Ergodic Control in HRI

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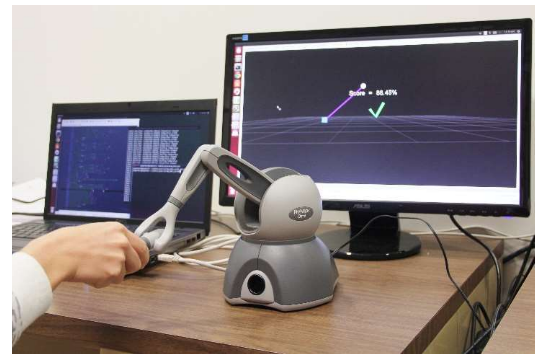
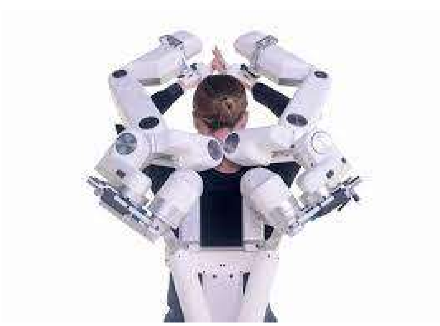
HUMAN ROBOT INTERACTION

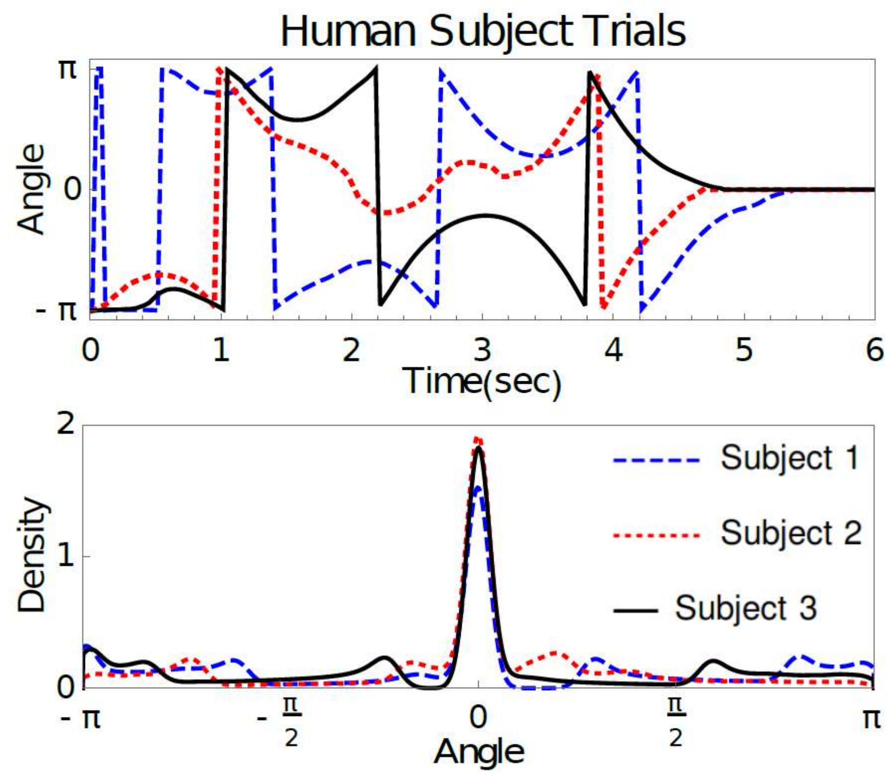
- Social Robots
- Workplace Robots
- Rehabilitation Robotics
- Virtual Training & Haptics
- Learning From Demonstration





VARIATION IN HUMAN MOTION

- Substantial variation between equally successful trials within and between individuals
- Using statistical representations of the task enables one to use information measures to assess the quality of motion.



Human Motion Assessment

Task-Specific Measures

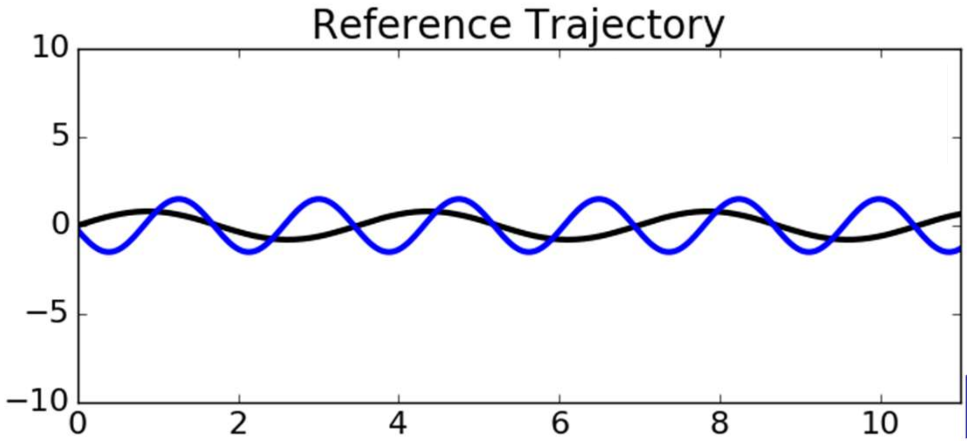
- Outcome-based (e.g., success/failure)
- Narrowly defined (e.g., work area or physical target)
- Do not generalize to other tasks
- Does not enable principled interpretation

Human Motion Assessment

Engineering Measures

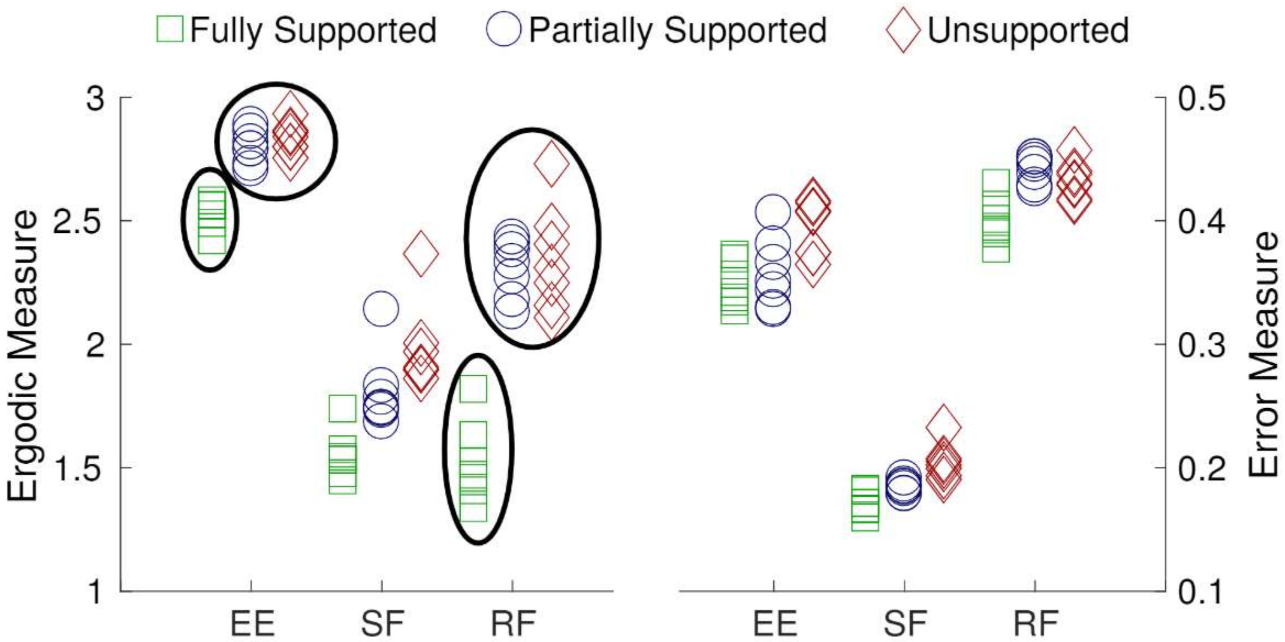
- Principled interpretation
- Independent of the task
- Established control synthesis techniques

IF we have a task definition in the form of a time-series of states.



