Learning Control Sharing Strategies for Assistive Cyber-Physical Systems

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Why Do We Need Shared Autonomy in Assistive Cyber-Physical Systems?

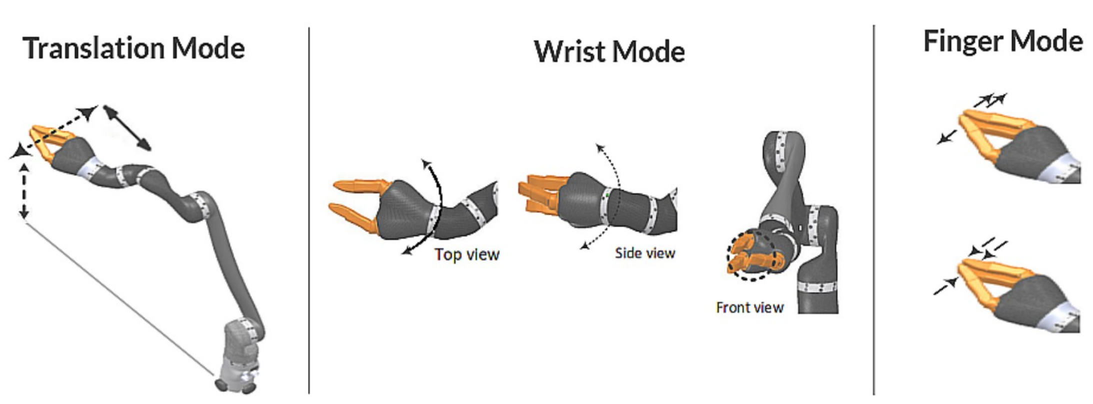


Figure 1: 7DoF robotic arm. Control interfaces: 2D joystick and 1D head array (Top). An example of partitioning of 7D control space to form control modes for operating the robotic arm (Bottom).

Aim: To develop principled approaches to shared control of complex assistive cyber-physical systems, such as a 6-DoF robotic arms via simple low-dimensional control interfaces that are accessible to persons with severe motor impairments such as 2D joysticks and 1D Sip-N-Puff interfaces (Figure 1, Top).

Why: The dimensionality mismatch between high-dimensional robots and low-dimensional control interfaces requires the control space to be partitioned into *control modes* (Figure 1, Bottom). For full control of the robot the user switches between these partitions and this is known as *mode switching*. Mode switching adds to the cognitive workload and degrades task performance. *Shared autonomy* helps to alleviate some of the task burden by letting the robot take partial responsibility of task execution.

We investigated different paradigms for assistive mode-switching: a) Data-driven approaches to learn individual mode-switching behavior and b) identifying control modes that will elicit more informative control commands from the human which will help the robot to perform more accurate intent inference.

Relevance to Cyber-Physical Systems

Synergy: The intersection of robotic manipulation, human rehabilitation, control theory, machine learning, human-robot interaction and clinical studies.

Science of CPS: Development of mathematical models to quantify the interaction dynamics between the user and system. Development of new interfaces and interaction modalities with strong theoretical foundations.

Engineering of CPS: Deployment of algorithms on real hardware and evaluation of proposed assistive paradigms with able-bodied and spinal cord injured users.

Learning Mode Switching

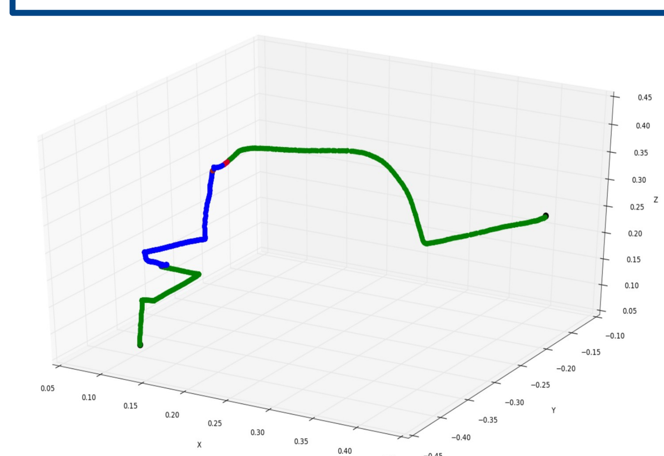


Figure 2: Automated mode switching for a Cartesian trajectory. Translational mode (green), Wrist mode (blue), Wrong predictions (red).

