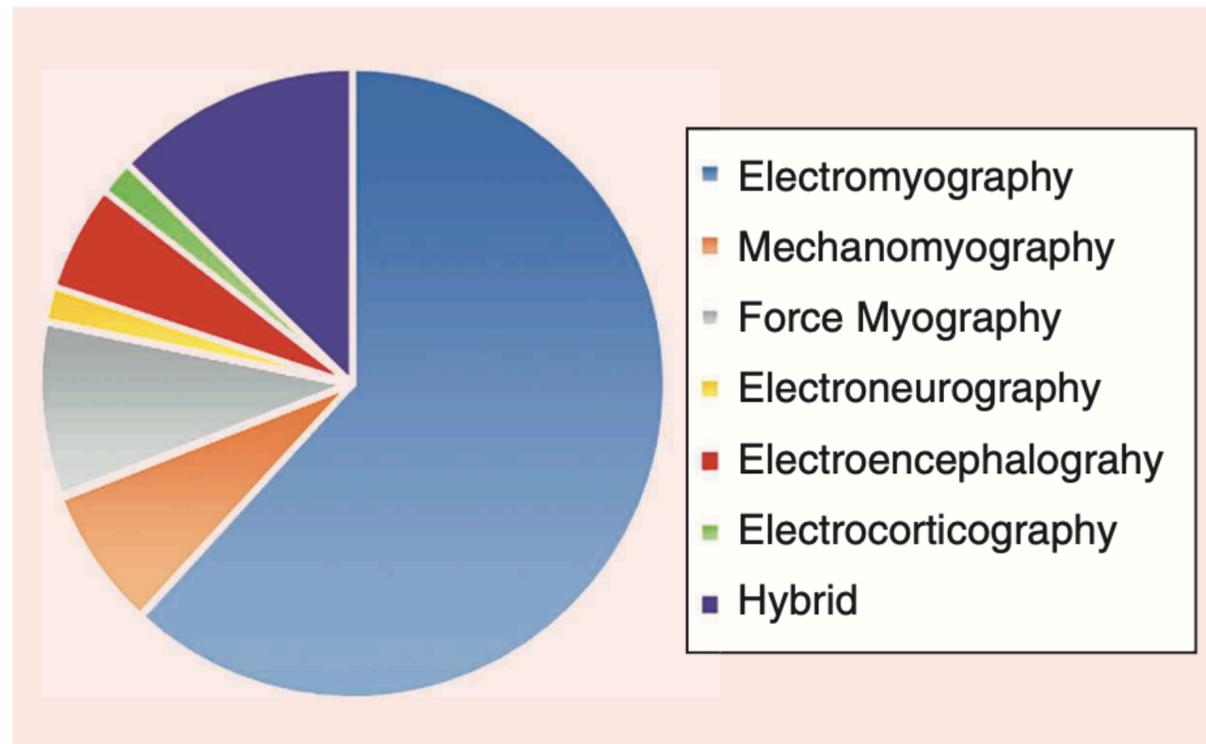
FIGURE 1. The prevalence of different types of biosignals used as the basis of HMIs in selected papers.
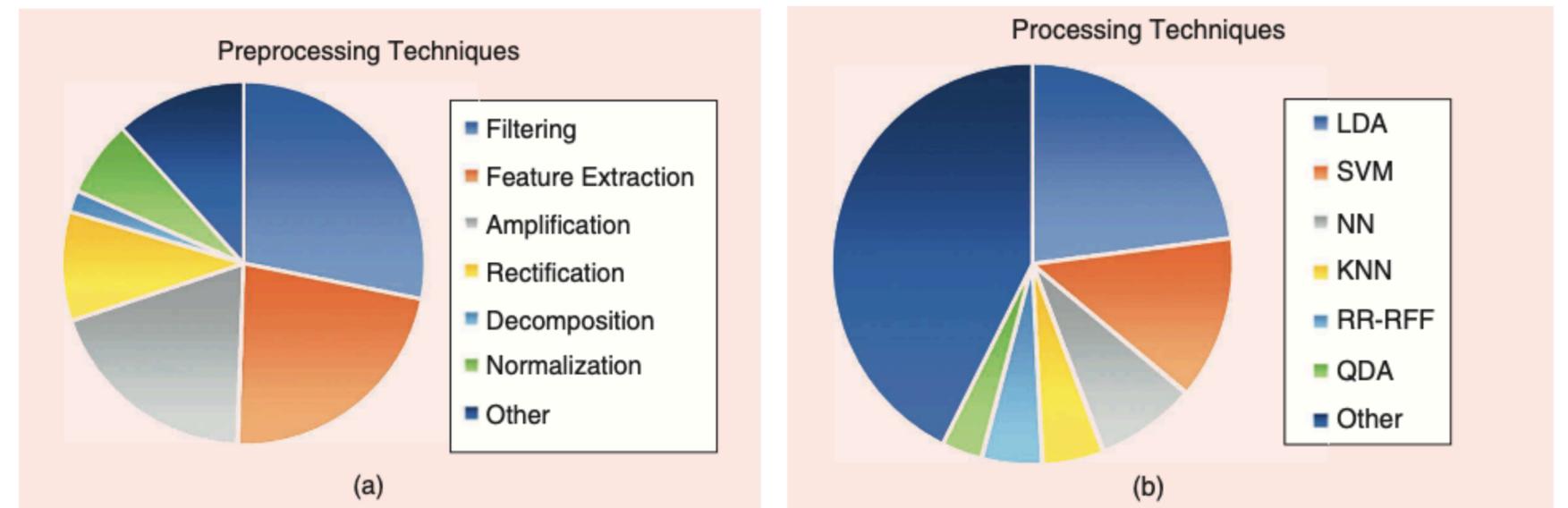
FIGURE 2. The prevalence of (a) preprocessing and (b) processing techniques used in EMG-based studies. LDA: linear discriminant analysis; SVM: support vector machine; NN: neural network; KNN: k-nearest neighbors; RR-RFF: ridge regression with random Fourier features; QDA: quadratic discriminant analysis.

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.

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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

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Robotics - Thinking Machines

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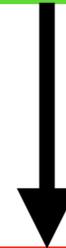
Overview of Robotics Considerations

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)

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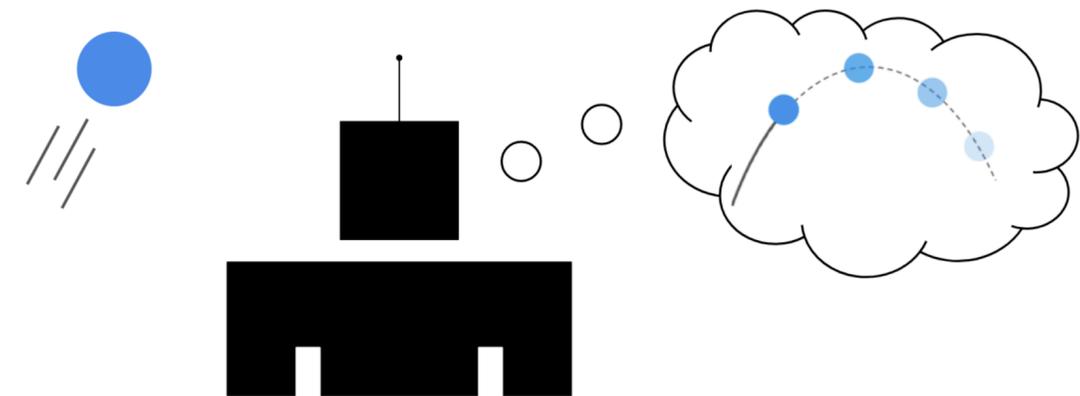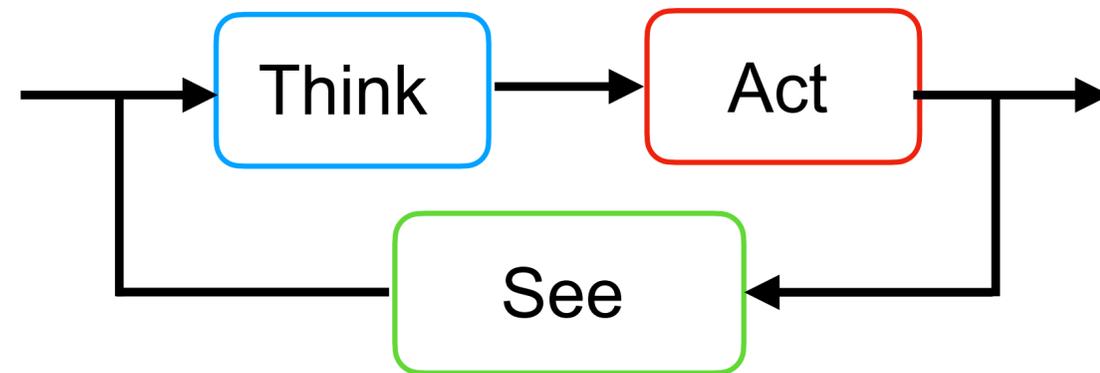
Robotic Perception
Ego or Environment Observation
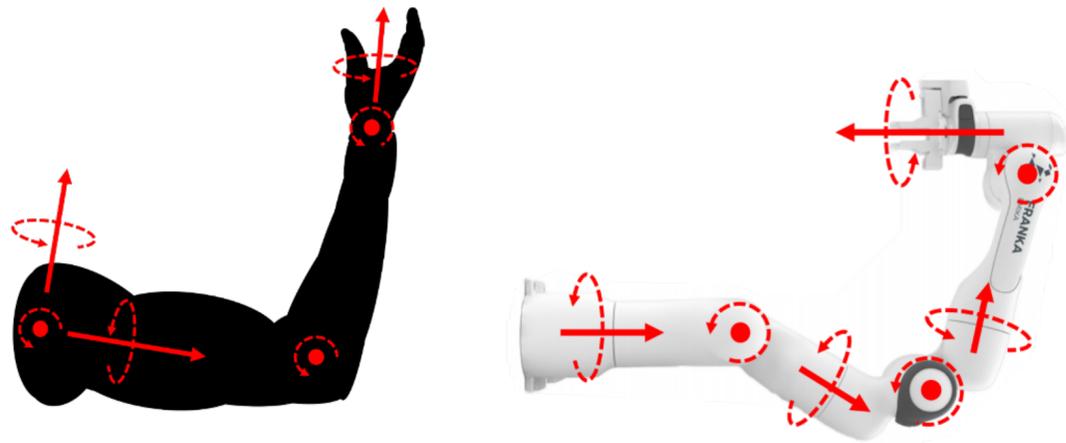
Proprioception: sense of embodiment - perception/awareness of the position and movement of the body