ERGODICITY DETECTS DEFICIT and ASSISTANCE

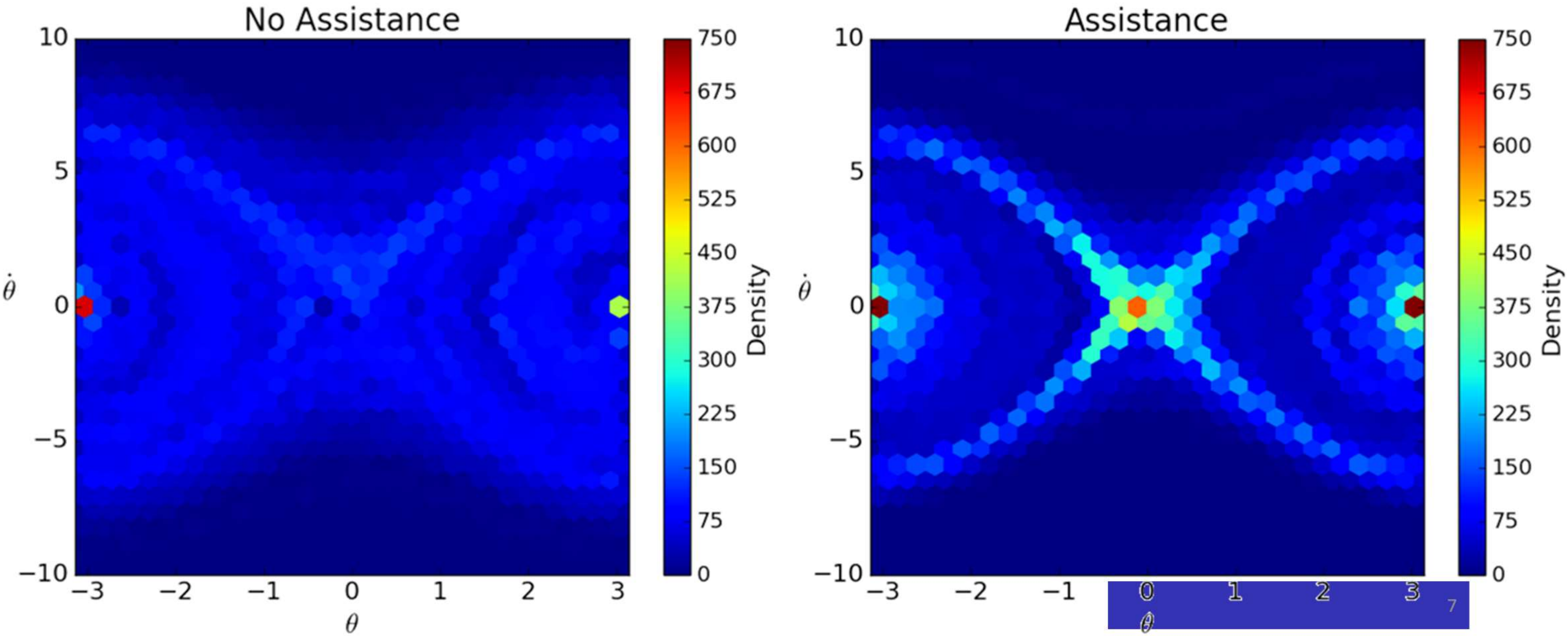
Target Reaching in Stroke



EE – Elbow Extension SF – Shoulder Flexion RF – Reach Forward

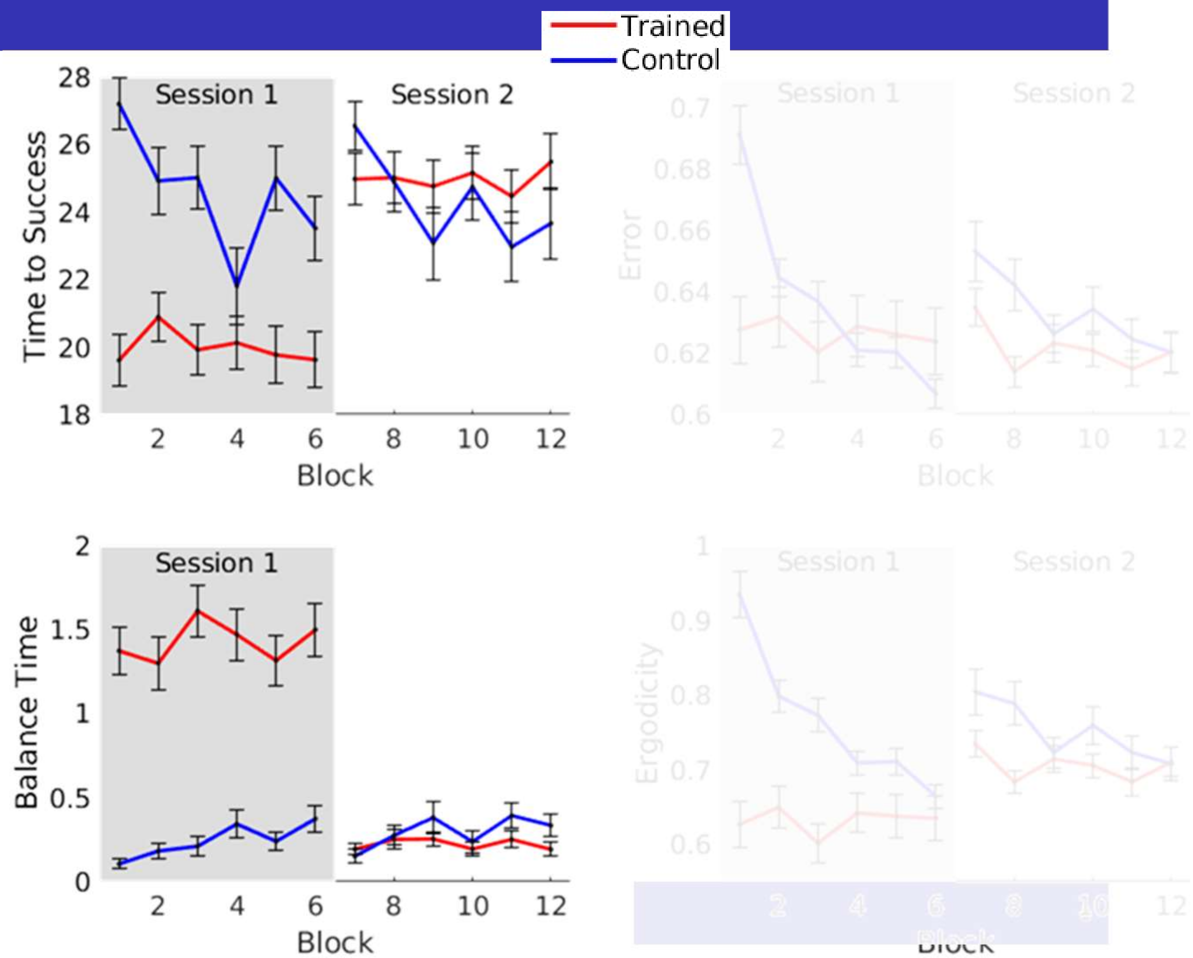
ERGODICITY DETECTS DEFICIT and ASSISTANCE