Idea: To develop models that capture the mode switching behavior of humans.

Why: Machine learning techniques can be leveraged to tailor mode switch assistance systems to individuals' mode-switching habits which will integrate more smoothly with the user's teleoperation.

How: The user teleoperates the robotic arm and trajectories are recorded. A classifier is trained on these examples to predict the control mode at every point in the trajectory (Figure 2).

Results: A pilot study was conducted on uninjured subjects and model generalization and task generalization were evaluated.

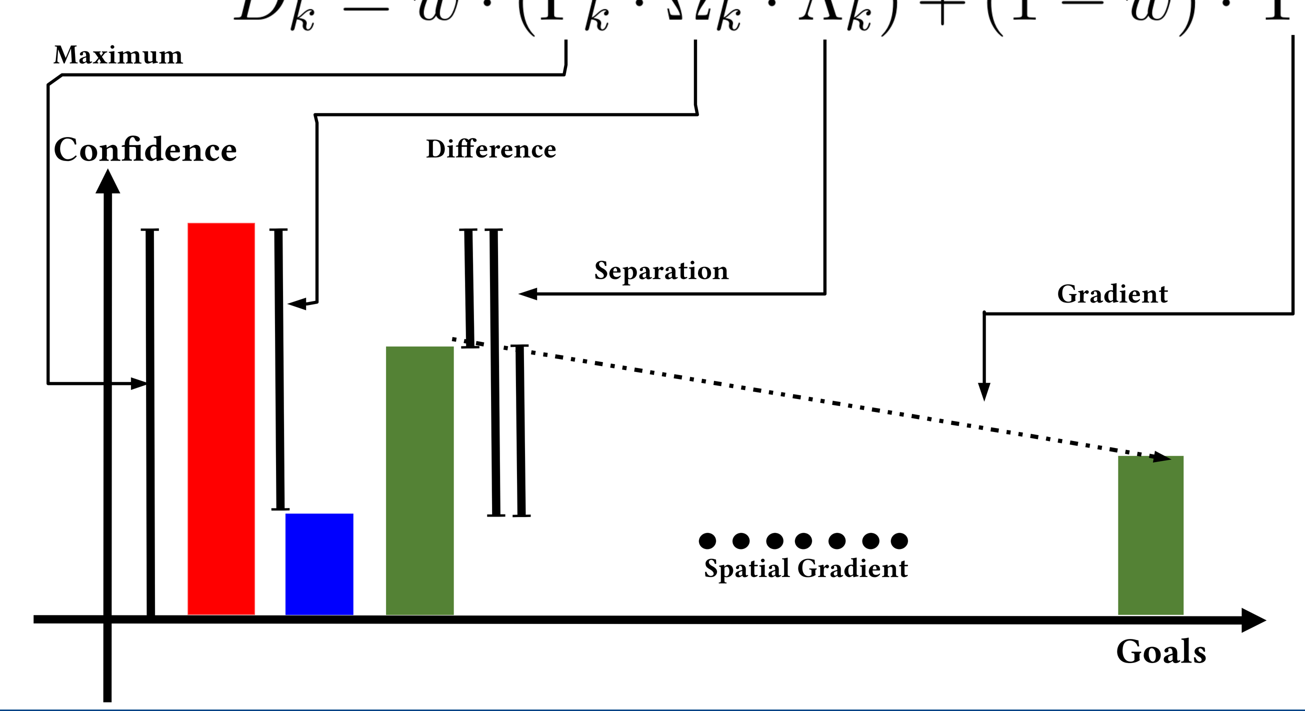
Control Mode Selection to Disambiguate Human Intent Maximally

