

A probabilistic approach for learning and adapting shared control skills with the human in the loop

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Motivation

Assistive robots with shared control can provide support and agency to people with disabilities.

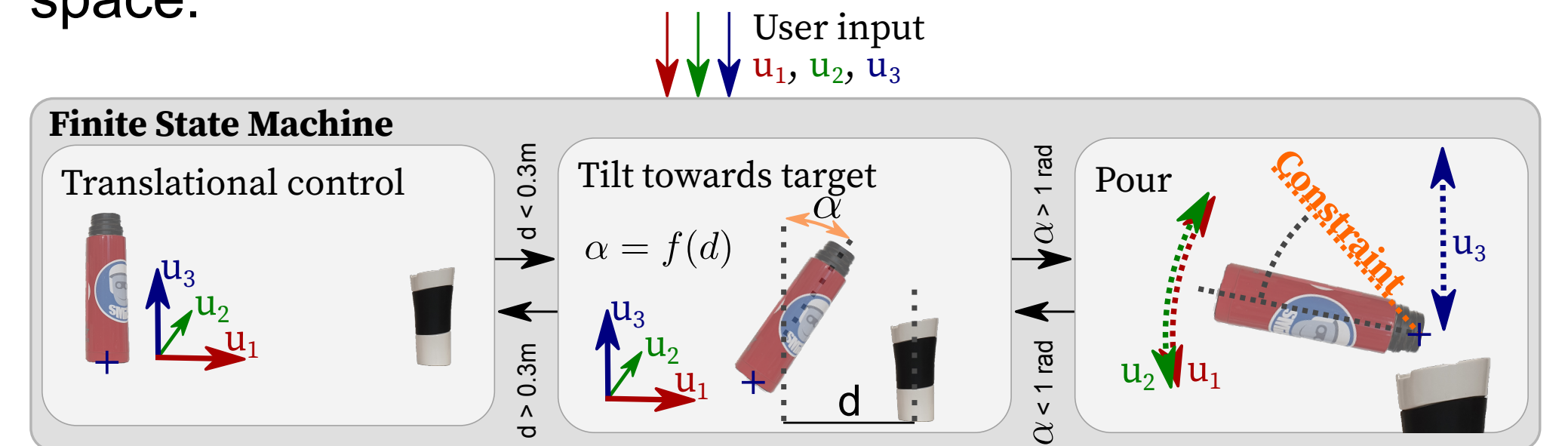
Our goal is to provide shared control skill which are robust, legible and easy to design.

We propose a method to **learn active constraints from demonstrations** with a probabilistic model, Kernelized Movement Primitives. Furthermore, those constraints can be **adapted directly via user commands**.

Shared Control Templates (SCT)

An SCT is a finite-state machine tailored to shared control, where each state can define:

- Input mappings: map user commands to end-effector velocities.
- Transition conditions: switch between states.
- Active constraints: restrict the end-effector pose in task space.



[G. Quere et al., Shared Control Templates for Assistive Robotics. ICRA (2020)]

Kernelized Movement Primitives (KMP)

Parametric trajectory

$$\xi(s) = \Phi(s)^T w, \quad w \sim \mathcal{N}(\mu_w, \Sigma_w)$$

Kernelized solution

$$\mathbb{E}[\xi(s^*)] = k^* (K + \lambda_1 \Sigma)^{-1} \mu$$

$$\mathbb{D}[\xi(s^*)] = \alpha (k^{**} - k^* (K + \lambda_2 \Sigma)^{-1} k^{*T})$$

with:

k^*, K are evaluations of s^* and $s_{n=1, \dots, N}$ using a kernel function $k(s_i, s_j)$

$\lambda_1, \lambda_2 > 0$ are regularization factors

$$\Sigma = \text{blockdiag}(\Sigma_1, \dots, \Sigma_N)$$

$$\mu = [\mu_1^T, \dots, \mu_N^T]^T$$

Reference trajectory distribution

$$\{\mu_n, \Sigma_n\}_{n=1}^N$$

[Y. Huang, L. Rozo, J. Silvério and D.G. Caldwell, Kernelized Movement Primitives. IJRR (2019)]

Adaptation

Adding a via-point

$$\{\mu_n, \Sigma_n\}_{n=1}^N \cup \{\bar{\mu}, \bar{\Sigma}\}$$

Null-space action

$$\mathbb{E}[\xi(s^*)] = k^* \Psi \mu + [k^* - k^* \Psi K] \hat{\xi}, \quad \Psi = (K + \lambda_1 \Sigma)^{-1}$$