Cart-Pendulum Inversion in Healthy Subjects



ERGODICITY DETECTS TRAINING

- Task-specific measures capture assistance but not training



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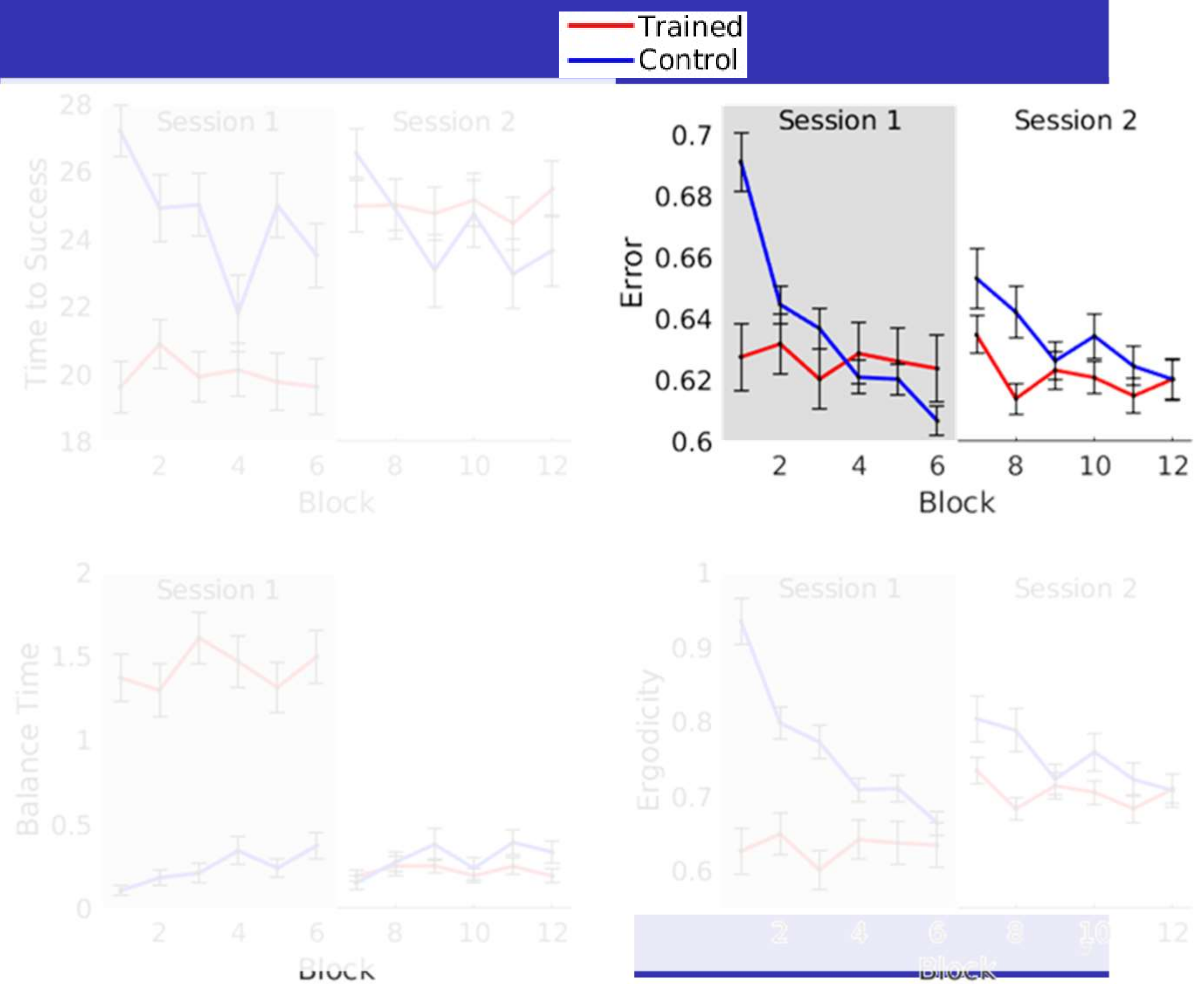
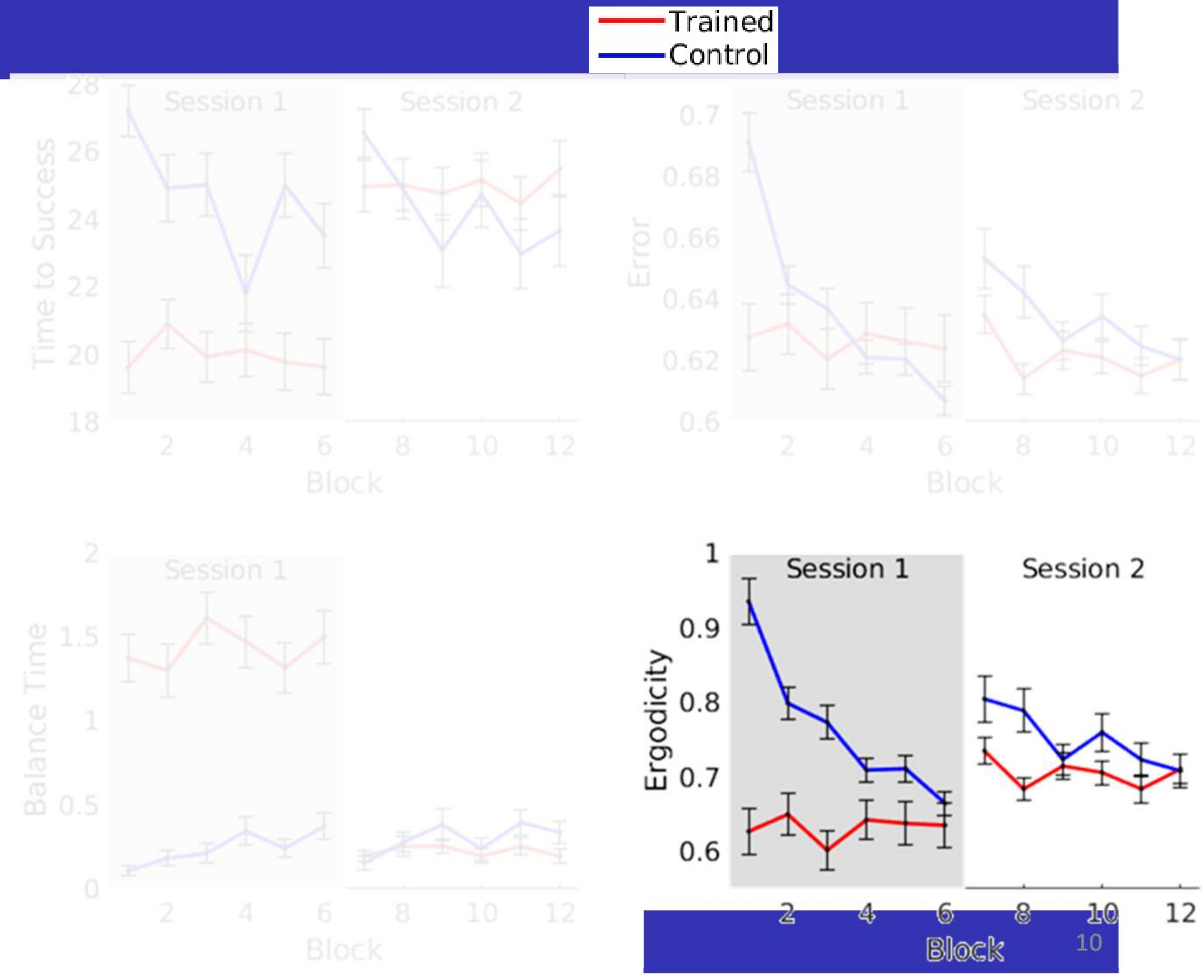


ERGODICITY DETECTS TRAINING

- Task-specific measures capture assistance but not training
- Error captures training but not assistance
- Ergodicity capture both effects

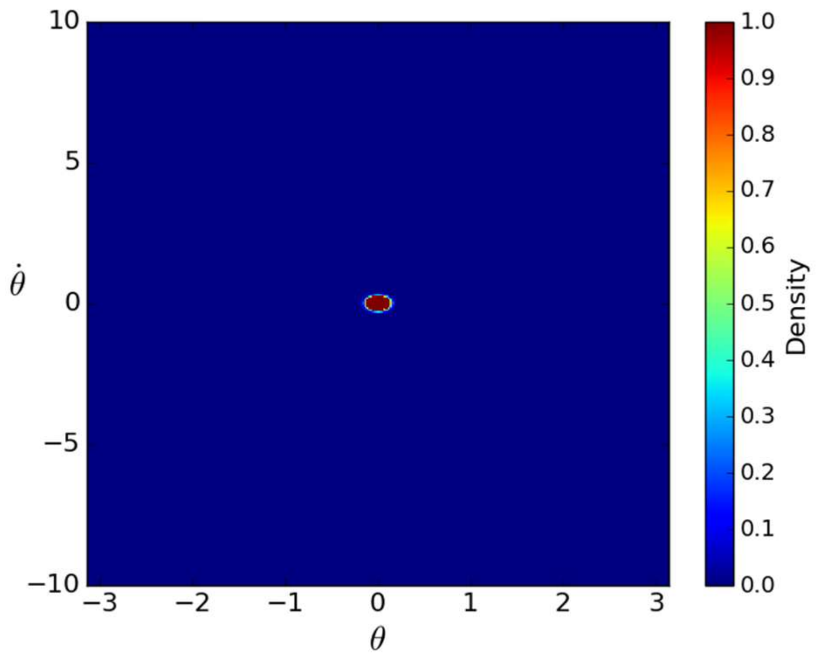


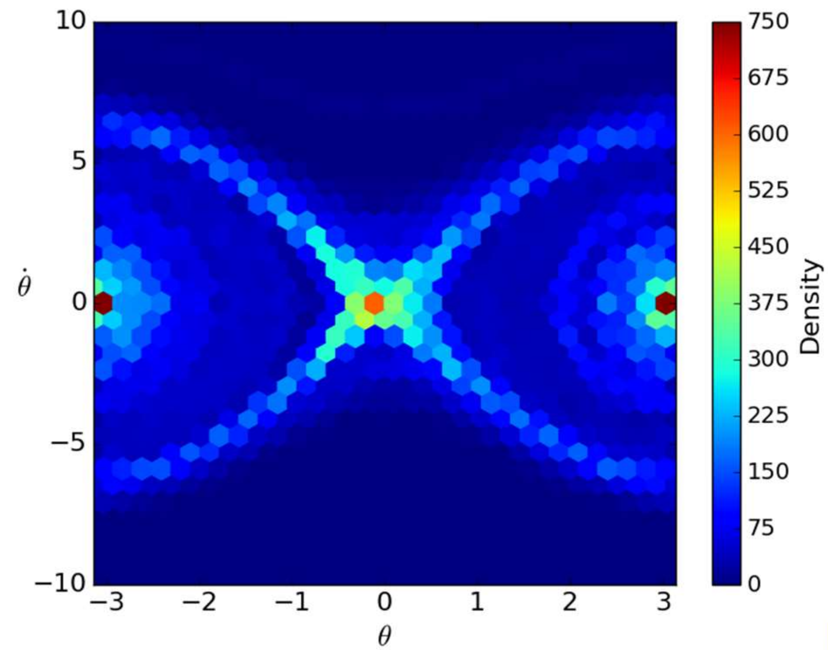
Defining 'Good' Movement

Specify a goal state and choose a probabilistic model (e.g. Dirac Delta)