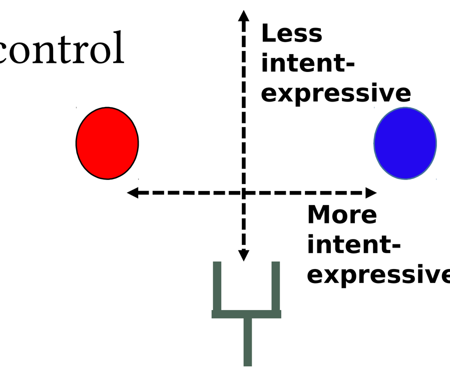
Aim: To enhance robot's intent inference by identifying control dimensions and modes that disambiguate human intent *maximally* by *eliciting* more **intent-expressive** commands from the user.

Disambiguation Metric: Characterizes the disambiguation capabilities of control dimension.

$$D_k = w \cdot (\Gamma_k \cdot \Omega_k \cdot \Lambda_k) + (1-w) \cdot \Upsilon_k$$

Task-specific weight





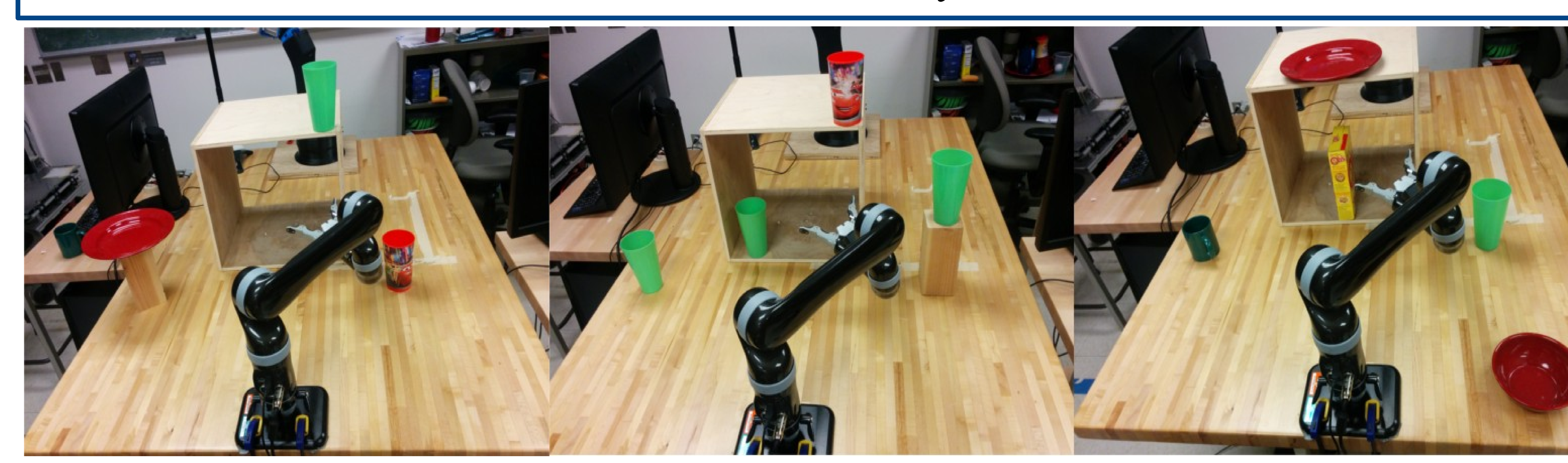
$$D_m = \sum_k D_k \;\; k \in m$$

Disambiguation metric for control mode m.