Vision: optical observation of the environment

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

Intel Realsense Camera

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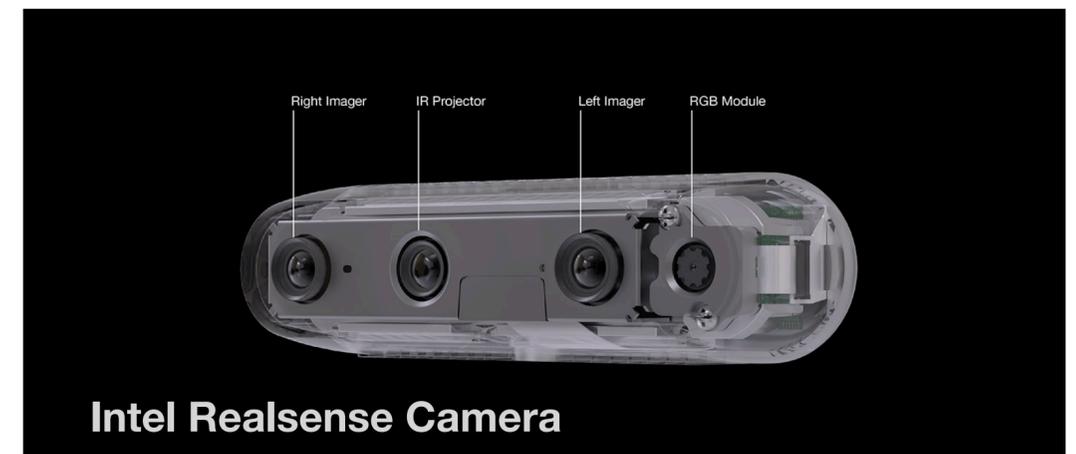
Robotic Intelligence
Ego, Teammate and Task/Environment Modeling

state S_t

reward R_t

action A_t

R_{t+1}

S_{t+1}
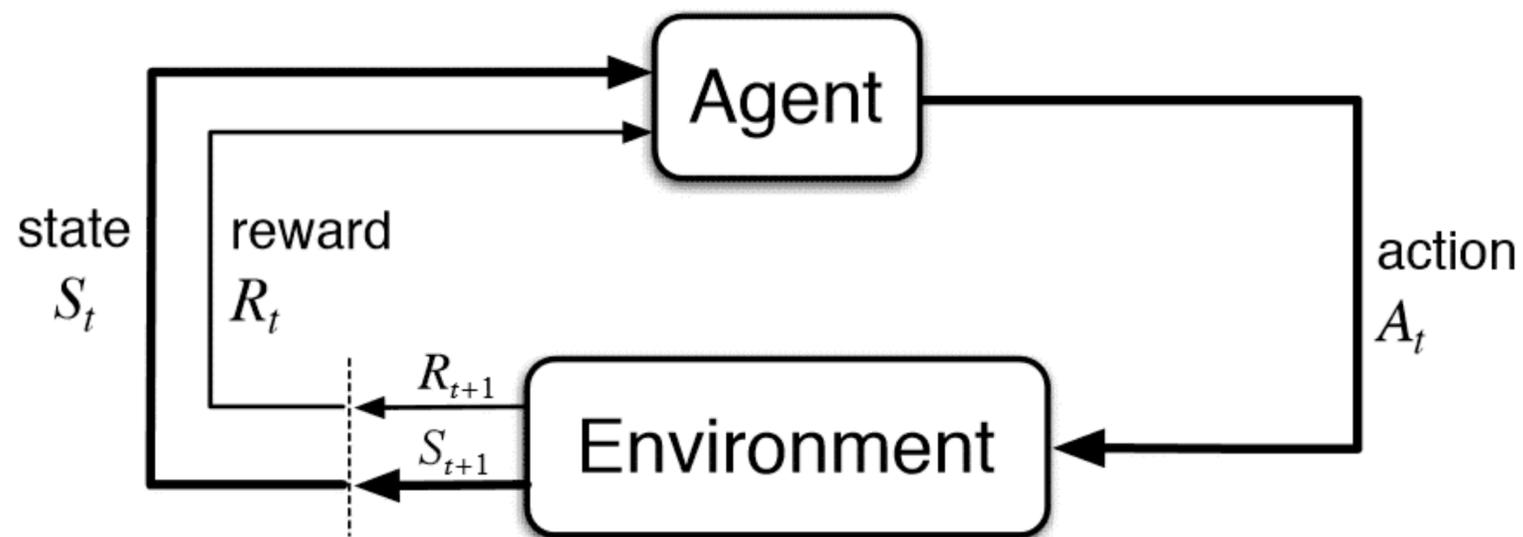
Reinforcement Learning Paradigm:
What action leads to the best reward?

RoIAlign

class
box

conv

conv

https://pytorch.org/tutorials/intermediate/torchvision_tutorial.html
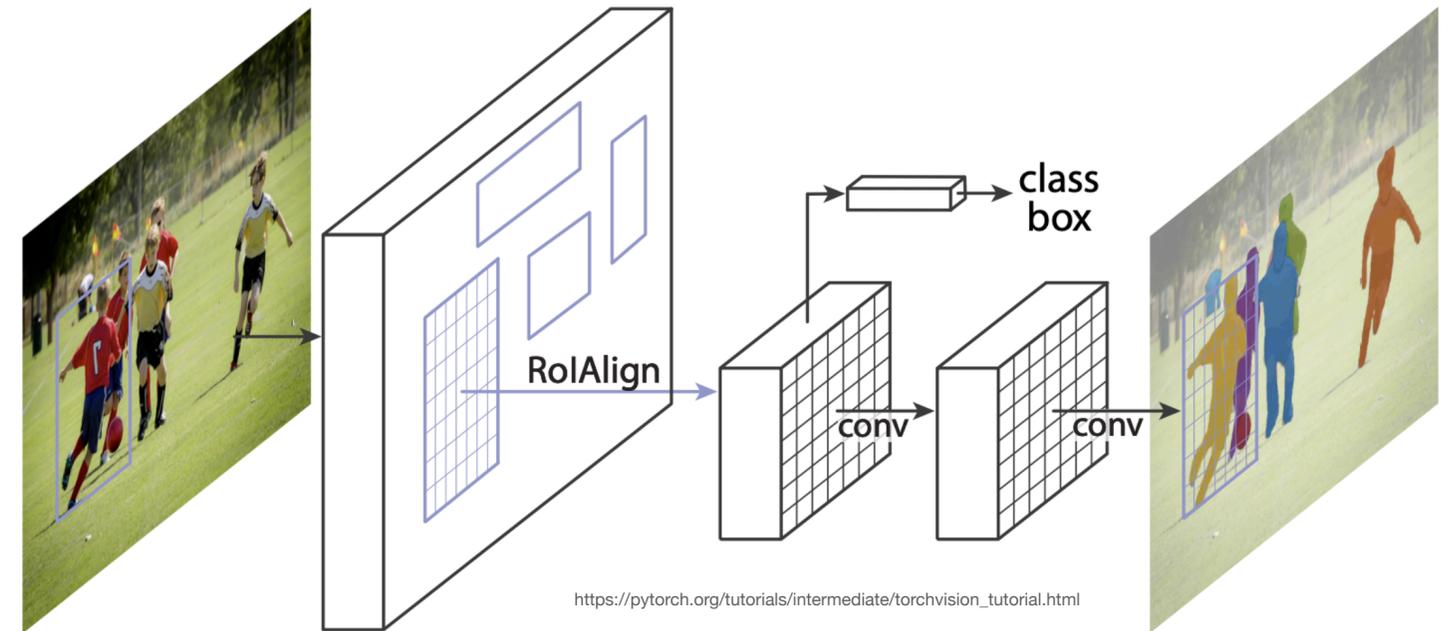
Vision interpretation: Shown is a Convolutional Neural Network (CNN) determining the location of people in an image

left wheel speed

right wheel speed

right wheel

left wheel

IR scan areas

IR scan areas
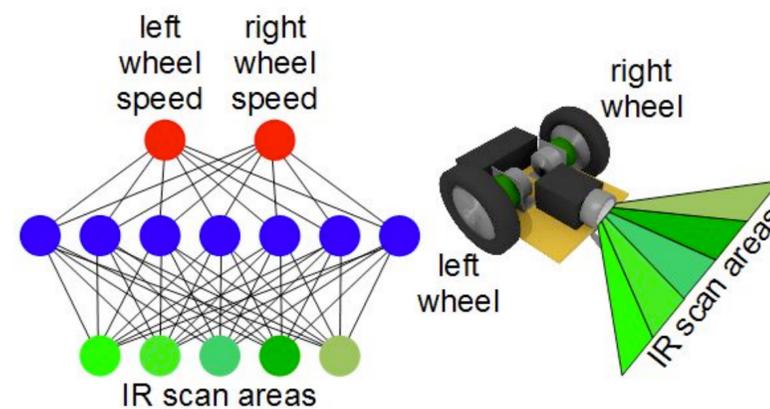
Neural Network (multi-layer perceptron) for decision making

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

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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

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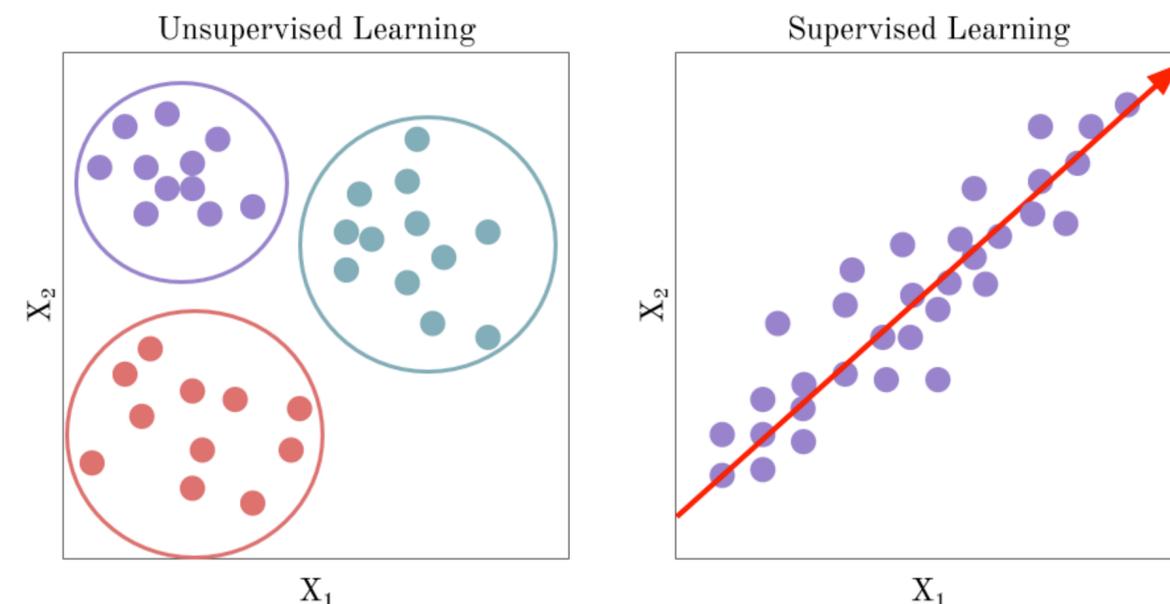
Robotic Perception
Human Perception