OR

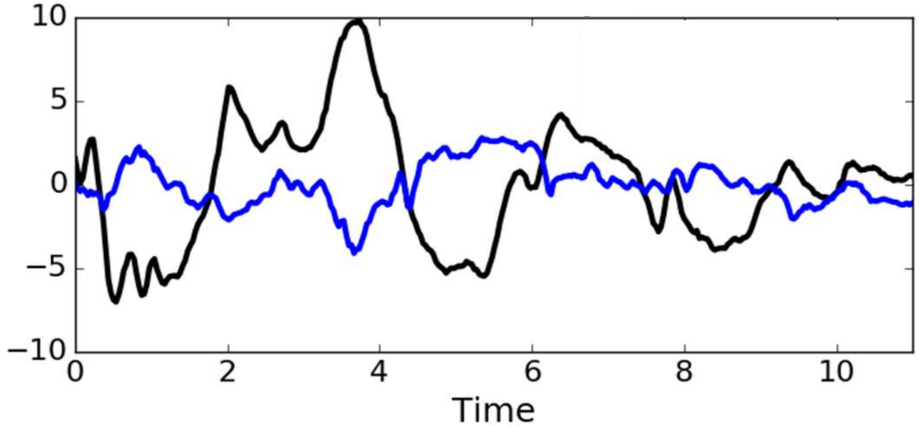
Use a collection of observations to form a distribution

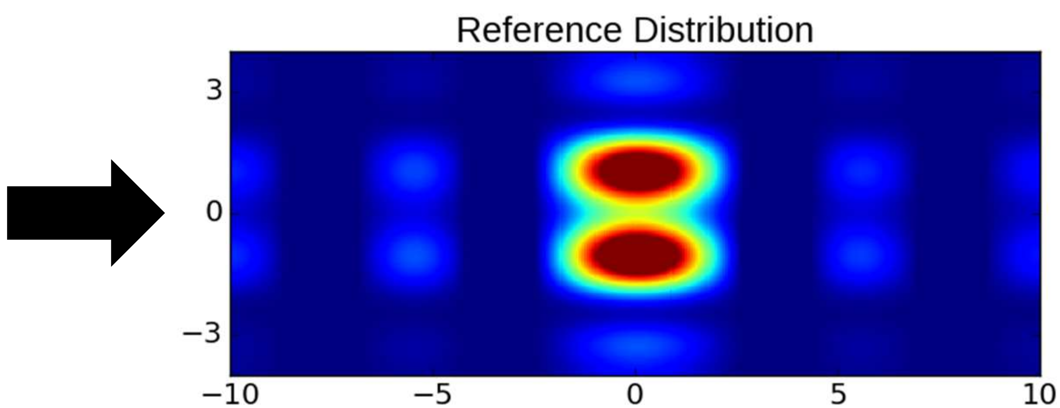




QUANTIFYING ERGODICITY

- Using Fourier Coefficients scales as $\mathcal{O}(|k|^n)$
- Periodic basis functions leads to artifacts
- Alternative is a sample-based measure of the Kullback-Leibler Divergence[1]





I. Abraham, A. Prabhakar, and T.D. Murphey, "An Ergodic Measure for Active Learning from Equilibrium," Transactions on Automation Science and Engineering (2020).

QUANTIFYING TASK INFORMATION

Sample-Based K-L Divergence Measure

- Approximate the trajectory as a mixture distribution

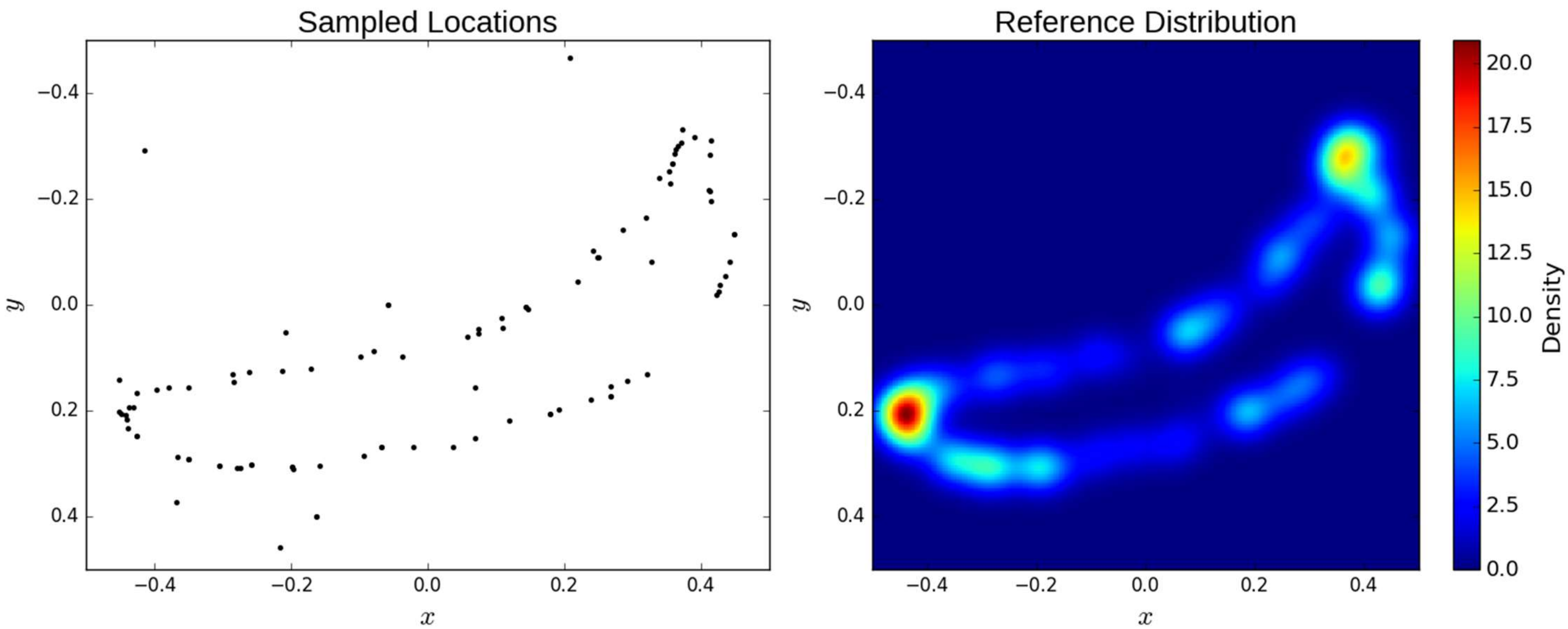
$$q(s|x(t)) = \frac{\eta}{t_f - t_0} \int_{t_0}^{t_f} exp\left[-\frac{1}{2}(s - x(t))^T \Sigma (s - x(t))\right] dt$$

$$D_{KL}(p(s)||q(s)) \quad = \quad \int_{\mathcal{X}} p(s) ln \frac{p(s)}{q(s)} ds$$

