Task and Motion Planning for Human-Robot Collaboration using Non-Linear Programming and Hierarchical Motion Prediction

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Abstract

- We tackle the problem of human-robot coordination in sequences of manipulation tasks by integrating hierarchical human motion prediction with Task and Motion Planning (TAMP).
- First, We devise a hierarchical motion prediction approach by combining Inverse Reinforcement Learning and short-term motion prediction using a Recurrent Neural Network.
- Second, we propose a dynamic version of the TAMP algorithm Logic-Geometric Programming (LGP) [1], which replans periodically to handle the mismatch between the human motion prediction and the actual human behavior.

Motivation & Related works

- As robots become more capable; they will increasingly share space with humans. Consider the case of tidying a kitchen, where the human is interested in having maximal support from the robot while requiring a minimal amount of interference with its task objectives.
- The robot is a member of a mixed human-robot team, where members share a common goal. Shared task planning and interactive motion planning allow for higher-level collaboration.
- To schedule coordinated actions, many works have explored how to model the capabilities of the agents in the workspace [2]. Some works include high-level symbolic planning in order to find a human-aware robot plan [3, 4] and also combining task and motion planning has shown success for human-aware HRC [5, 6]. However, no work proposes to integrate a full hierarchical predictive model of human behavior.

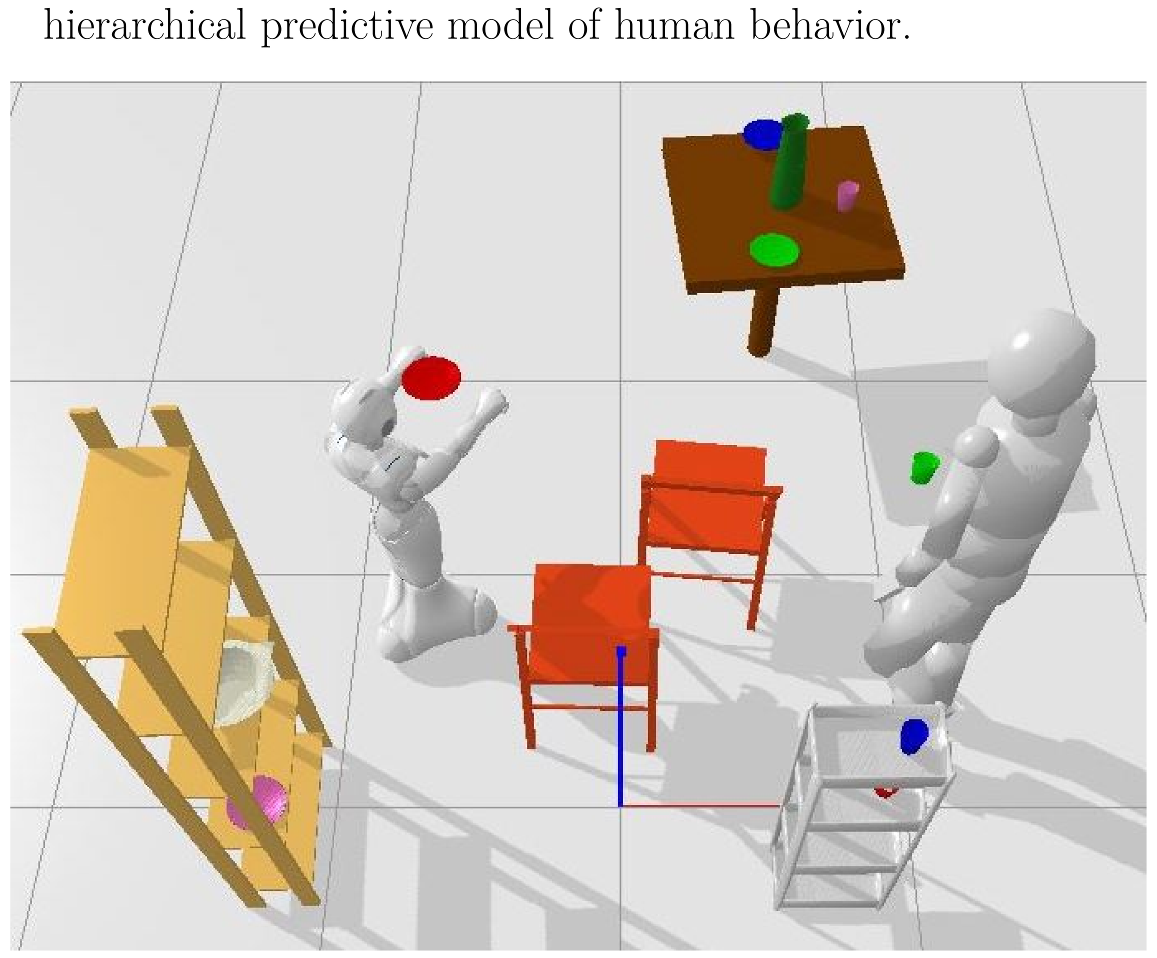

Figure: Pepper carries a plate while the human from the MoGaze dataset is carrying a green cup. The supporting motion plan for setting the table resulting with from Dynamic LGP minimally interferes with the human task.