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

Brain Computer Interfaces (BCI)

Gaze detection and Augmented Reality (AR)

External Vision

(surface) electromyography (EMG)

Joint position/force detection

Foot pressure sensors

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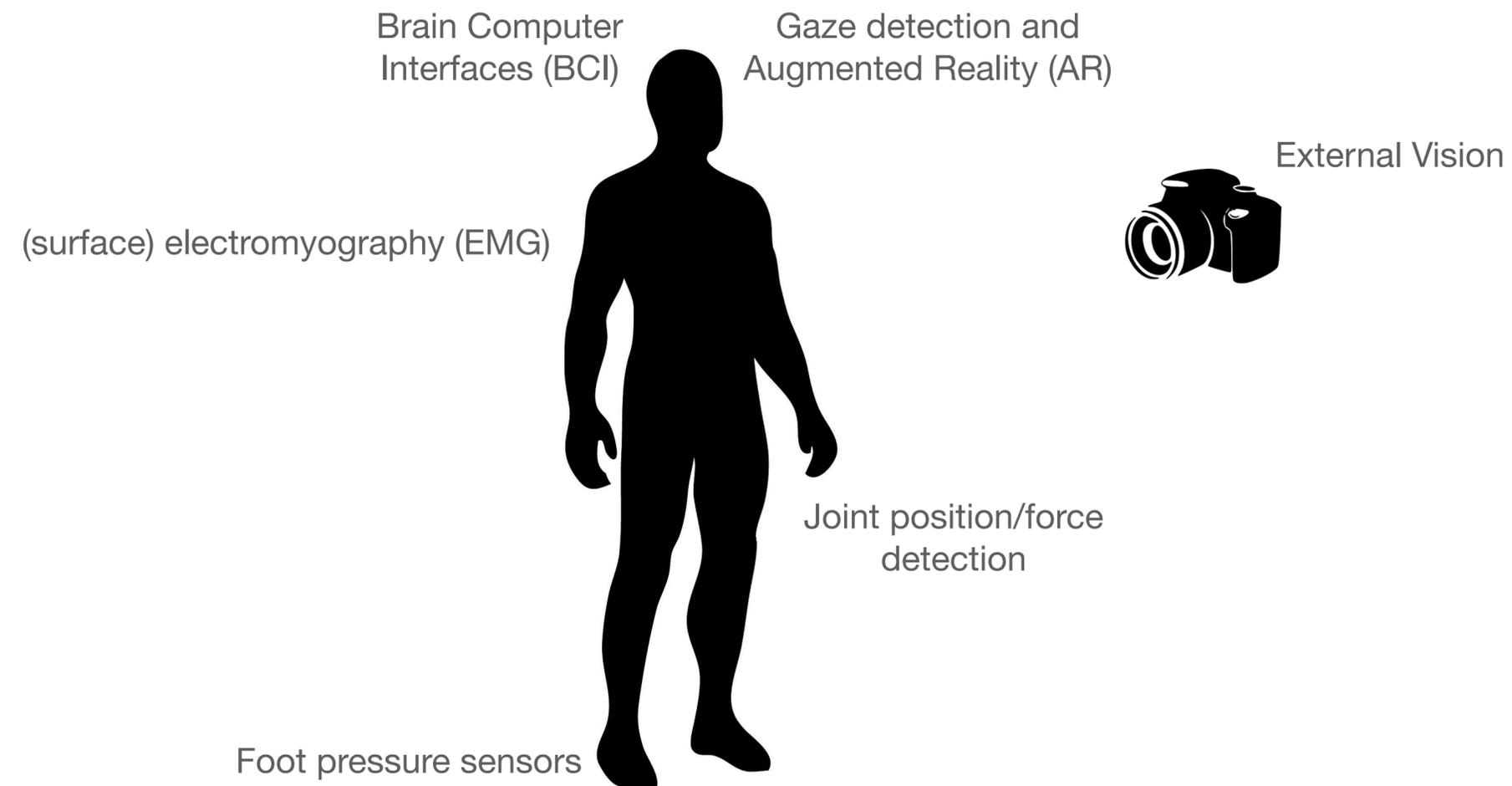
Robotics Role in Assistive Technology

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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

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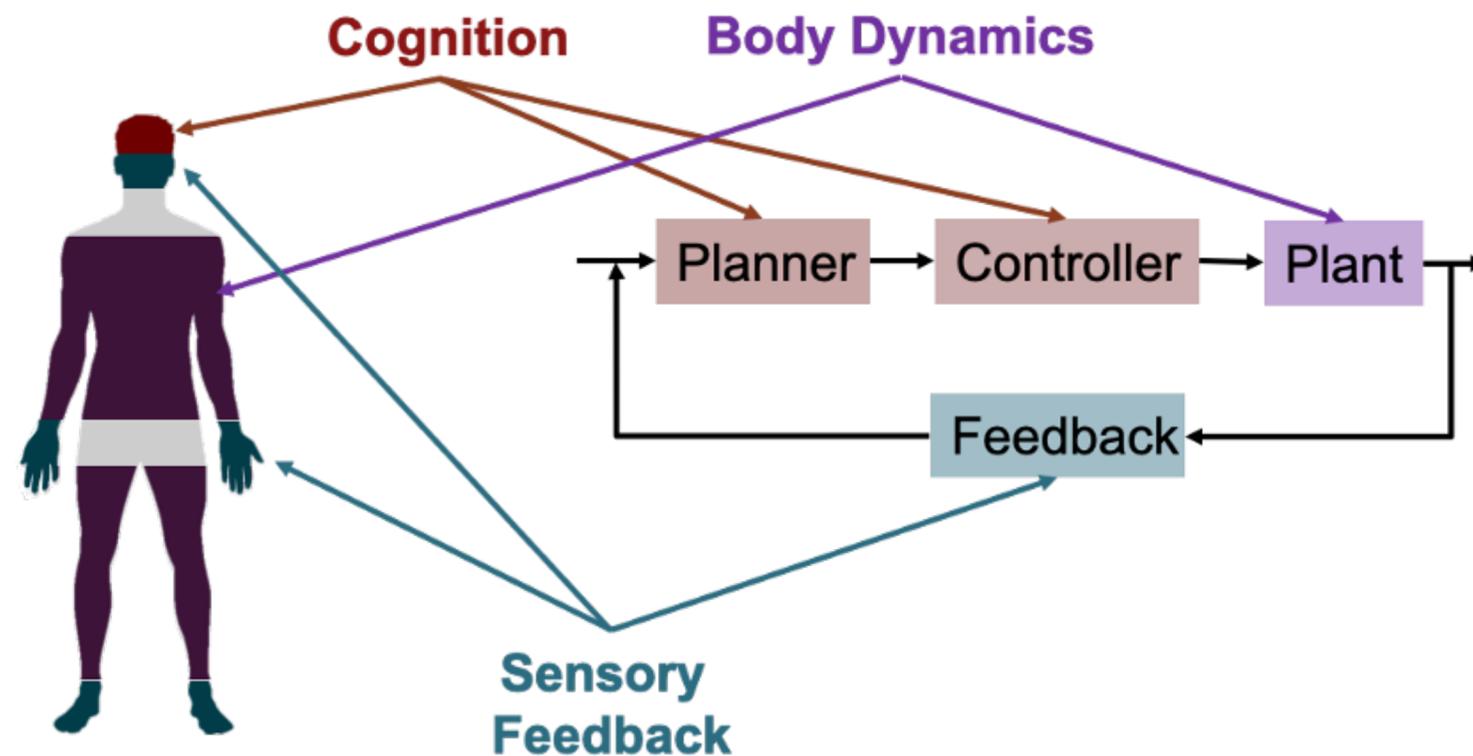
Robotics Fills the Gap
Wearable Robotics
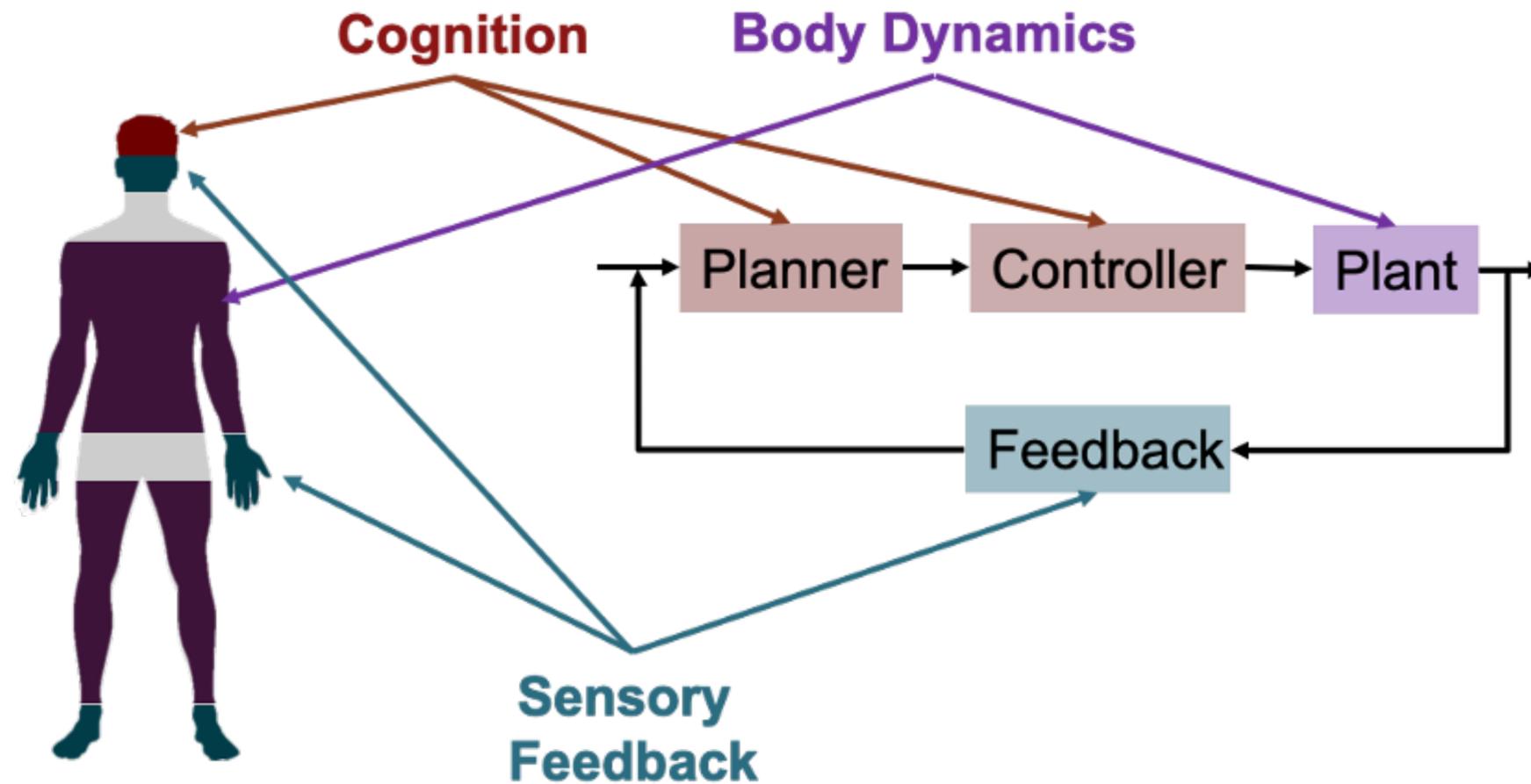
Particularly for wearables, what part of the human is being augmented or substituted?