- Approximate the Kullback-Leibler Divergence using N randomly sampled points

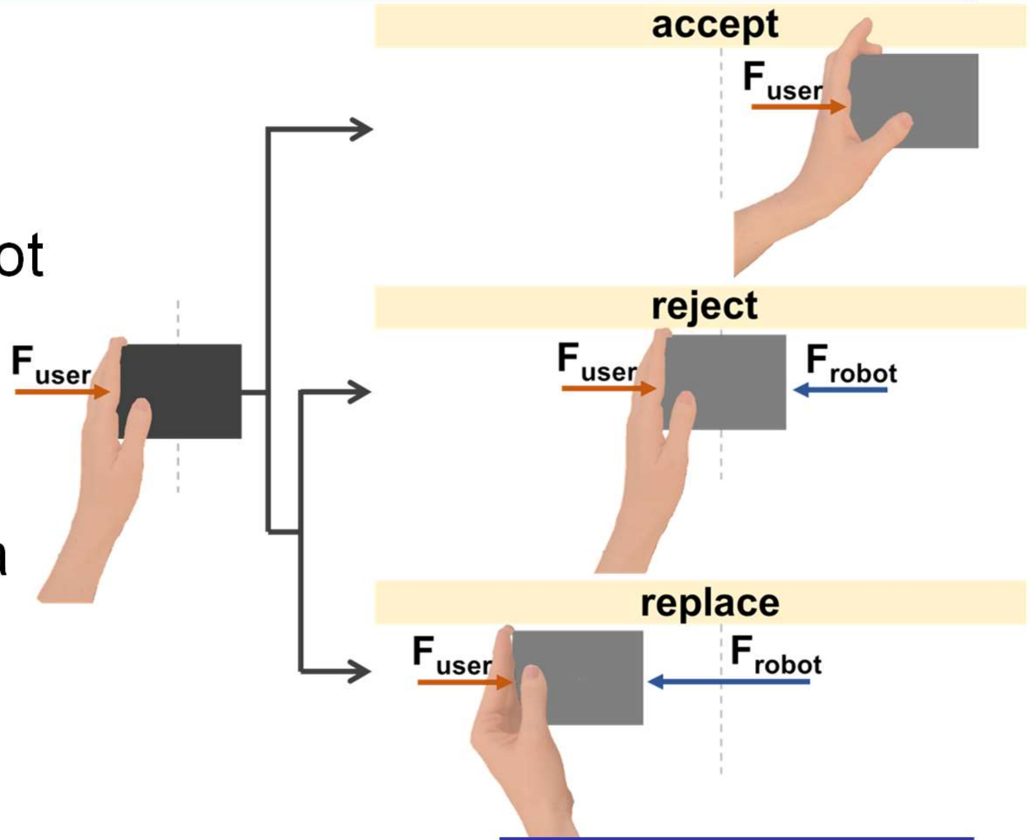
$$\varepsilon_{KL} = \sum_{i=1}^{N} p(s_i) ln \int_{t_0}^{t_f} exp\left[-\frac{1}{2}(s_i - x(t))^T \Sigma (s_i - x(t))\right] dt$$

Sample-Based K-L Divergence Measure



HYBRID SHARED CONTROL

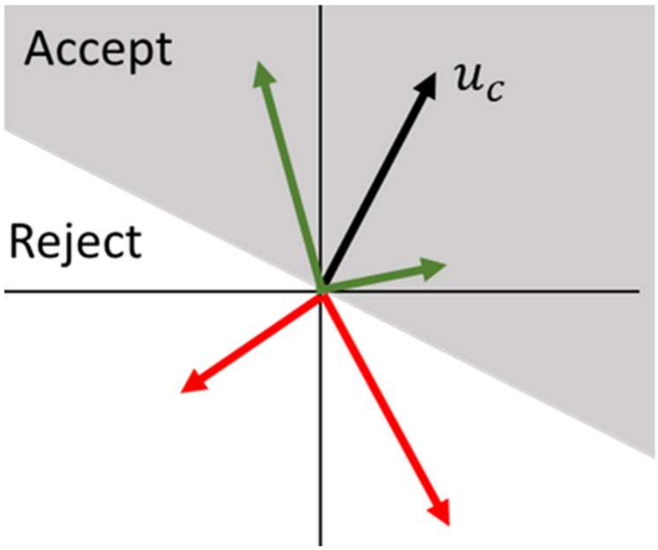
- Does not provide guidance or augment error
- Selectively rejects (but does not replace) user actions
- Adapts to user needs using task-based acceptance criteria



HYBRID SHARED CONTROL

Task-Based Criteria: Inner Product

- Compute the nominal controller, u_c
- Calculate the inner product $\langle u_c, u_{user} \rangle$
- Calculate the angle Φ between u_c and u_{user}



$\langle u_c, u_{user} \rangle > 0$ **and** $\Phi \leq \gamma$

HYBRID SHARED CONTROL

Task-Based Criteria: Mode Insertion Gradient (MIG)

Used in optimal control mode scheduling

$$u_2(t) = \begin{cases} u_{user} & t \leq t_s \\ u_1 & t_s \leq t \leq T \end{cases}$$

$\frac{dJ}{d\lambda}(\tau) =$ The sensitivity of the cost to the user input

$$\int_{t_{now}}^{t_{now}+T} \frac{dJ}{d\lambda}(t)\delta t \leq 0$$

When the integral is negative, u_2 is a descent direction.

Implementing on Impedance Controller

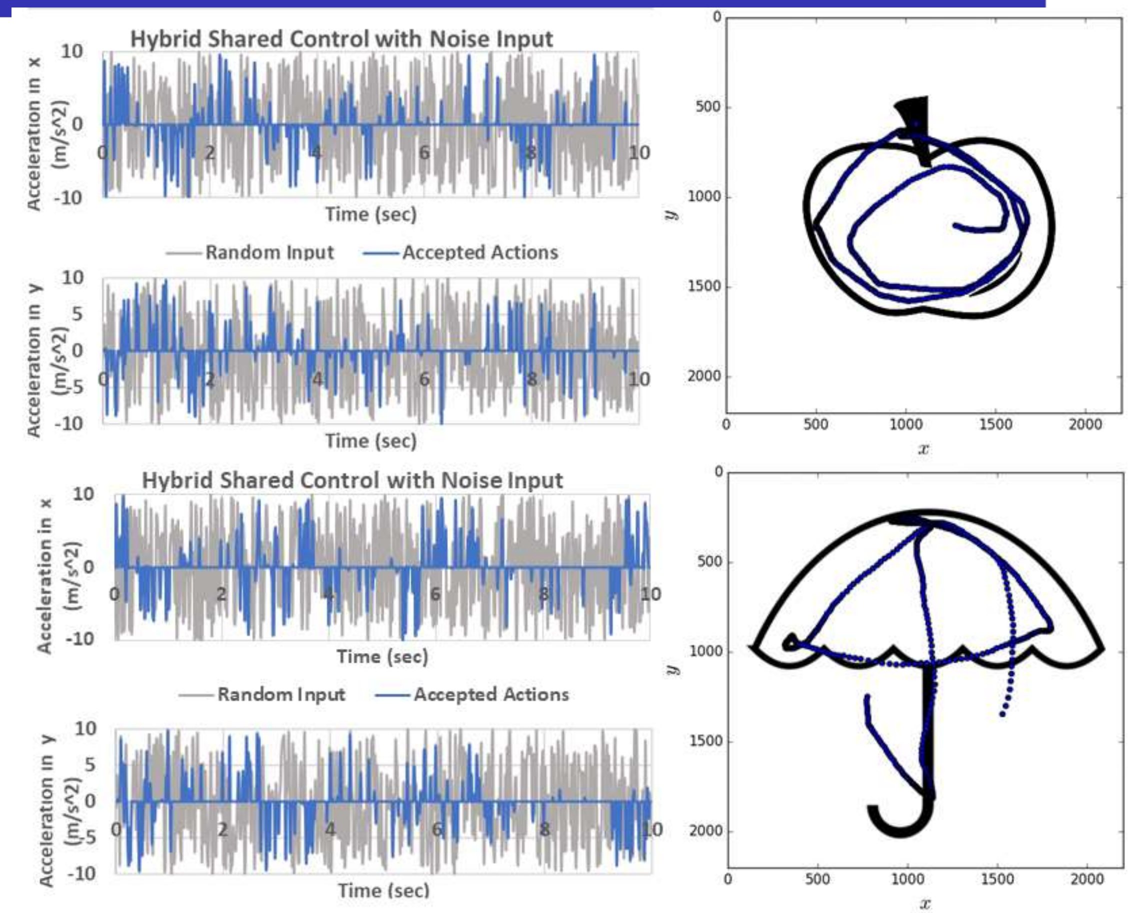
- When inputs are accepted, impedance is **0**
- When inputs are rejected, damping parameter of impedance control is updated

$$\begin{pmatrix} D_x \\ D_y \end{pmatrix} = \begin{pmatrix} sgn(v_x) & 0 \\ 0 & sgn(v_y) \end{pmatrix} \begin{pmatrix} \Delta v_x \\ \Delta v_y \end{pmatrix}$$