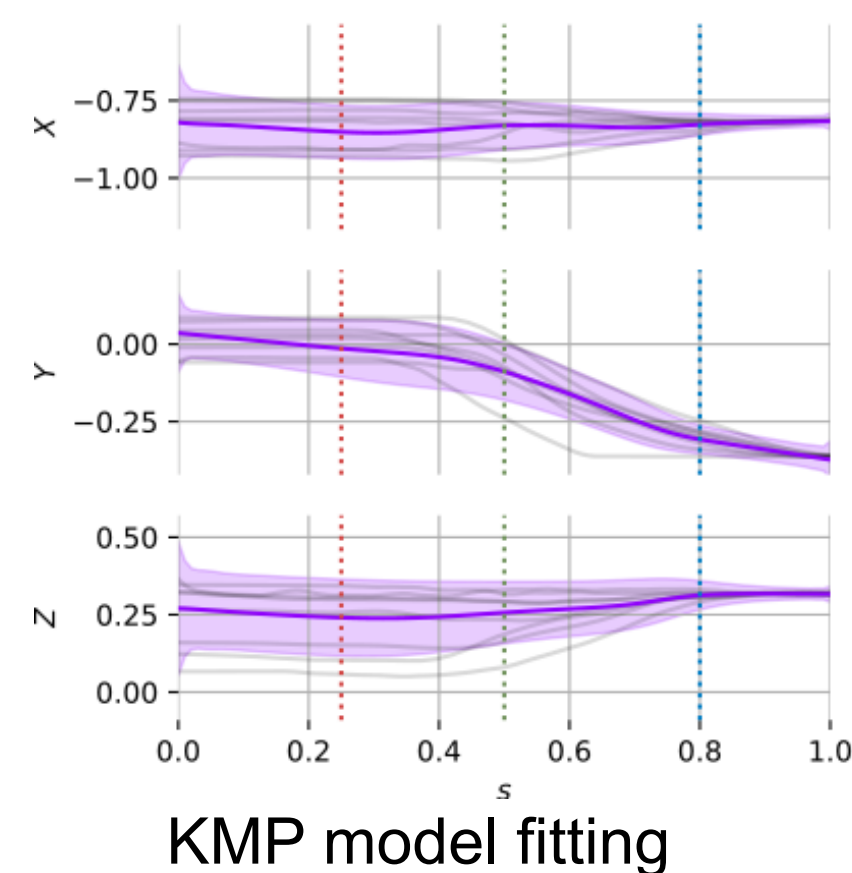
[J. Silvério and H. Yanlong, A Non-parametric Skill Representation with Soft Null Space Projectors for Fast Generalization. ICRA (2023)]

Proposed approach

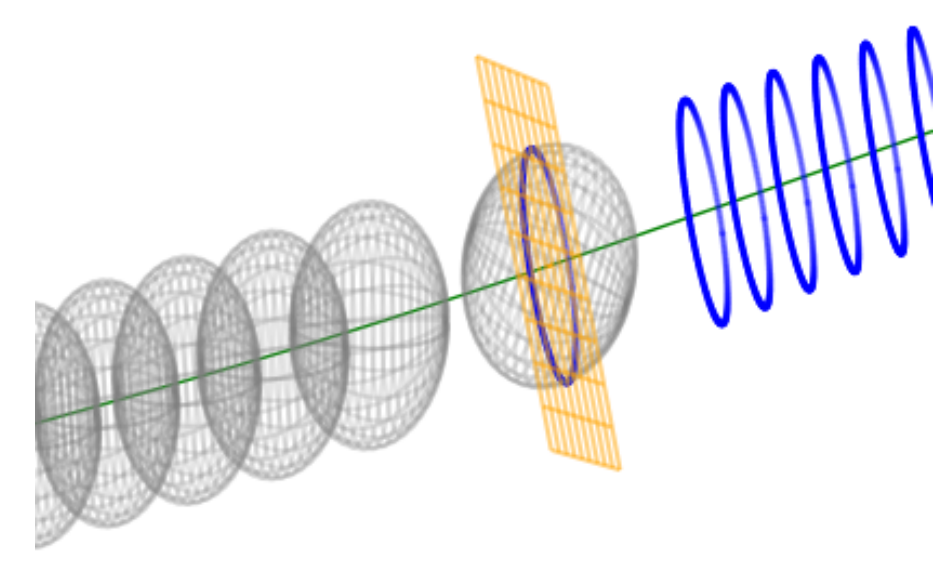
Derive active constraints from demonstrated trajectories