1. Is the robotic augmentation functionally adequate?

2. Does the presence of the robot feel 'natural' (easy to use)?

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Robotics Fills the Gap

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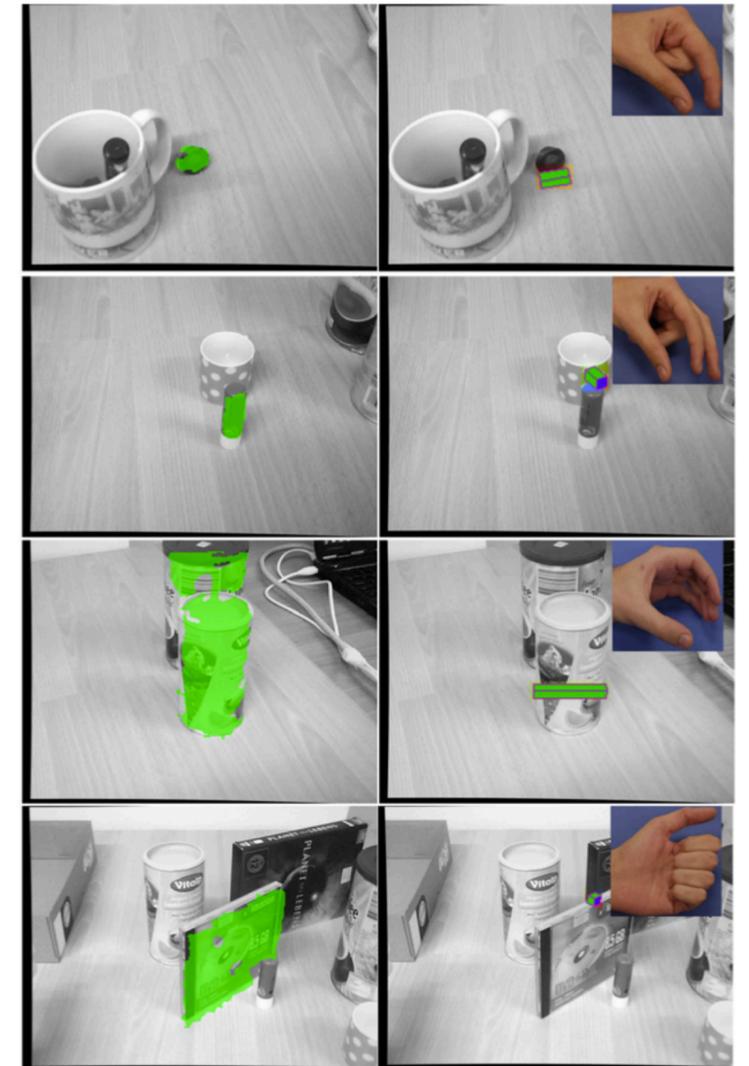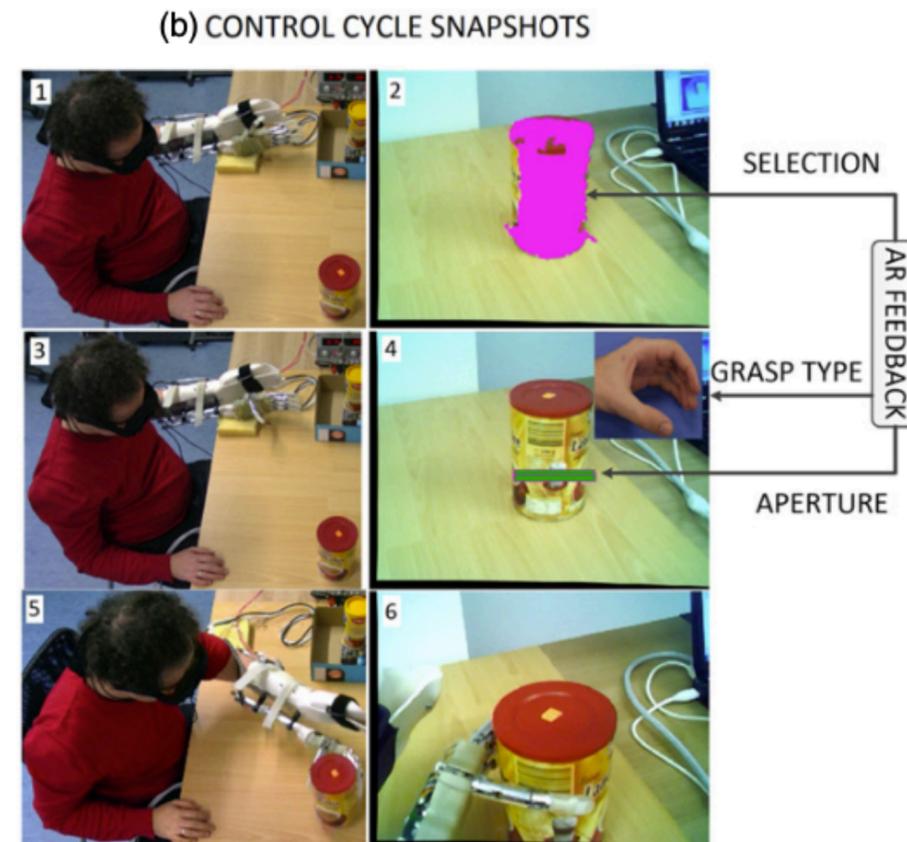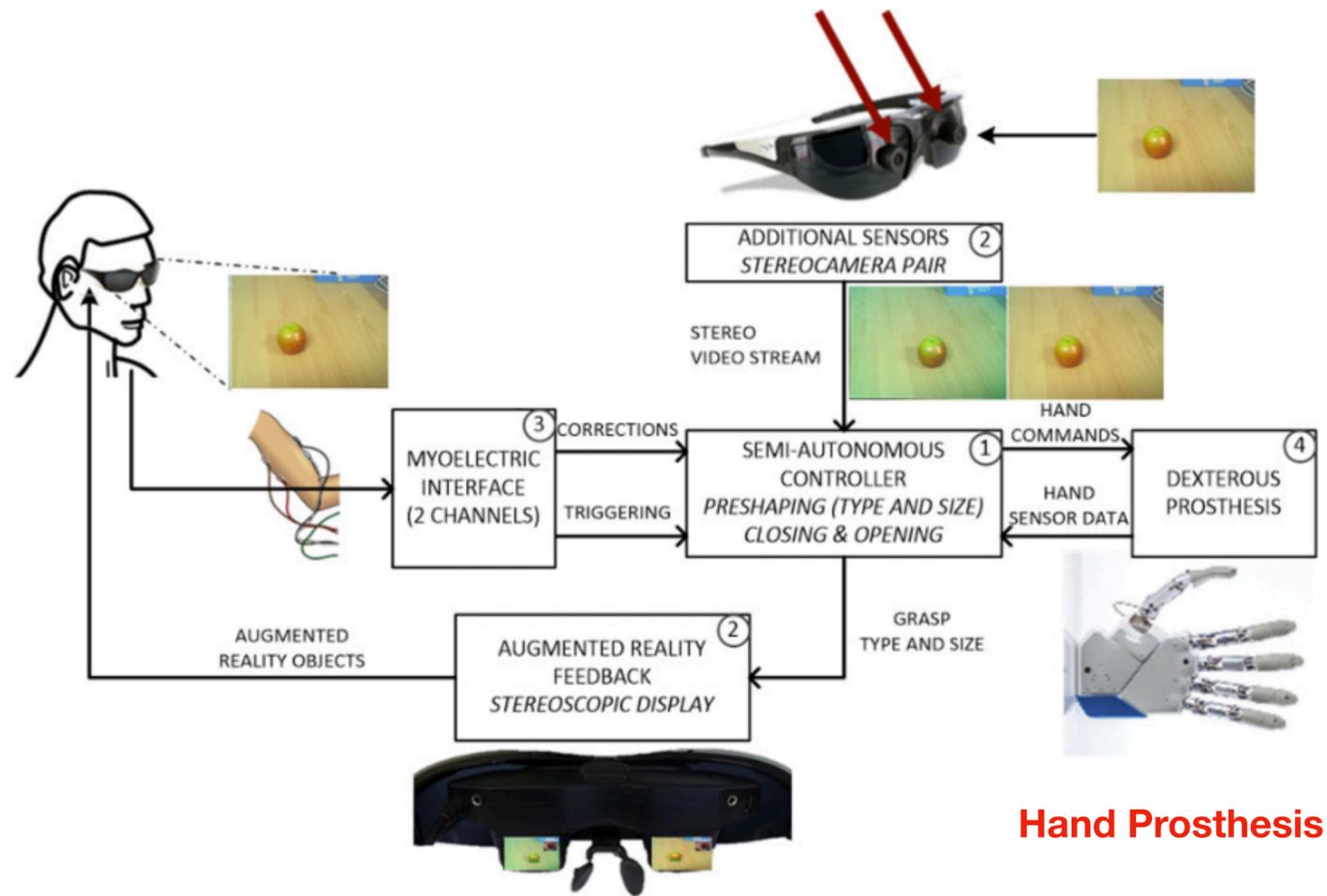
Hand Prosthesis

