

The Alan Turing Institute

Shared Autonomy for Enhancing Trajectory Optimization

SAPHRI @ ICRA 2022

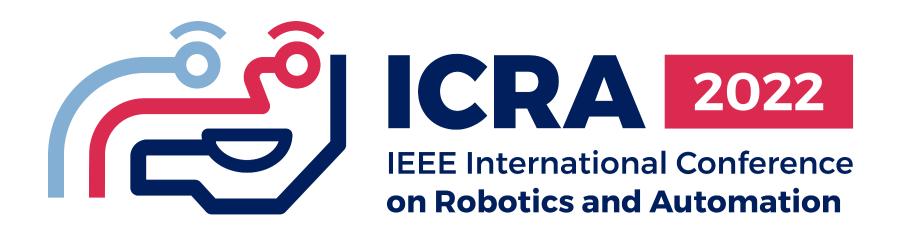
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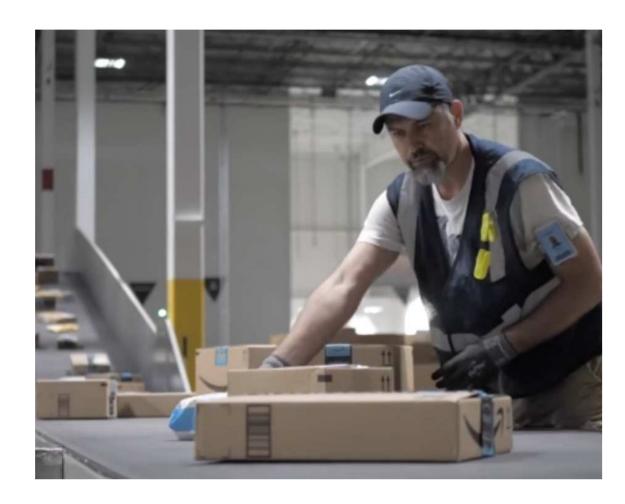
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This work was done while Christopher E. Mower was at the University of Edinburgh.



Key observation



- Humans exhibit a myriad of complex, adaptable motor skills, for example: non-prehensile manipulation (e.g. pushing, rolling, tilting).
- Without training, humans are able to adapt to a diverse range of object geometries and weight distributions.
- In contrast, such dexterous manipulation is currently not achievable on robots.

Overview

Why? What? How?

Dexterous manipulation in changing environments is required by robots in industrial applications.

Enabling Model Predictive Control for Shared Autonomy with changing environments is difficult. Our proposed concept maps operator input onto the solver to improve performance (i.e. success rate, convergence).

Problem formulation

We formulate trajectory optimization as a constrained mixed-integer program

$$x^*, u^*, z^* = \underset{x,u,z}{\arg\min} \phi(x, u, z) + \int \psi(x, u, z) dt$$
 (1a)

subject to

$$\dot{x} = f(x, u, z), x \in \mathbb{X}, u \in \mathbb{U}, z \in \mathcal{Z}$$
 (1b)

where x are states, u are controls, z are integers, $\phi(\cdot)$ models the task goal, $\psi(\cdot)$ describes ideal motion, f is the equations of motion, and X, U, Z are the feasible regions. Furthermore, equation (1) can be thought of as the mapping

$$x^*, u^*, z^* \leftarrow TO(x^0, u^0, z^0).$$
 (2)

where x^0, u^0, z^0 is the initial seed.

Solving (1) is typically intractable for online computation. Our goal is to improve solver performance by harnessing the human's innate ability to perform complex tasks through an interface $h \in \mathbb{H}$.

Conclusions

- An approach for improving solver performance for trajectory optimization utilizing a shared autonomy.
- Empirical evidence supports hypothesis that method improves solver performance.
- Future work: explore the scalability of the proposed approach (e.g. place item on shelf).

Proposed method

Heuristic models

A heuristic model $H(\cdot)$ maps human input to the decision variable space, i.e. $\mathbb{H} \to \mathbb{X} \times \mathbb{U} \times \mathcal{Z}$, given by $x_H, u_H, z_H = H(h)$. **Initial seed warm-starting**

The heuristic model is substituted into (2), i.e. TO(H(h))

Regularization models

Include an additional cost term into (1a) given by $\rho(x, u) = ||x - x_H||^2 + ||u - u_H||^2$.

Reduce the number of decision variables

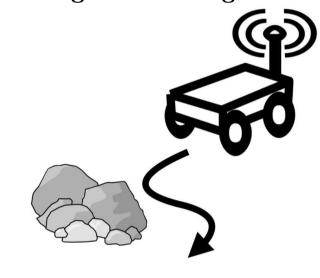
Mixed-integer solvers and problems with a large decision variable space are often slow in practice. Enforcing additional constraints can reduce the complexity. For example, $z = z_h$ converts (1) into a fully continuous problem.

Findings

Experimental comparisons

- We compare the following conditions:
- (C1) straight line initial seed,
- (C2) human as the initial seed, and
- (C3) human as the initial seed and regularization term.
- Metrics: solver success rate, and number of iterations.

Navigation through clutter



- Plan a collision-free path from a start to goal position.
- Through a GUI interface, the human provides a trajectory demonstration.
- Method reduces number of iterations, and success rate.

Non-prehensile manipulation



- Plan a motion for the robot to *push an object* from a start to goal position *utilizing a switch of contact*.
- The human provides a demonstration using a joystick and the trigger button (collects: position, contact sequence, contact timings).
- All three conditions succeed, (C2/C3) lead to lower number of iterations.