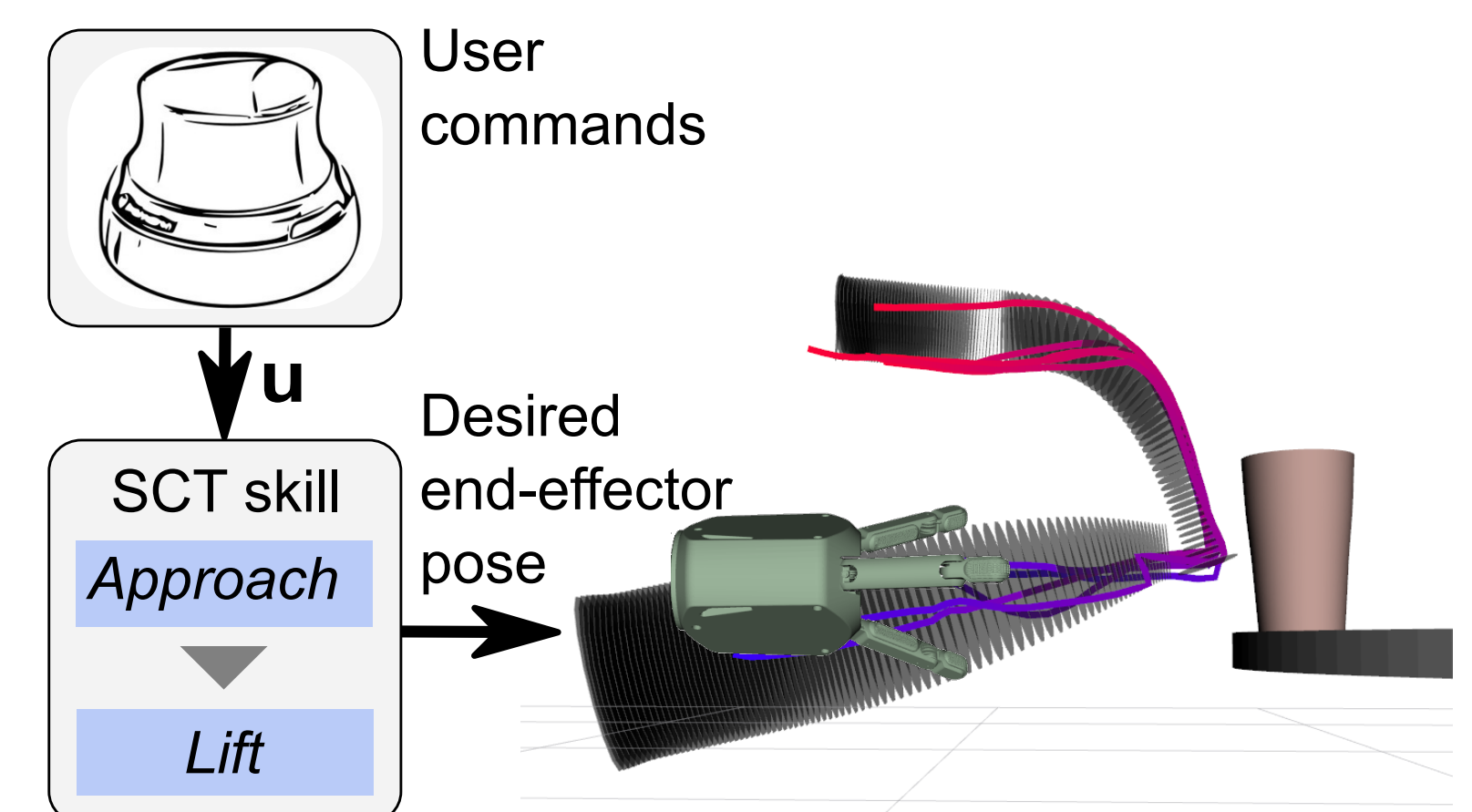
Kinesthetic teaching



KMP model fitting



Generalized cylinders acting as active constraints are derived from the KMP covariance ellipsoids