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
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Assistive Robotics and Manipulation Laboratory

Intelligent Wearables - Intelligent Prosthetic Arm

ARMLab Project:
Intelligent Prosthetic Arm

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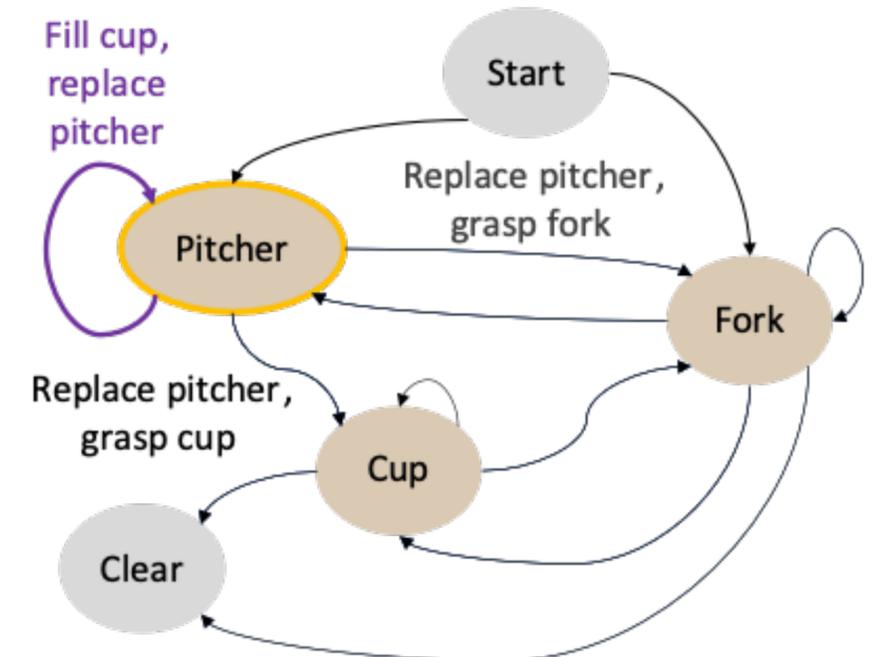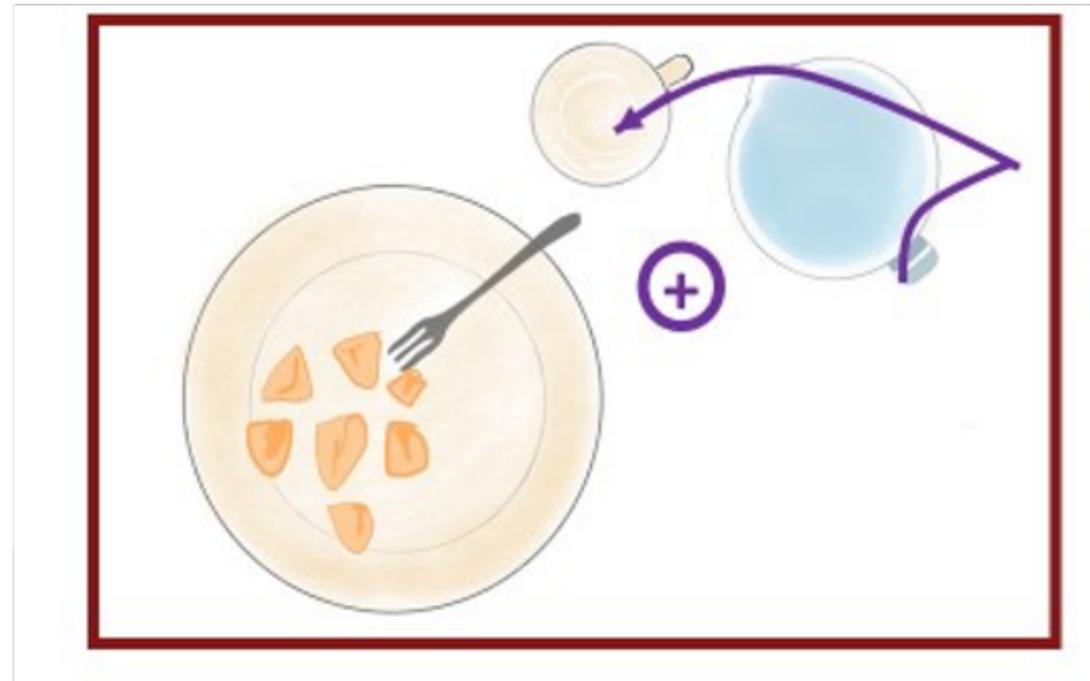# Assistive Robotics and Manipulation Laboratory

Intelligent Wearables - Intelligent Prosthetic Arm
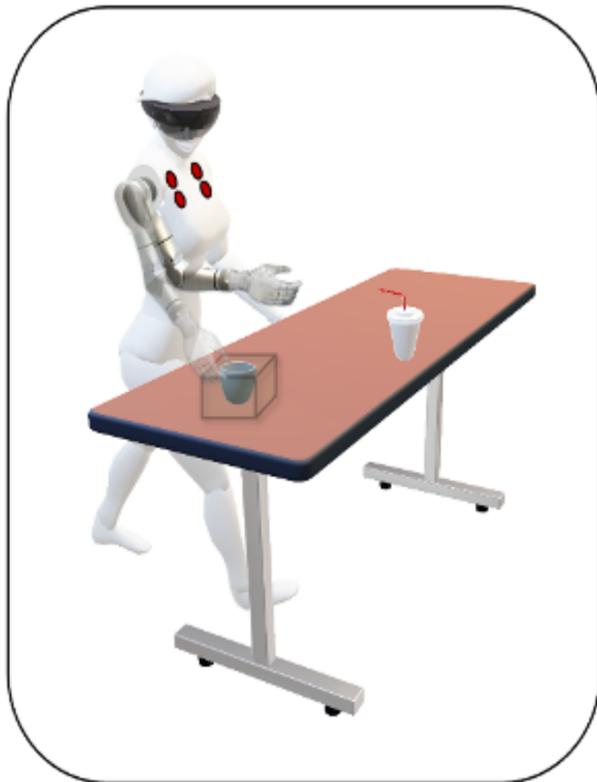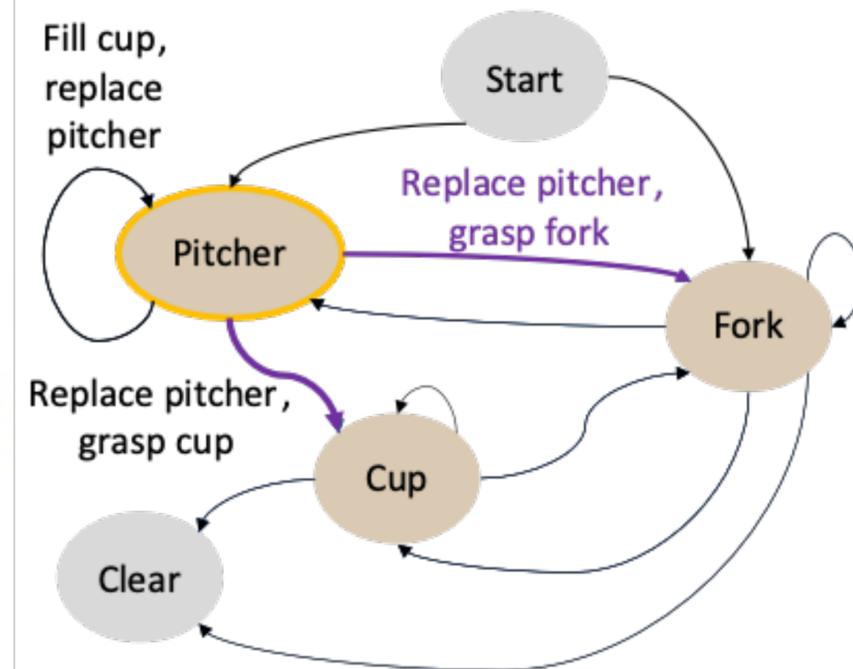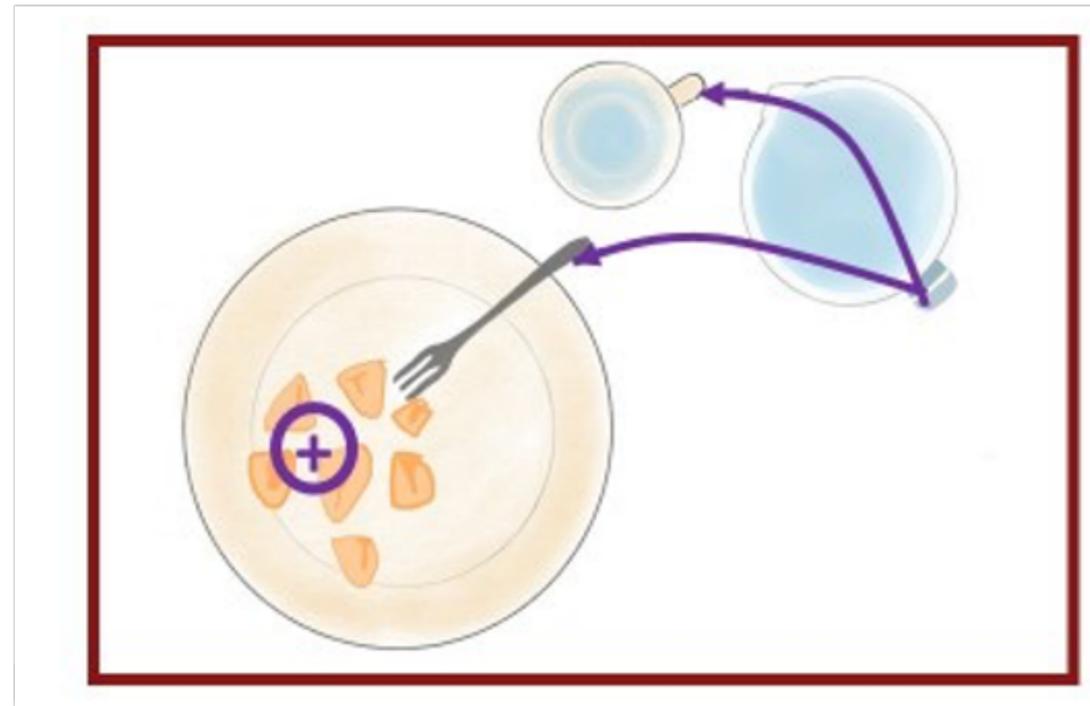