Methods

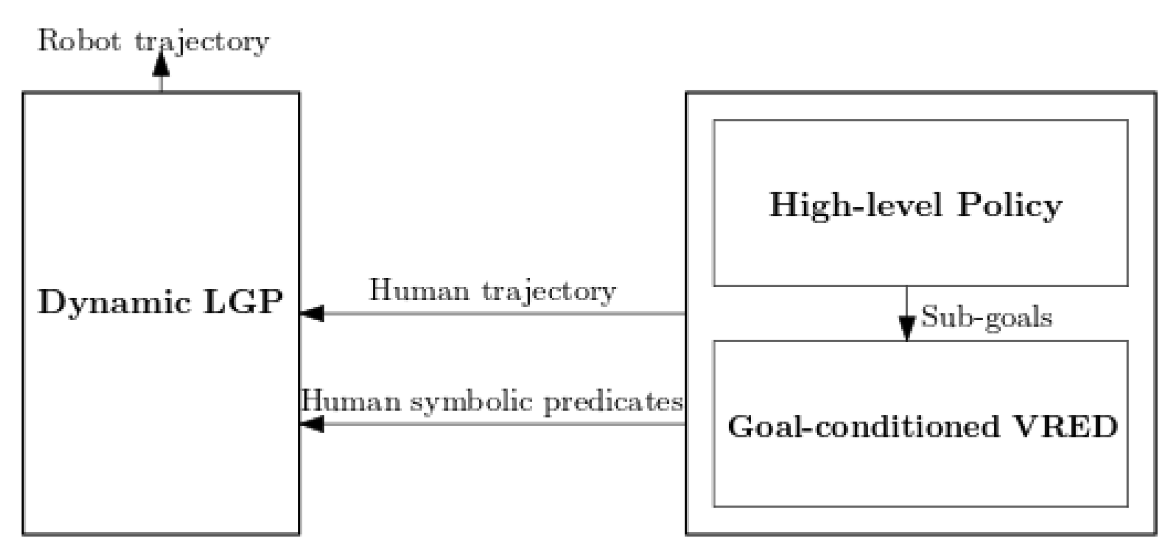

Figure: Overview architecture

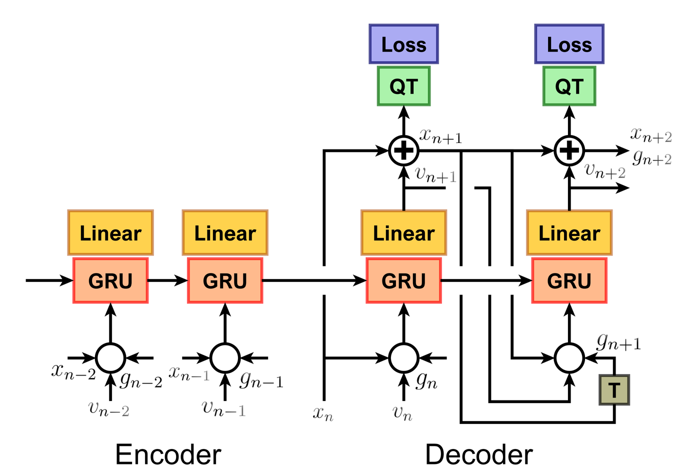

Figure: Goal-conditioned VRED [7]

Single planning: The task is then to find a global path $x : t \mapsto x_t$, which minimizes the following LGP:

$$
\begin{aligned}
&\min_{x,a_{1:K},s_{1:K}} \int_0^{KT} c(x(t),\dot{x}(t),\ddot{x}(t),s_{k(t)})\mathrm{d}t \\
\text{s.t.}\quad & x(0)=x_0,\ h_{\text{goal}}(x(KT))=0,\ g_{\text{goal}}(x(KT))\le 0 \\
& \forall t\in[0,KT]: h_p(x(t),\dot{x}(t),s_{k(t)})=0, \\
& \qquad g_p(x(t),\dot{x}(t),s_{k(t)})\le 0 \\
& \forall k\in\{1,\dots,K\}: h_{sw}(x(t),\dot{x}(t),a_k)=0 \\
& s_k\in \text{exec}_{a_k}(s_{k-1}) \\
& s_K\in \mathbb{S}_{\text{goal}}
\end{aligned}
$$

Dynamic planning:

Algorithm 1: Dynamic LGP

input: Init state x_0, goal set $\mathbb{S}_{\text{goal}}$
Infer symbolic state s_0 from x_0;
Search $\Gamma_0(s_0, \mathbb{S}_{\text{goal}}, I)$;
Set $\kappa = a_{1:K_0} \in \Gamma_0$ as best feasible skeleton;
Set elapsed time $\tau = 0$;
while $\mathbb{S}_{goal}$ *not reached at current* t **do**
  Update system kinematics and human position;
  Infer current symbolic state s_t;
  if $\mathbf{F}(\kappa, s_t) = 0$ **then**
    Search $\Gamma_t(s_t, \mathbb{S}_{\text{goal}}, I)$;
    Update $\kappa = a_{1:K_t} \in \Gamma_t$ as best feasible skeleton;
    Set elapsed time $\tau = 0$;
  end
  Optimize NLP (Level 3 in [1]) of κ from time τ;
  Execute current action of the skeleton κ;
  $\tau = \tau + 1$;
  Wait for next trigger;
end