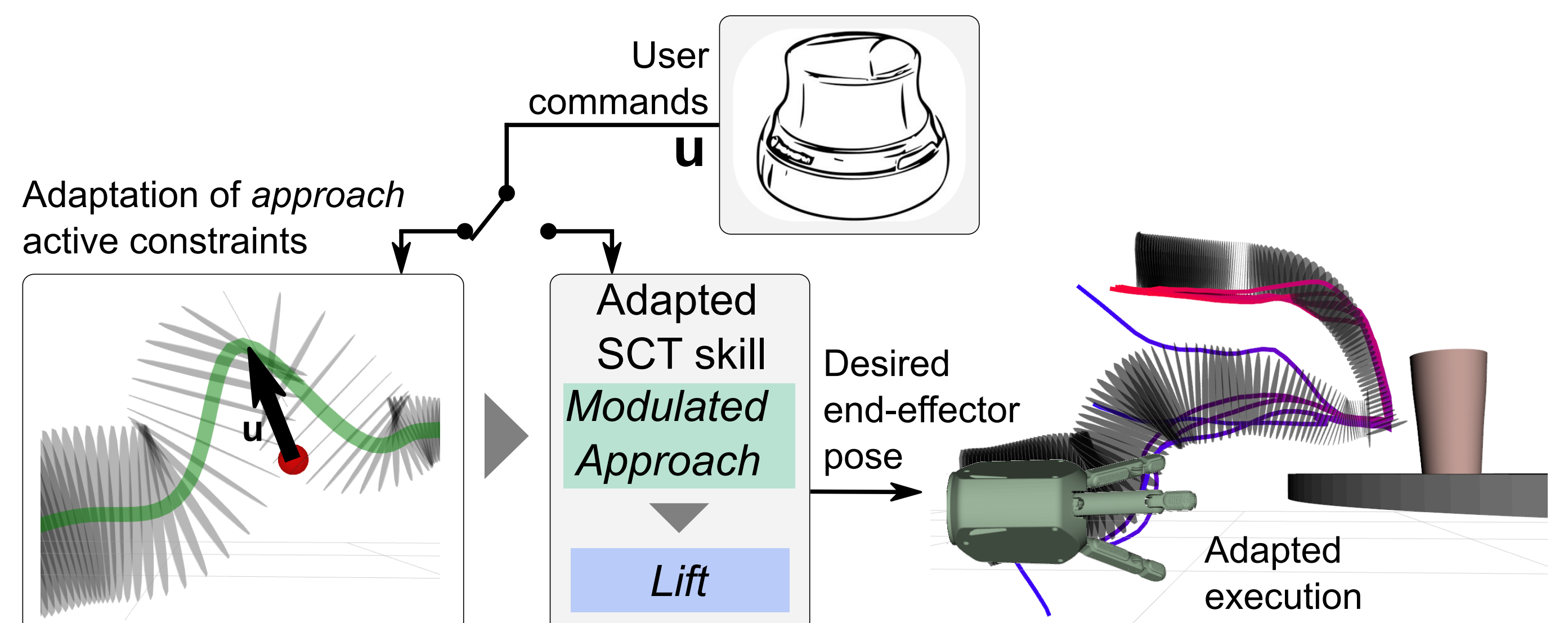
Correction mode

Adjust the constraints to a new environment with user commands

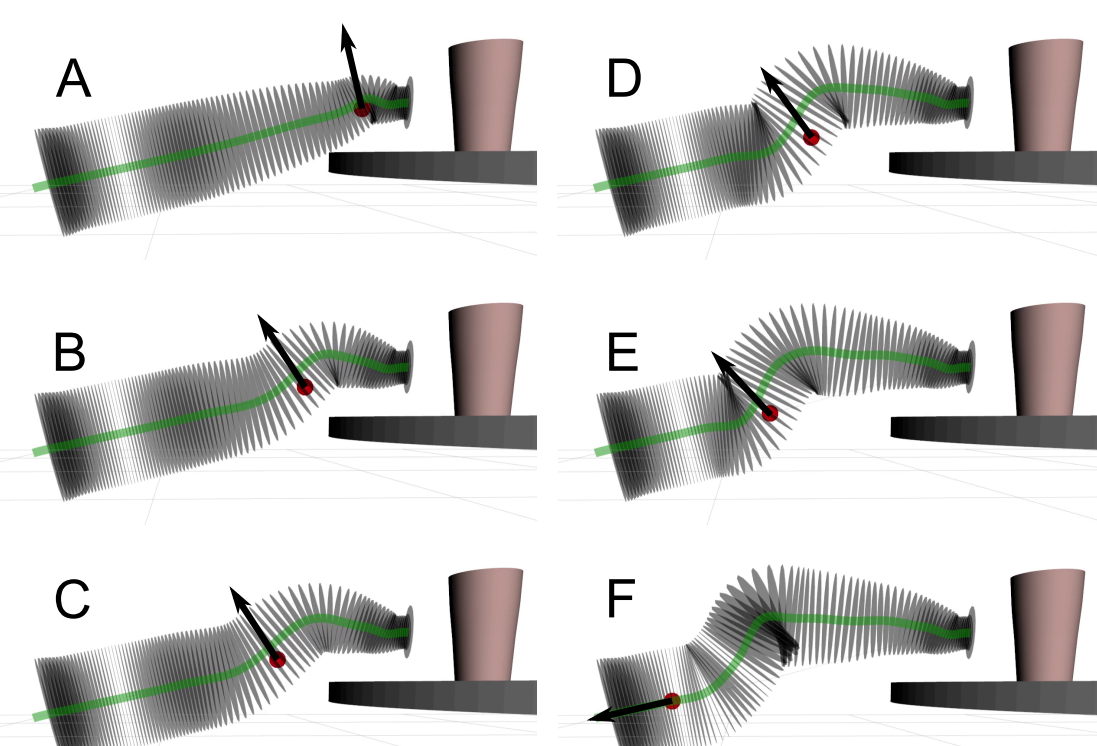
$$\hat{\xi}(\hat{s}) = \int_{t_0}^{t_1} u(t) dt$$