ARMLab Project: Intelligent **P**rosthetic **Arm**

Human Model

Robot Model

Task Model

Robot

Human Model ↔ Robot Model ↔ Task Model

Perception / **Action**   Mixed-reality   **Action** / Perception

EMG Measurements

Human (user/collaborator)

Task/Environment
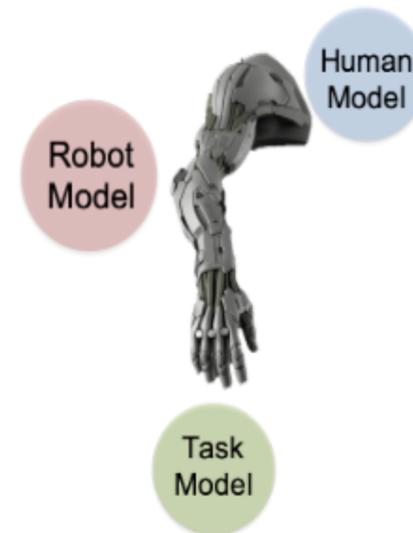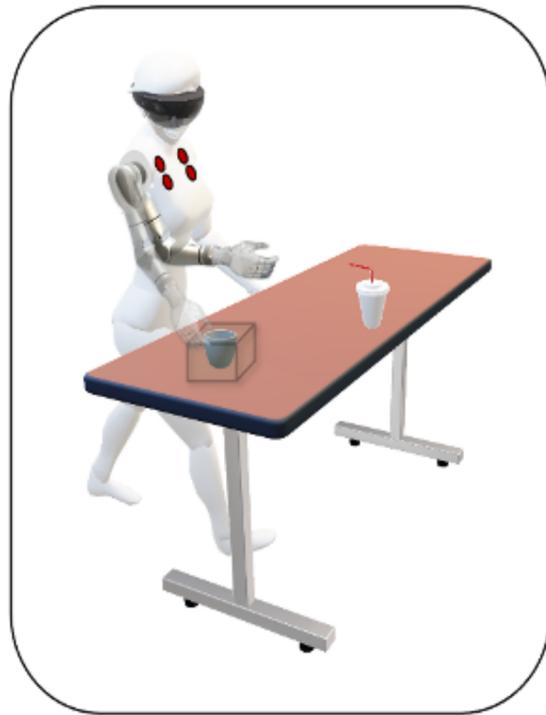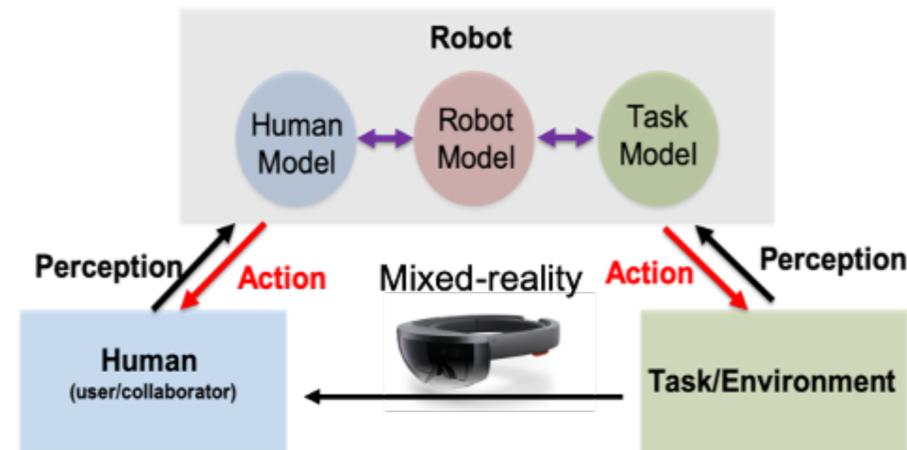
Visuo-Tactile Measurements

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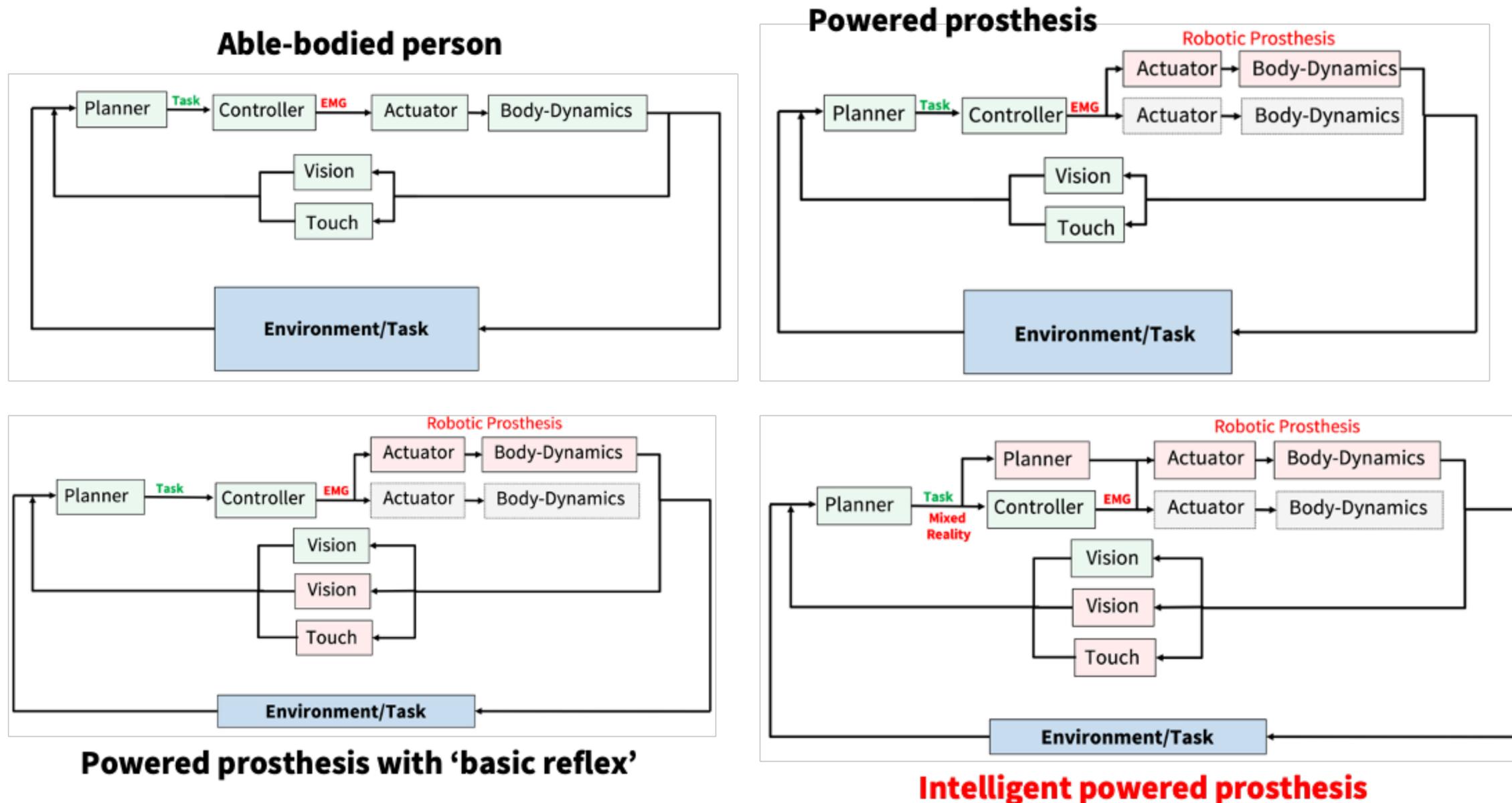
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Intelligent Wearables - Intelligent Prosthetic Arm

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

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Intelligent Wearables - Intelligent Prosthetic Arm
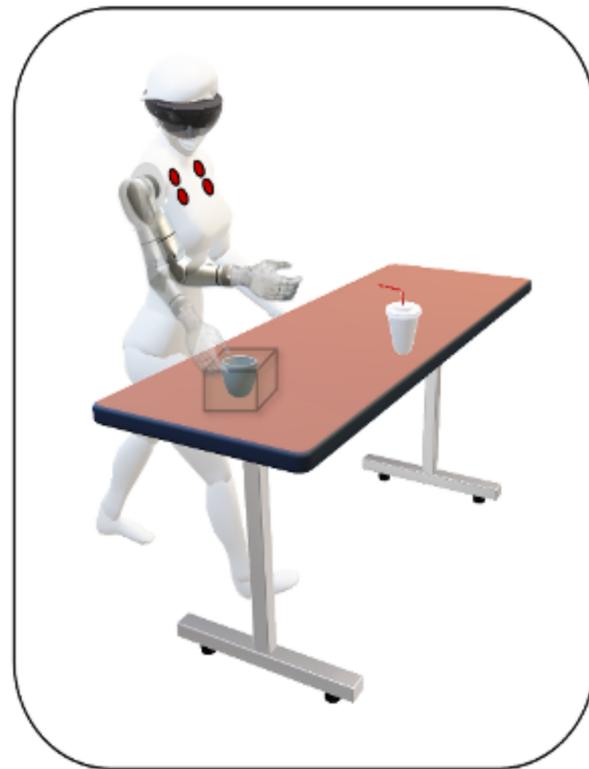