ERGODIC SHARED CONTROL

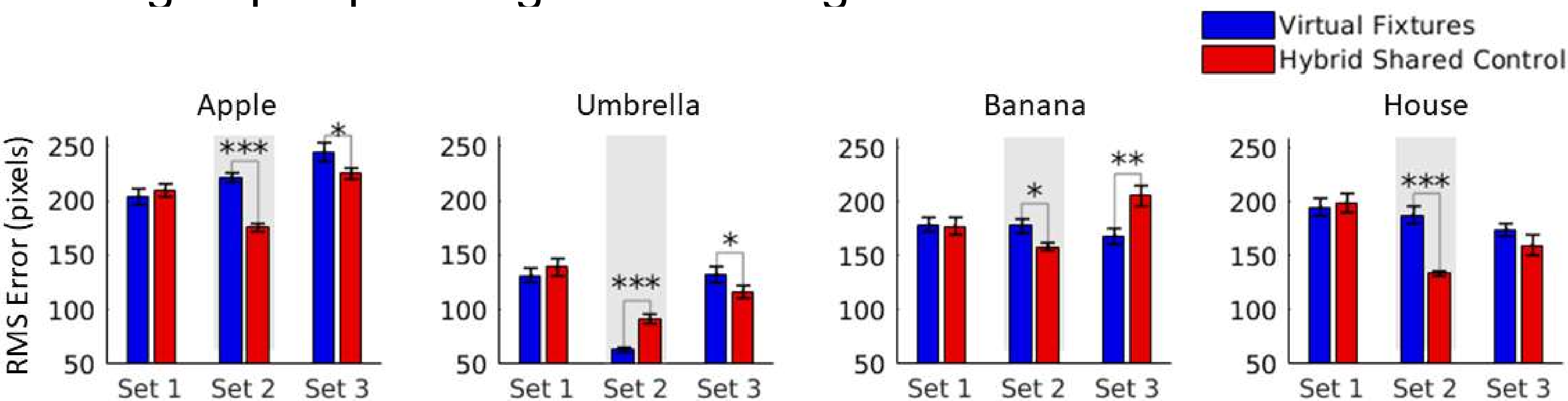
Simulation Results

- Double Integrator System
- Random Inputs from uniform distribution
- Transforms random walk into something resembling original image



TRAINING OUTCOMES - ERROR

- Computed root mean square of d_p in pixels
- ANOVA of Set 1 and Set 3 showed significant interaction effect of training group and set
- VF group exploited guides leading to fixed distance from lines



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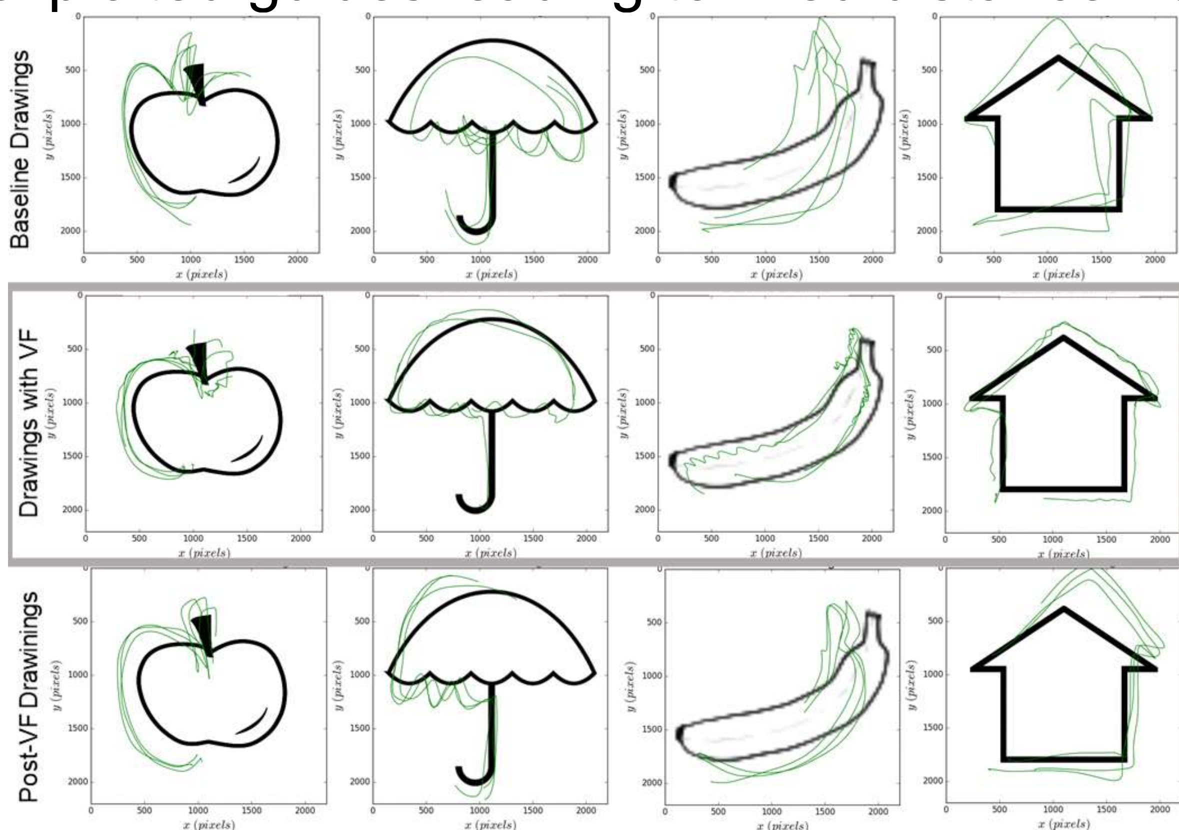
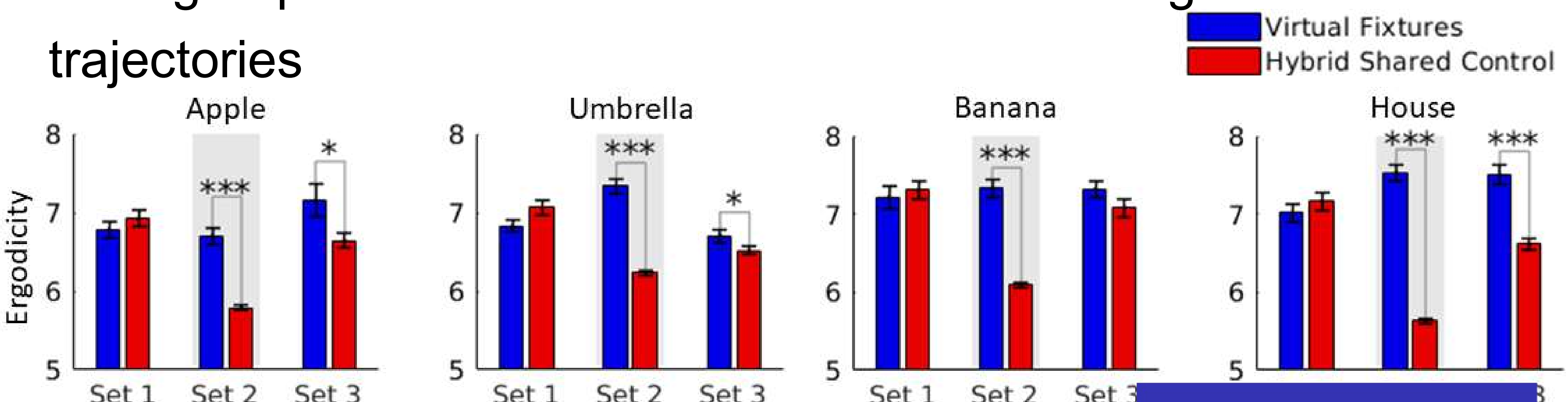


TRAINING OUTCOMES - ERGODICITY

- Computed using sample-based K-L Ergodic measure
- ANOVA of Set 1 and Set 3 showed significant interaction effect of training group and set
- HSC group encoded more information about image into their trajectories