Decorrelation of actions

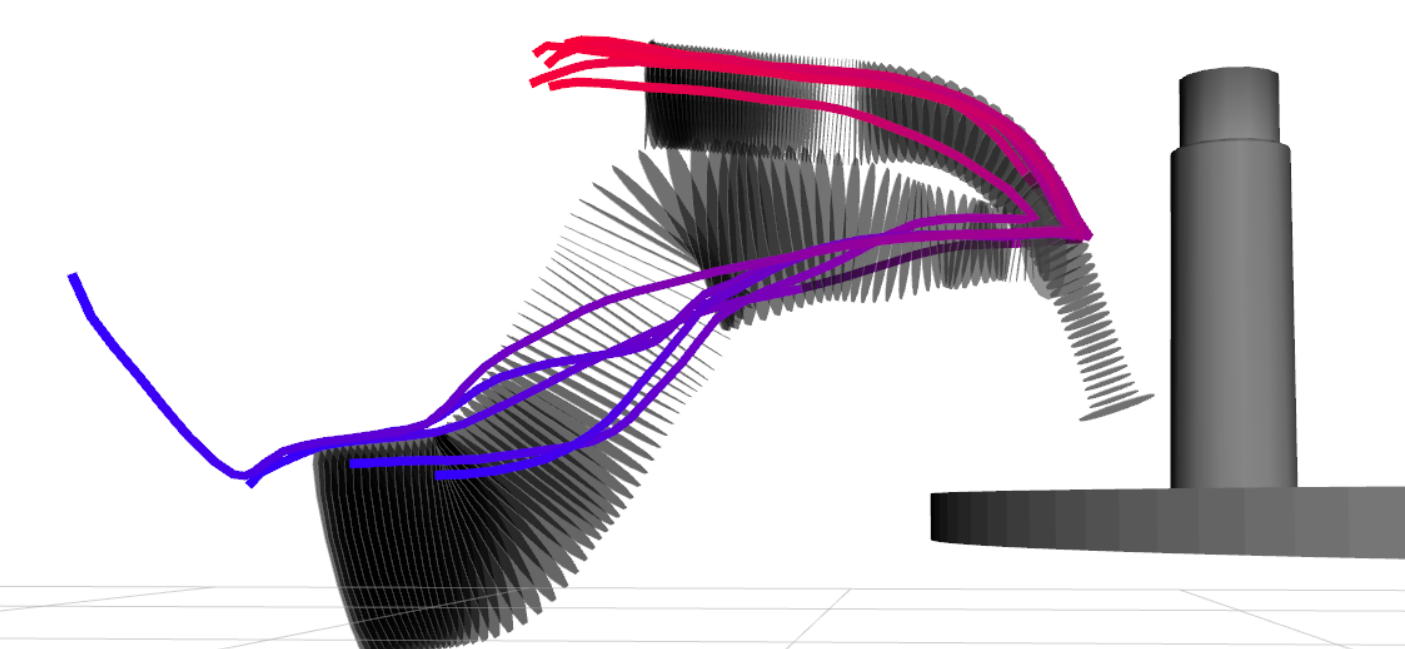
$$\mathbb{E}[\xi(s^*)] = k^* \Psi \mu + \sum_{j=1}^D \bar{S}_j [k^* - k^* \Psi K] \hat{\xi}_j$$



Experimental results



KPI	Participant					
	Author	A	B	C	D	E
Modulation time (s)	30	71	87	79	40	62
Deformation %	5	10	34	18	10	20



Conclusion

We proposed an approach using probabilistic skill representations to learn and adapt shared control skills.

Successful learning, executions and adaptation of a pick skill were shown on the assistive robot EDAN.

Five able-bodied users were as well able to adapt a skill and successfully execute it, suggesting that the proposed approach is intuitive and easy to use.