$$m^* = \operatorname{argmax}_m D_m$$

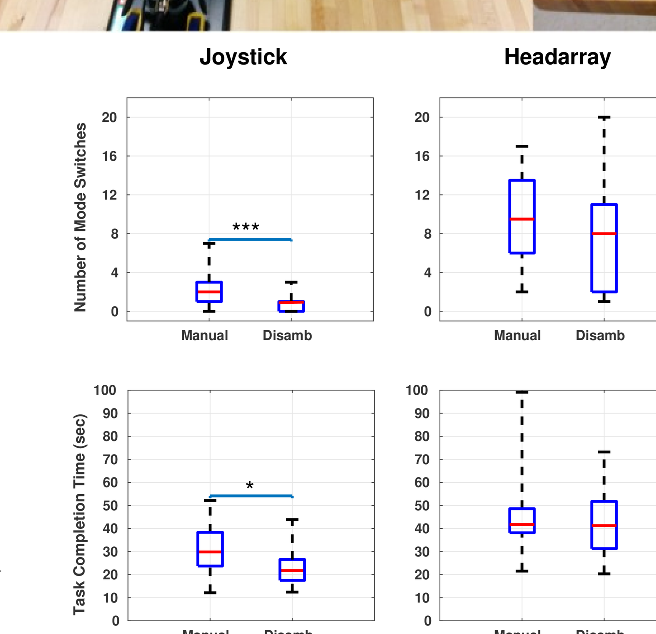
Mode with **highest disambiguation** capability.

Pilot Study



Control Mappings		
Mode	**Head Array**	**Joystick**
1	v_x	v_x, v_y
2	v_y	v_x, v_z
3	v_z	ω_z, ω_y
4	ω_z	ω_x
5	ω_y	—
6	ω_x	—

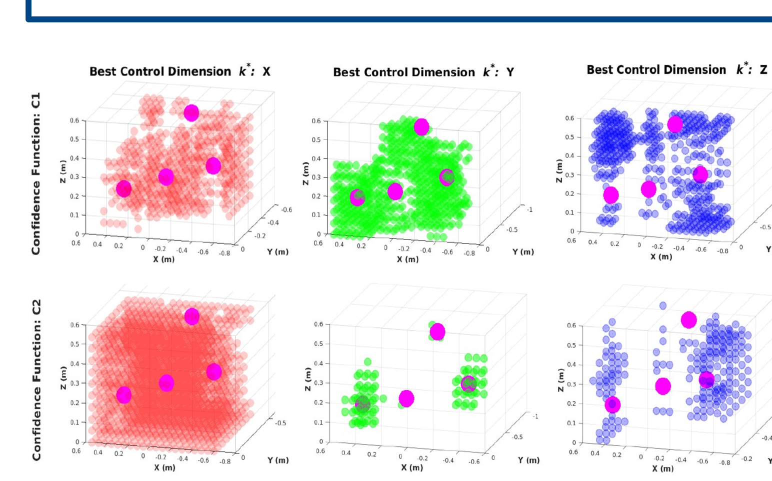
4 subjects (lab members), Two interfaces.
Starting Mode: Randomized or m^*.



Number of Mode Switches
Decrease with disambiguation.

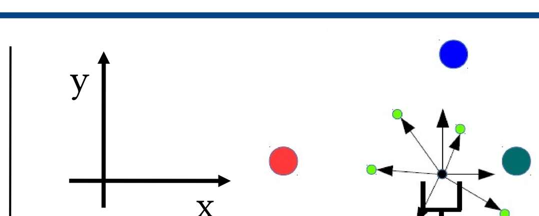
Task Completion Time
Decrease with disambiguation.

Simulation Results



Best Control Dimension Distribution		
	C1	C2
X	579	1711
Y	615	93
Z	446	196
NULL	360	0

Impact of Confidence Functions on Disambiguation



n_g	3	4	5
Accuracy (%)	89.24	87.09	86.11

Characterization of Simplifying Assumptions