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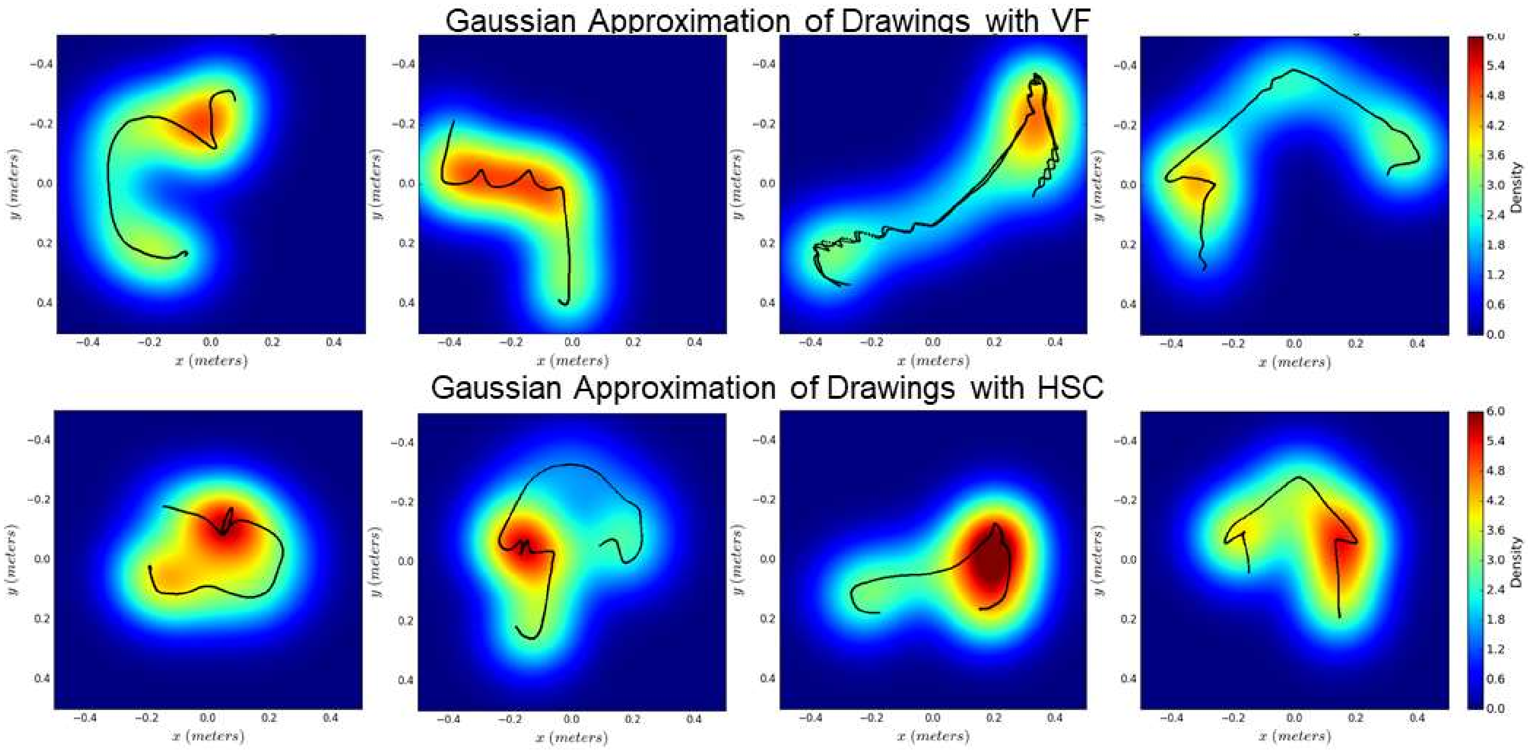
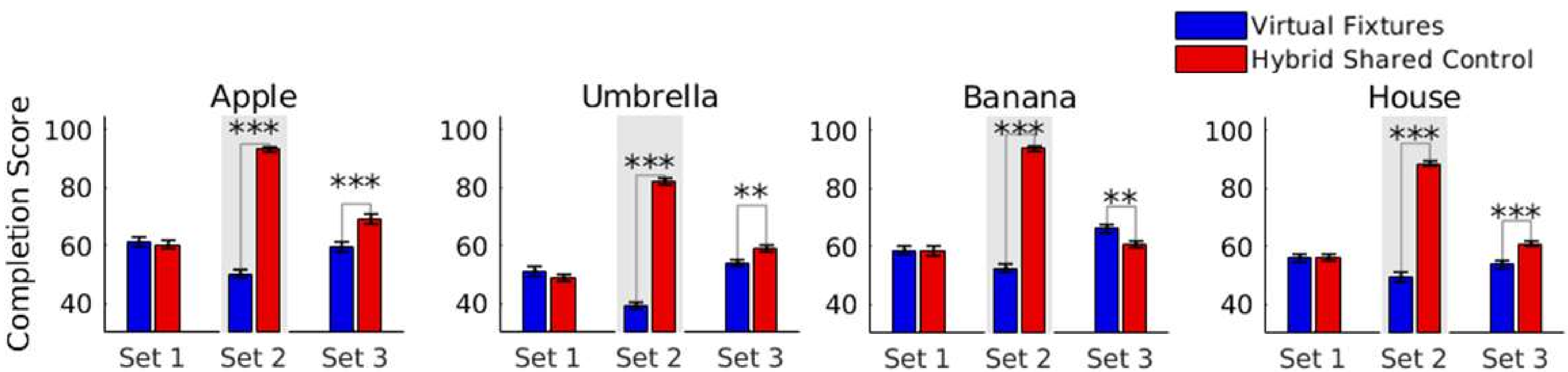


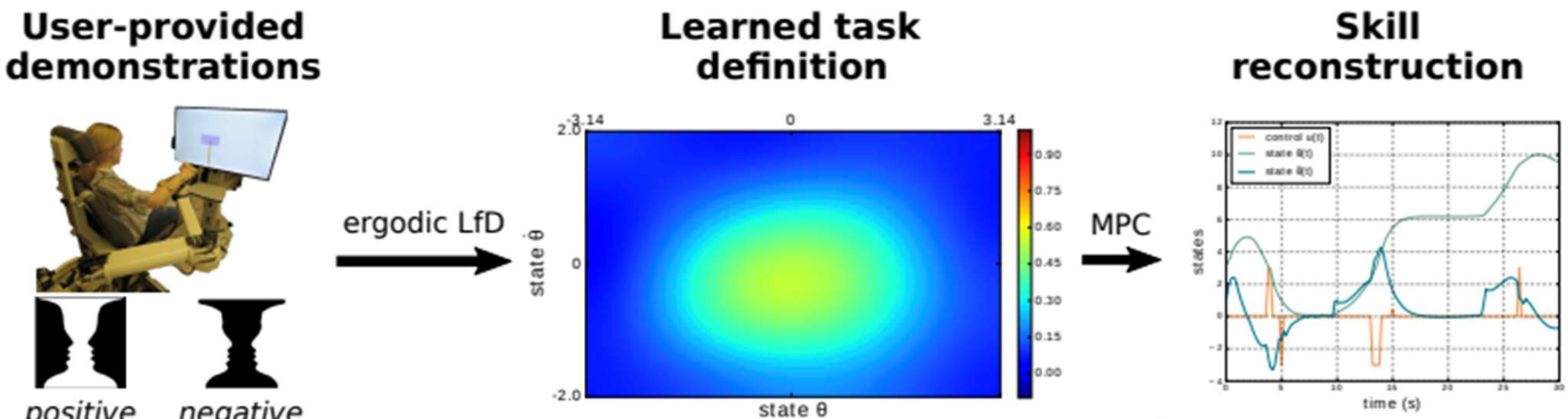
TRAINING OUTCOMES – COMPLETION

- Coded images were randomly assigned to scorers via an online survey
- ANOVA of Set 1 and Set 3 showed significant interaction effect of training group and set