ARMLab Project:
Intelligent Prosthetic Arm
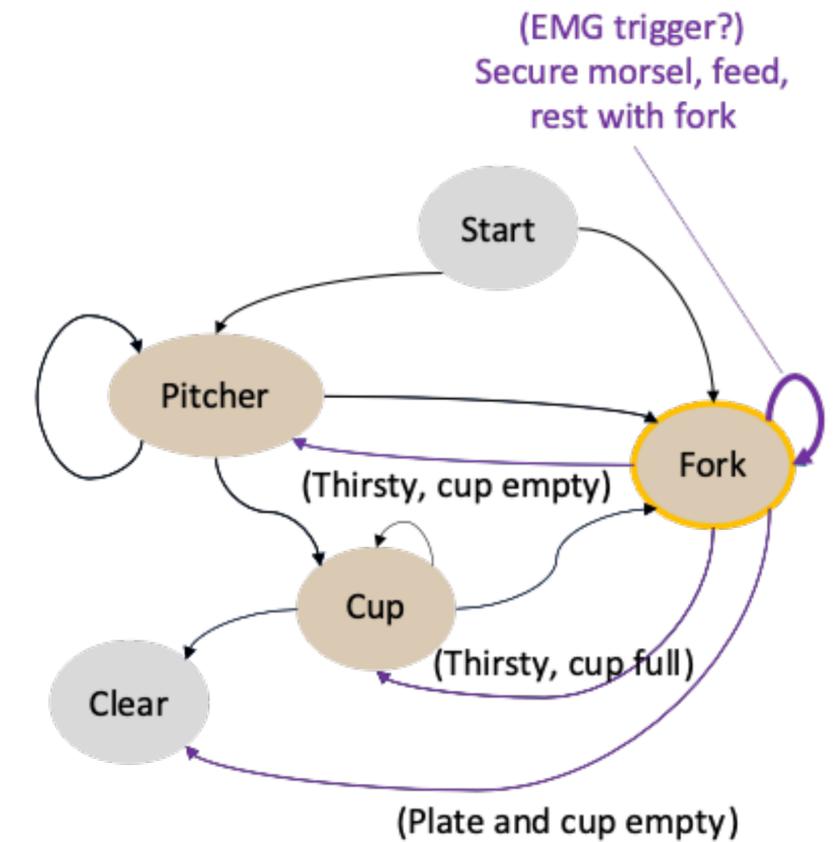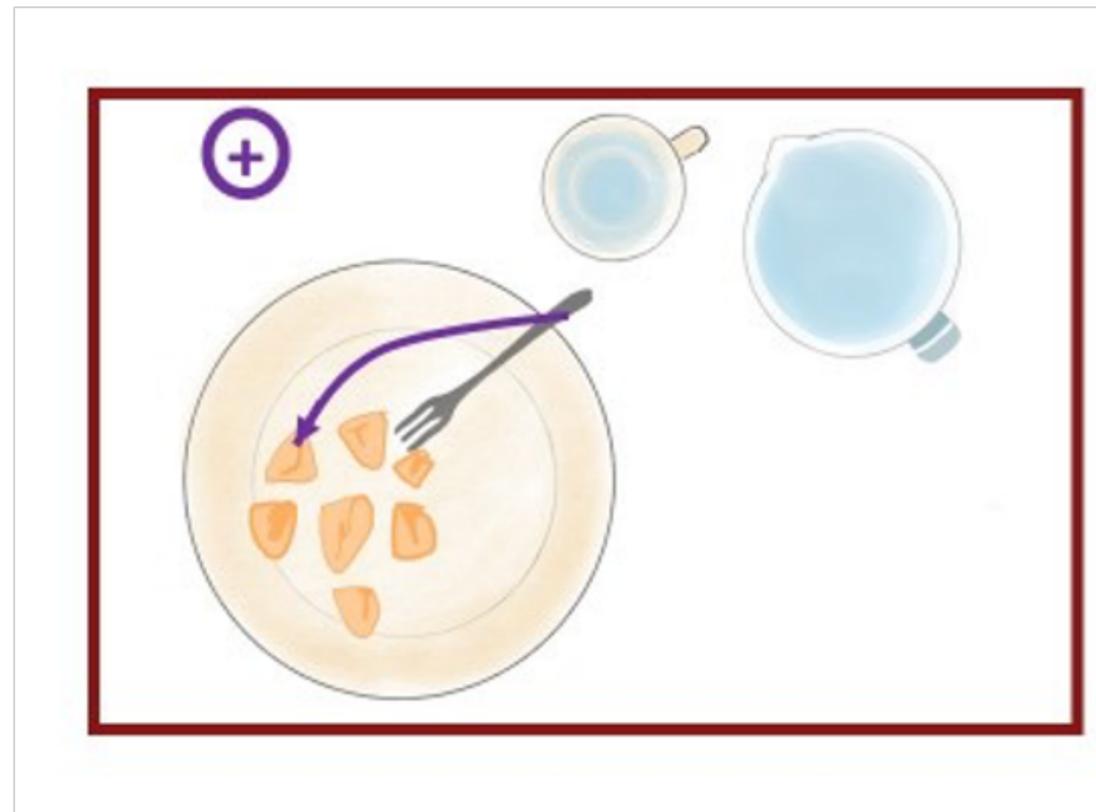

Example: IPArm state-machine for ADL

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Example: IPArm state-machine for ADL

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Example: IPArm state-machine for ADL

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Example: IPArm state-machine for ADL

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Object recognition

Task understanding

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Gaze tracking

EMG interpretation

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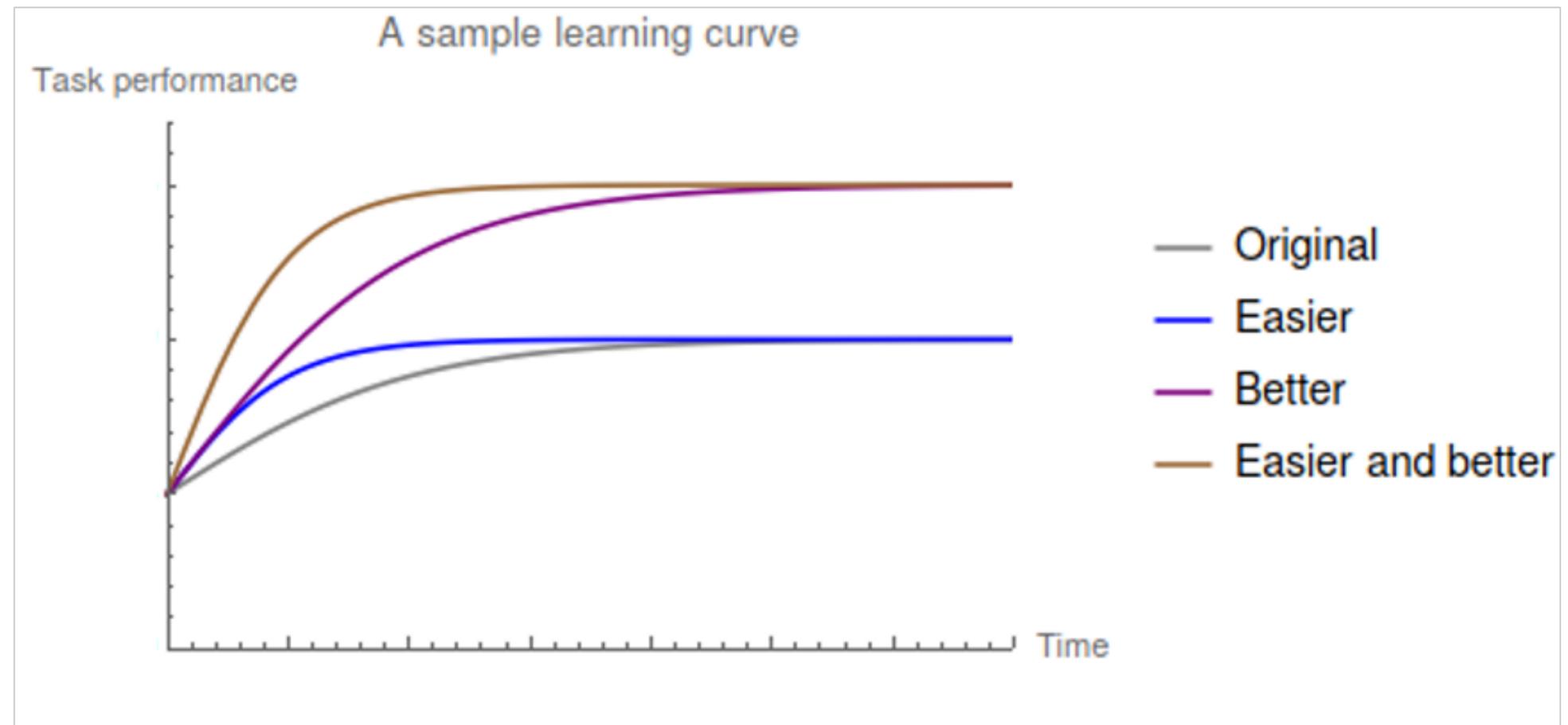## Intelligent Wearables - Intelligent Prosthetic Arm

ARMLab Project:
Intelligent **P**rosthetic **Arm**

A sample learning curve

Task performance

Original
Easier
Better
Easier and better

Time

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Intelligent Wearables - Fall Prevention Sensor
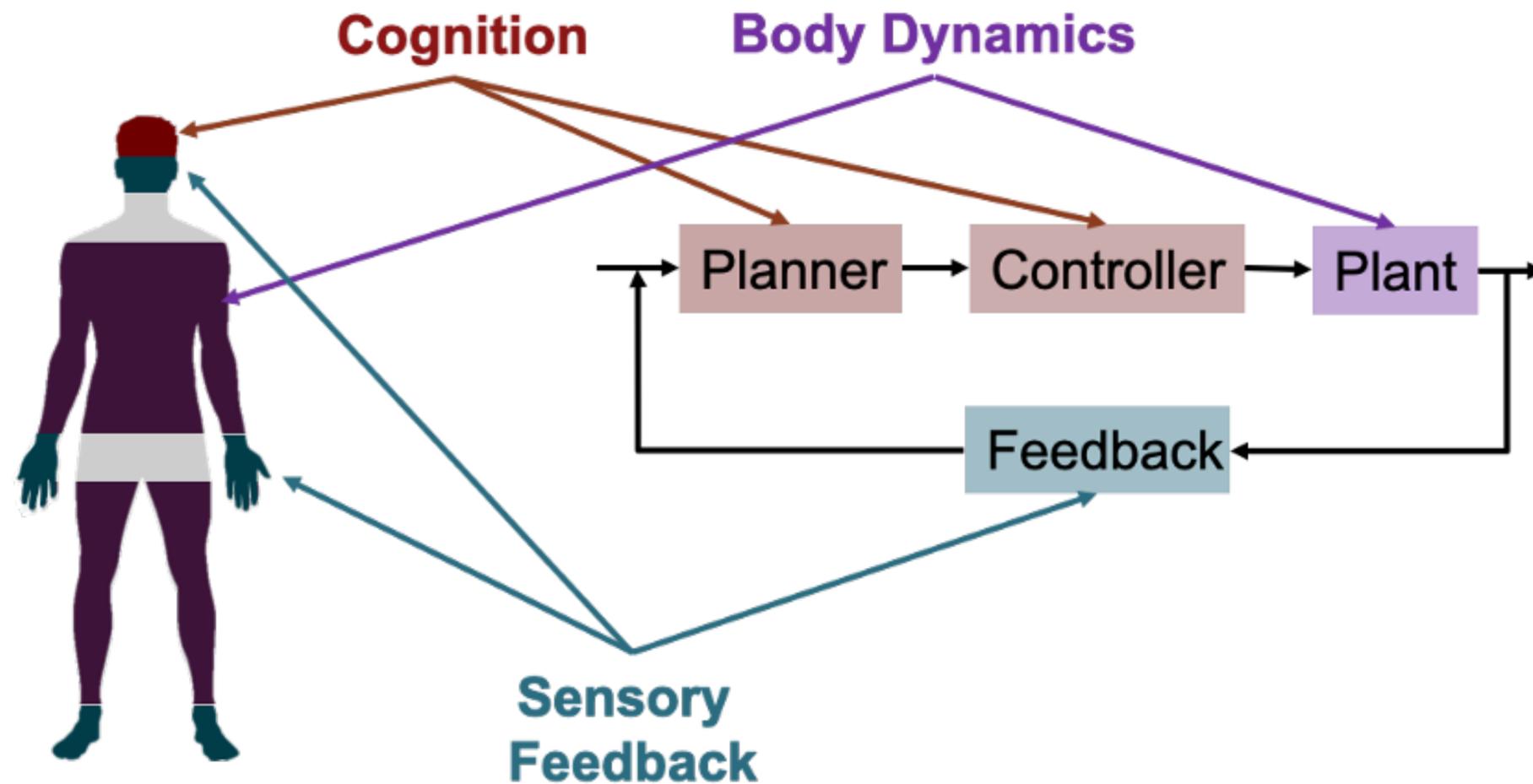
Ability enhancing device usually **improves sensory feedback** concerning the world