Start State	(0, 4, 0, 1, 0, 3, 1, 0, 1, 2)
Actions	Go to white shelf
	Pick up cup
	Go to table
	Place
End State	(1, 3, 0, 1, 0, 3, 1, 0, 1, 0)

Table: Example high-level trajectory

(on X Y)	check if exists a stable 3D $xy\phi$ joint from X to Y
(at X Y)	check if $x_X - x_{Y2} \le r \vert r \in \mathbb{R}$
(carry X Y)	check if exists a stable free joint (6D) from X to Y

Table: Predicate inference

Experiments

- We first design the PDDL-syntax domain following the available objects in the MoGaze [8] dataset.
- We evaluate the accuracy of the Hierarchical motion prediction system given the MoGaze dataset.
- We test the adaptability of Dynamic LGP given the human trajectory output from the Hierarchical motion prediction system.

Long-Term Motion Prediction using Hierarchies:

- High-level: The learned policy solved the task in 80% of the cases. However, a perfect imitation was achieved solely in 16% of the test runs of the cross-validation.
- Low-level: The goal-conditioned prediction network achieves both a better angular loss of 7.99 instead of 10.14 and a significantly better position loss of 3.84 instead of 12.56, than the network without goal-conditioning.

Dynamic LGP with Long-Term Prediction:

- We select 63 task instances with different configurations, e.g. objects poses, human trajectories, etc. and we define the robot goal for each segment, e.g. $s_0 = \{$(agent-free), (agent-avoid-human), (on cup-green big-shelf), (on plate-blue small-shelf)$\}$
- The overall task Intersection over Union (IoU) between the set of objects the human and the robot must place on the table is 0.64 ± 0.30.
- We then run two planning modes, single planning, and dynamic planning, for each of the 63 segments. The task instance is considered successful if, at the end of the robot trajectory, the inferred symbolic state is in the goal set $\mathbb{S}_{goal}$. For dynamic planning, the task fails when the timeout for Algorithm 1 is reached while the goal set is not satisfied. For single planning, the task fails when no feasible skeleton is found.

	Single planning	Dynamic planning
Success rate	91.2%	100%
Symbolic plan time	$0.0005 \pm 0.0001(sec)$	$0.0006 \pm 0.0002(sec)$
Task time reduction	0.298 ± 0.078	0.300 ± 0.100
Path ratio	1.000	0.626 ± 0.155
LGP replan count	-	3.0 ± 0.87

Table: Dynamic LGP with Human Prediction

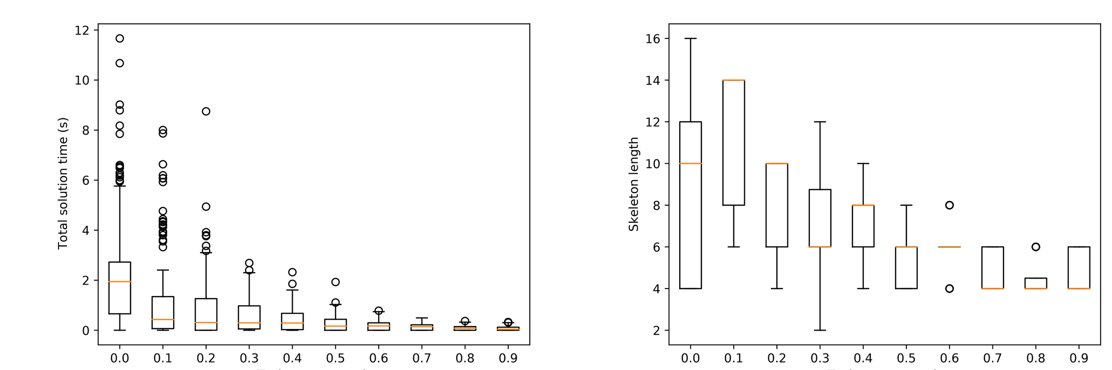

Figure: Total time (left) to find an overall feasible solution and skeleton length (right) over task progress.

Conclusion & Future Work

The proposed system is able to plan supporting motions that minimally interfere with human tasks. Notable results:

- Dynamic LGP replans periodically to handle the mismatch between the human motion prediction and the actual human motion behavior.
- The proposed Hierarchical motion prediction approach attempts to predict long-term human trajectory, therefore better informing the TAMP in robot side to plan globally optimal robot trajectory using LGP.

1. In future work, we aim to include collision avoidance in our hierarchical motion prediction framework and produce full-body robot motions using a Level 2 NLP for LGP (we refer the reader to [1]) to handle complete robot grasping configurations.
2. We also plan to port these results to the Pepper robot of the University of Stuttgart.

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