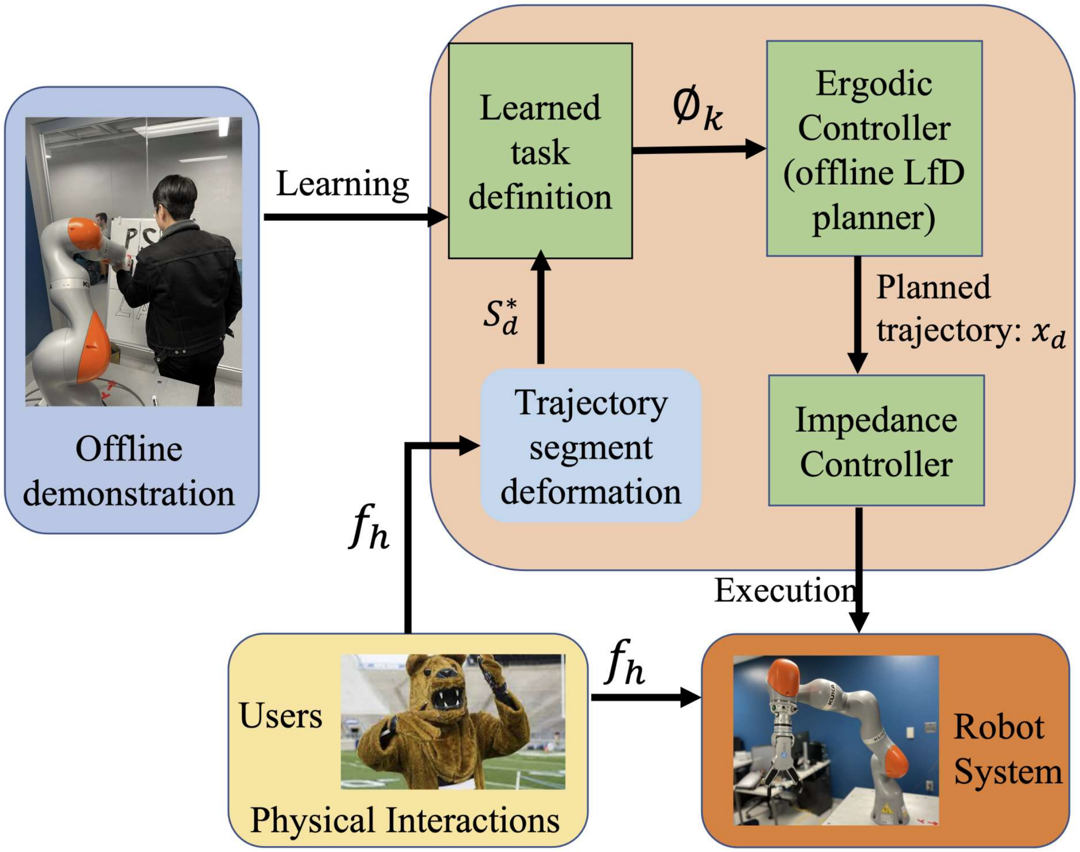


Ergodic Imitation Learning

- Ergodic control enables effective LfD under different initial conditions and system constraints
- There is a natural way to add demonstrations to the set
- The task definition encompasses the variability of the set

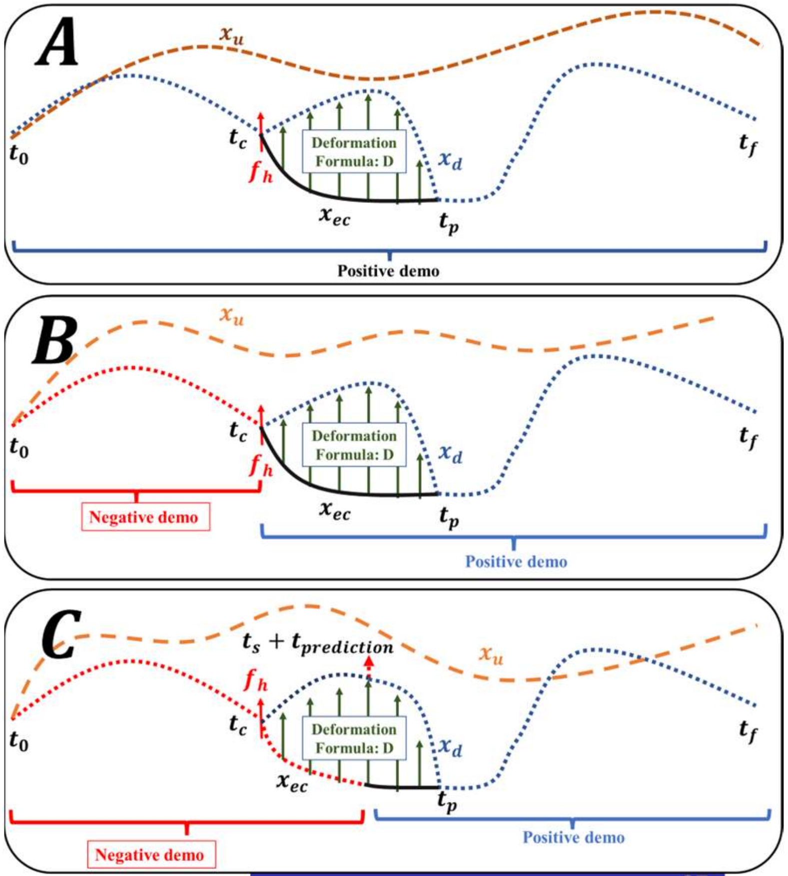


Learning from pHRI



Learning from pHRI

- We compute a trajectory deformation based on physical interactions
- The deformed trajectory can be used as a positive demo (A), negative demo (B), or a combination of both (C).



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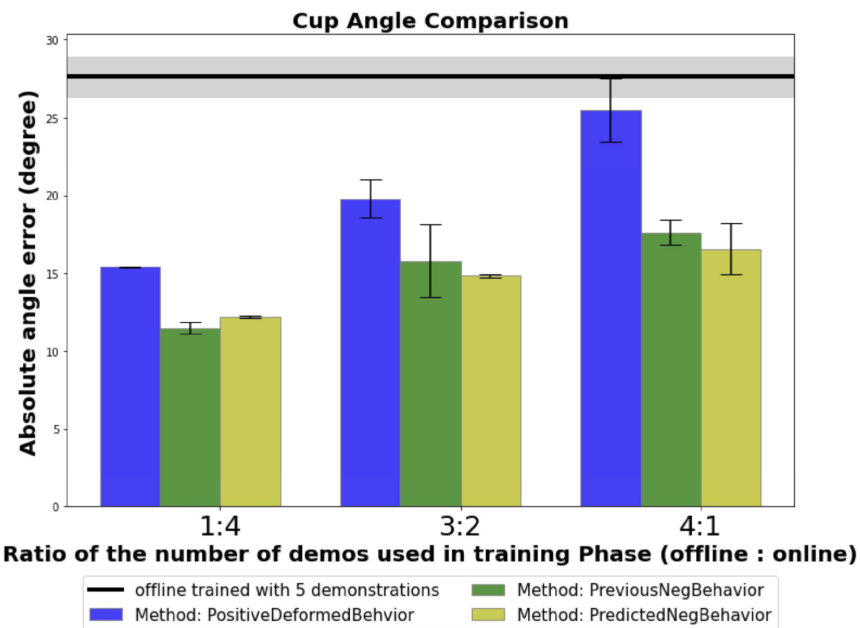
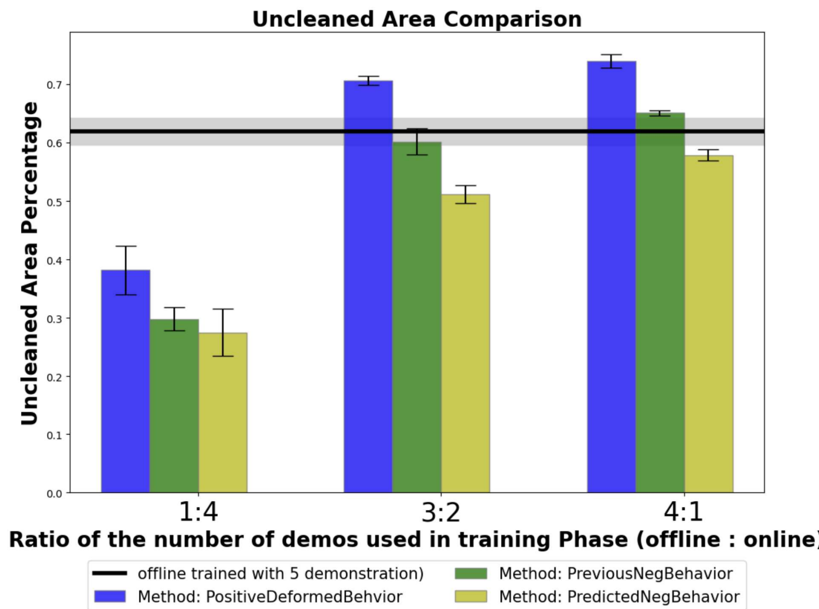
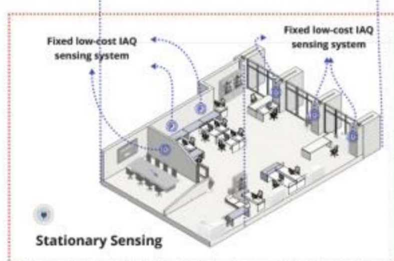


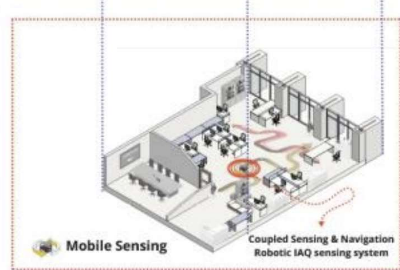


- Correction improve performance compared to offline demonstations only with relatively few corrective demonstrations.

Mobile Sensing for Human Comfort

Two Sensing Systems Stationary and Mobile Systems





Coupled Sensing & Navigation