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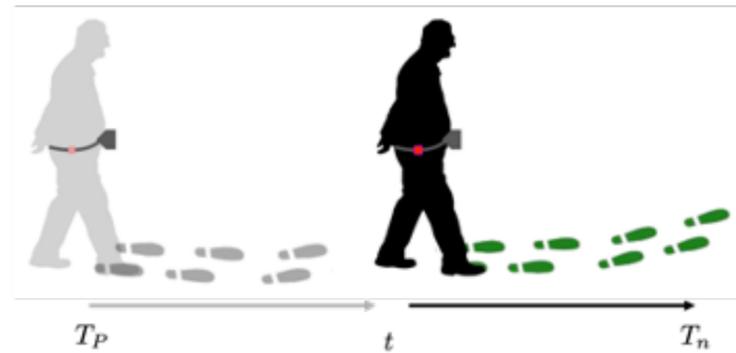
Expected outcomes:
Wearable sensor (with iterative user informed design) capable of predicting wearers path, gait and stability and warning user when risk of falling is significant.
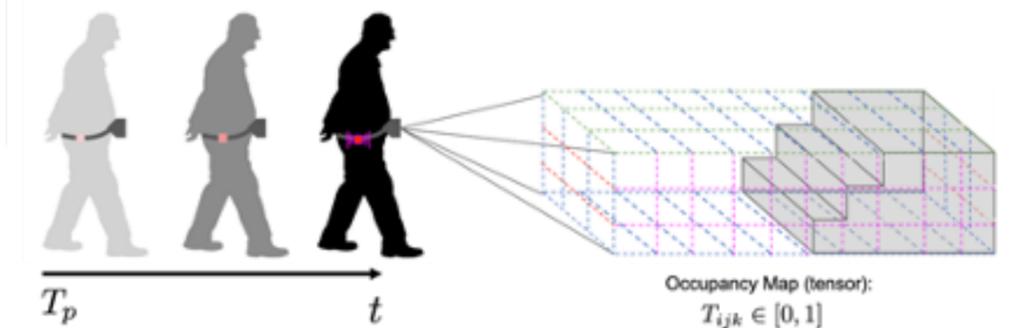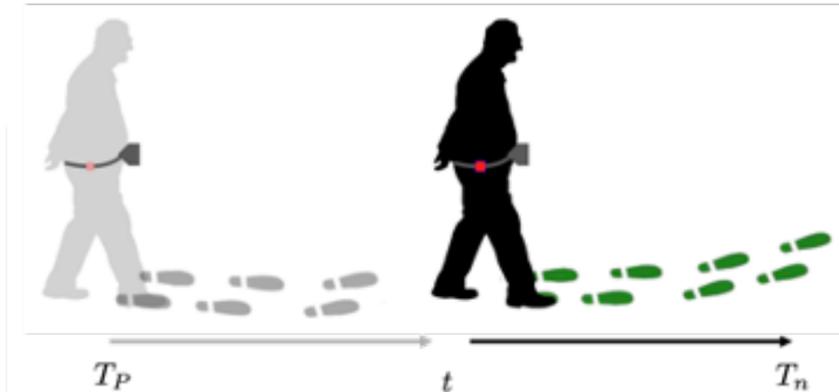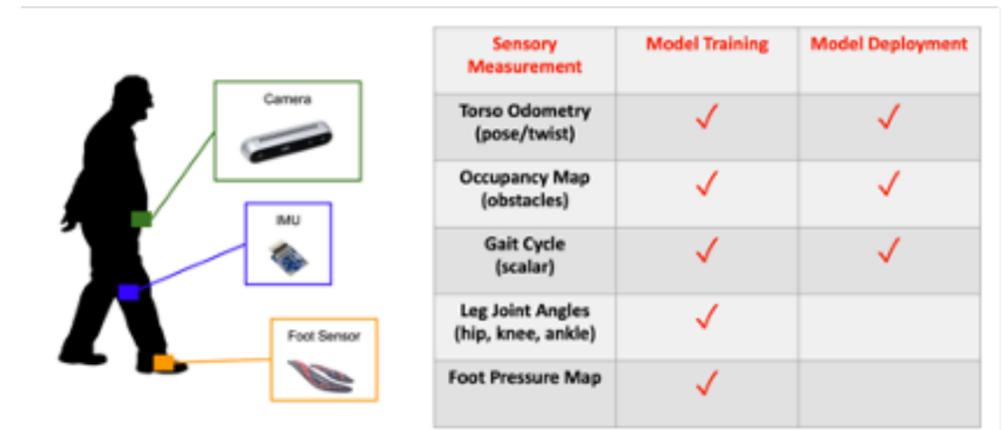
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Intelligent Wearables - Fall Prevention Sensor

Past Observation (path, gait, stability)

Future Prediction (path, gait, stability)

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)
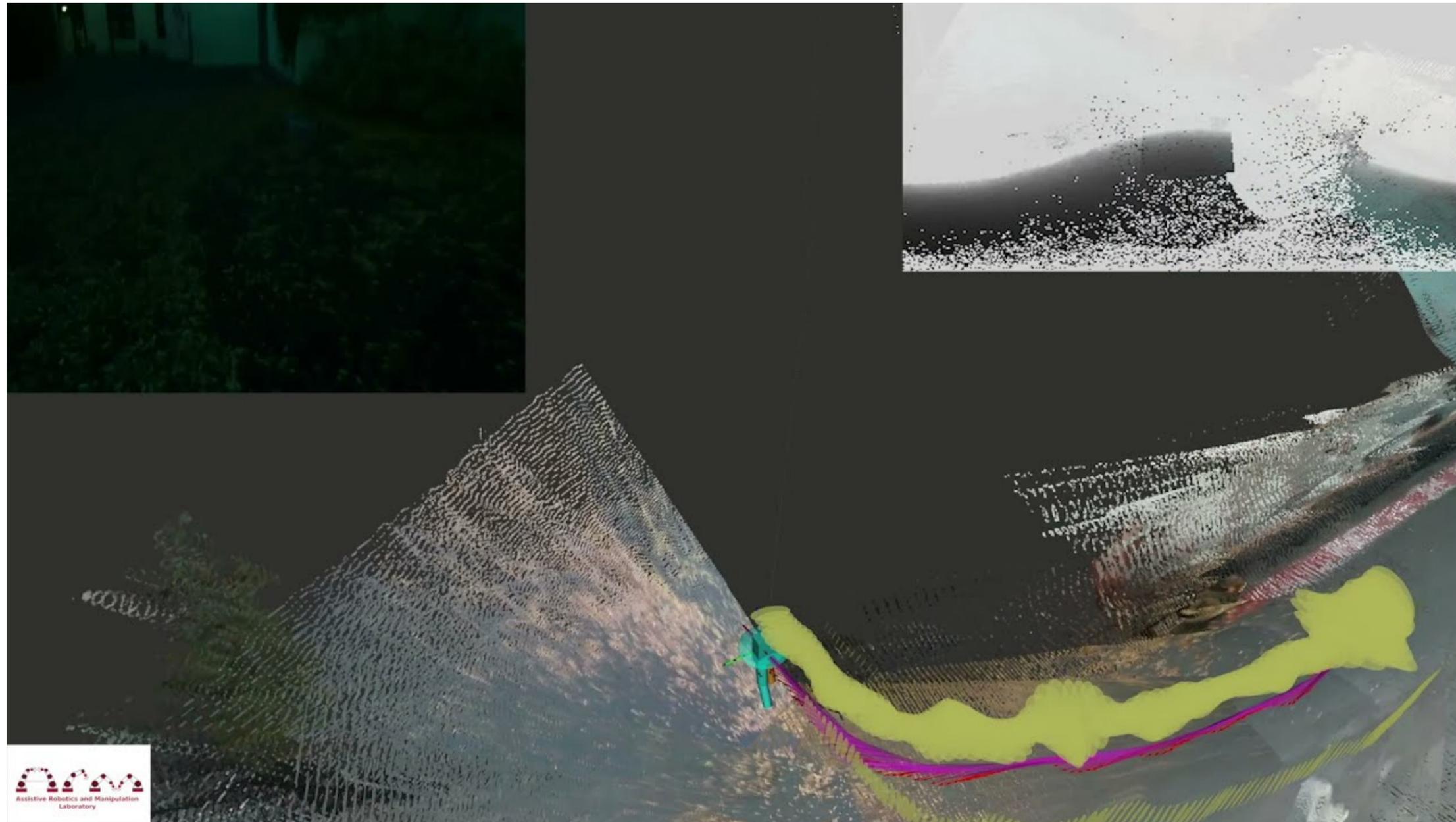
Outputs

Expected path, gait, stability

Alert user if instability is predicted

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Intelligent Wearables - Fall Prevention Sensor

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***

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Thank you!

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