Skill-based Shared Control

Robotics: Science and Systems, 2021

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Skills in industry

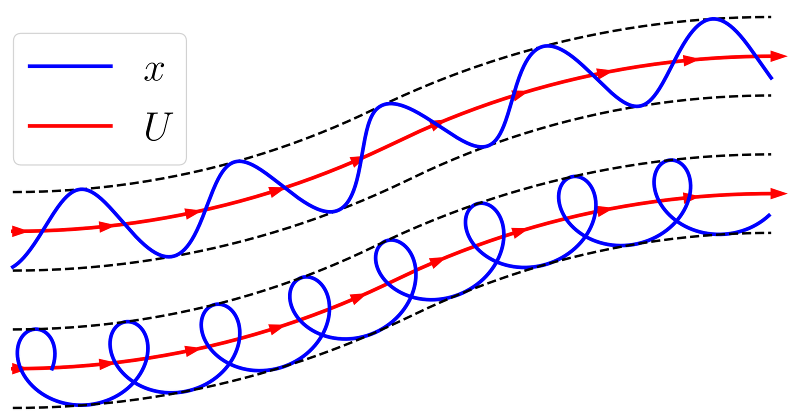
Skills: various motion patterns are performed by expert operators to achieve different goals.

Concrete spraying (left): deposition rate regulated by alternating between large sweeps and small circles.

Assisted welding (right): weave patterns used depending on the task goals, and operator expertise.

Key insight

Weave patterns utilized in welding



- States x are comprised of U and S, see Equation (1).
- *Underlying trajectory* (U): we model using *clothoids*.
- *Skill model* (S): analytical model, e.g. wave/cycloid.

Skill assistance?

Why?

Industrial devices often use direct control requiring experts. Expensive training and critical safety issues.

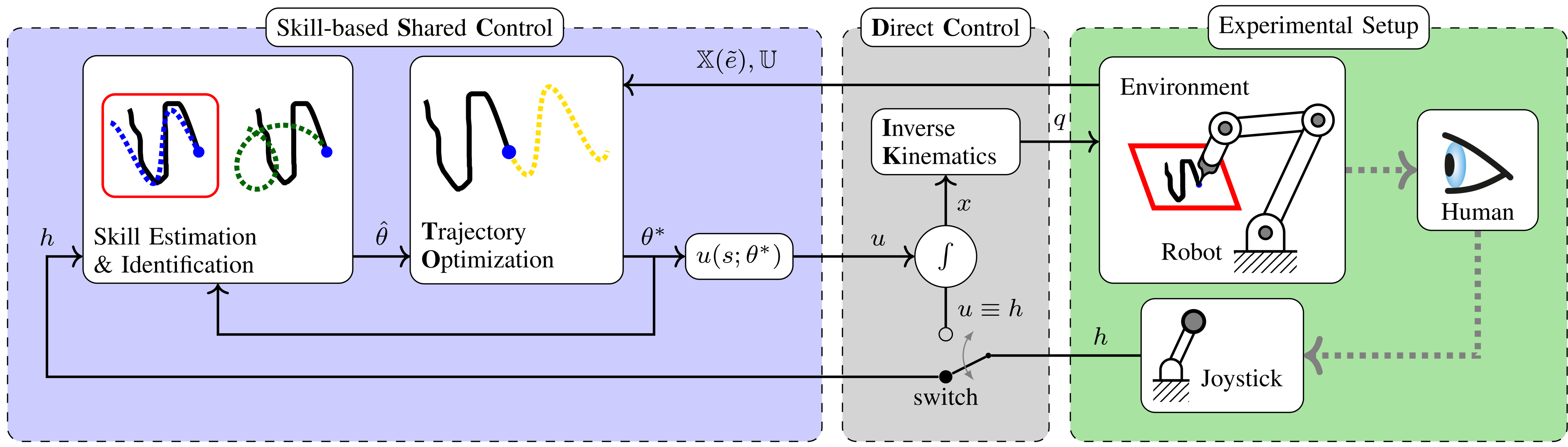
What?

Current methods restrict the robot to a safe region and do not assist operators to accurately reproduce skills.

How?

Our proposed framework plans motions that respect a skill whilst ensuring environment constraints are satisfied.

Proposed method



State representation

We propose a model-based representation for states x and controls u given by

$$x(\theta) = U(\phi) + S(\rho)U'(\phi) \tag{1}$$

where $\theta = (\phi, \rho)$ are model parameters, $U(\phi)$ is the underlying trajectory, $S(\rho)$ is a skill model, and controls are $u = x'$.

Estimate operator intention

Given several skill models $S_1, \dots, S_n$, for a previous time window $\mathbb{T}_p$ an operators intent is described by $\widehat{\theta}_i$ estimated by solving

$$\widehat{\theta}_i = \underset{\theta_i}{\arg\min} \int_{\mathbb{T}_p} \|u(\theta_i) - h\|^2 + R(\theta_i) \tag{2}$$

where h is the operator input, and $R(\theta)$ is a regularization term. The skill is classified by performing a model comparison.

Adapt motion to satisfy constraints

To ensure that constraints are satisfied, we find optimal parameters θ_i^* by solving

$$\theta_i^* = \underset{\theta_i}{\arg\min} \|\theta_i - \widehat{\theta}_i\|^2 \tag{3}$$

$$\text{subject to } x \in \mathbb{X}(\widetilde{e}), u \in \mathbb{U} \tag{4}$$

where $\widetilde{e}$ is the environment representation and states and controls are modeled over a future time horizon $\mathbb{T}_f$.

Performance evaluation

Skill switching

The method compares the cost of fitting (2) for a number of skills and adapts to changes in the operator intention.

Static obstacle avoidance

We chose a particular cost function (3) that improves computational feasibility given nonlinear constraints.

Dynamic obstacle avoidance

Our method adapts to dynamic obstacles by representing them as parameterized constraints in (4).

User study

Performance improved for complex skills and maintained for simpler skills.

Contributions

- **Model-based shared control framework** that combines skill and underlying trajectory models.
- Introduced clothoids as an **adaptive representation**.
- Novel **cost function** improving numerical feasibility.
- **MPC implementation** that respects skill and ensures (changing) **constraints**.
- **Hardware realization** on a KUKA-LWR robot arm.

Acknowledgements

This research was supported by the Costain Group Plc., The Alan Turing Institute, and EPSRC UK RAI Hub for Offshore Robotics for Certification of Assets (ORCA, EP/R026173/1).

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