PRIMP: PRobabilistically-Informed Motion Primitives for Efficient Affordance Learning from Demonstration

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Introduction

We propose PRIMP [1], a learning-from-demonstration method using probability densities on the full 6-dimensional workspaces of robot manipulators:

- **PRIMP** generates workspace trajectory distribution for basic motion primitives using Lie theories;
- **Workspace-STOMP** keeps the shape of the trajectory similar while maintaining the feasibility of the motion plan;
- A novel robotic system that combines LfD, motion planning, and affordance learning via simulation is proposed and physically demonstrated in a robot manipulator platform.

Features

- Adaptation to new situations: novel via-point poses with uncertainty, a change of viewing frame;
- Robot-agnostic: skills can be easily transferred to another robot;
- Avoid unseen obstacles while maintaining key features of the learned skills;
- Combine with a robot imagination method that learns object affordances via simulation to learn tool use.

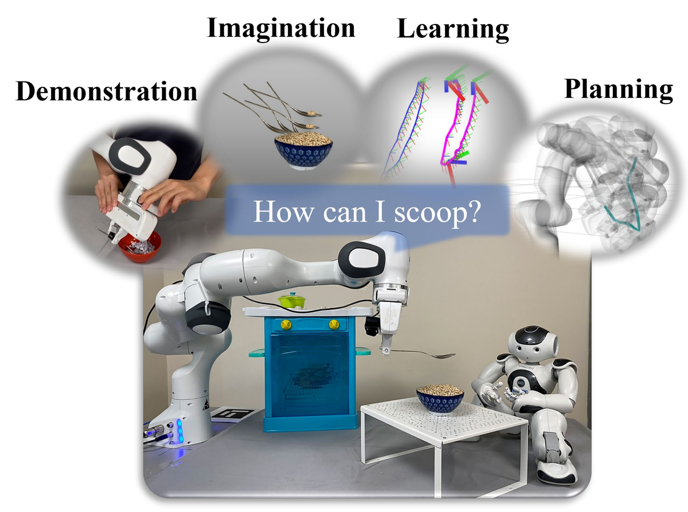
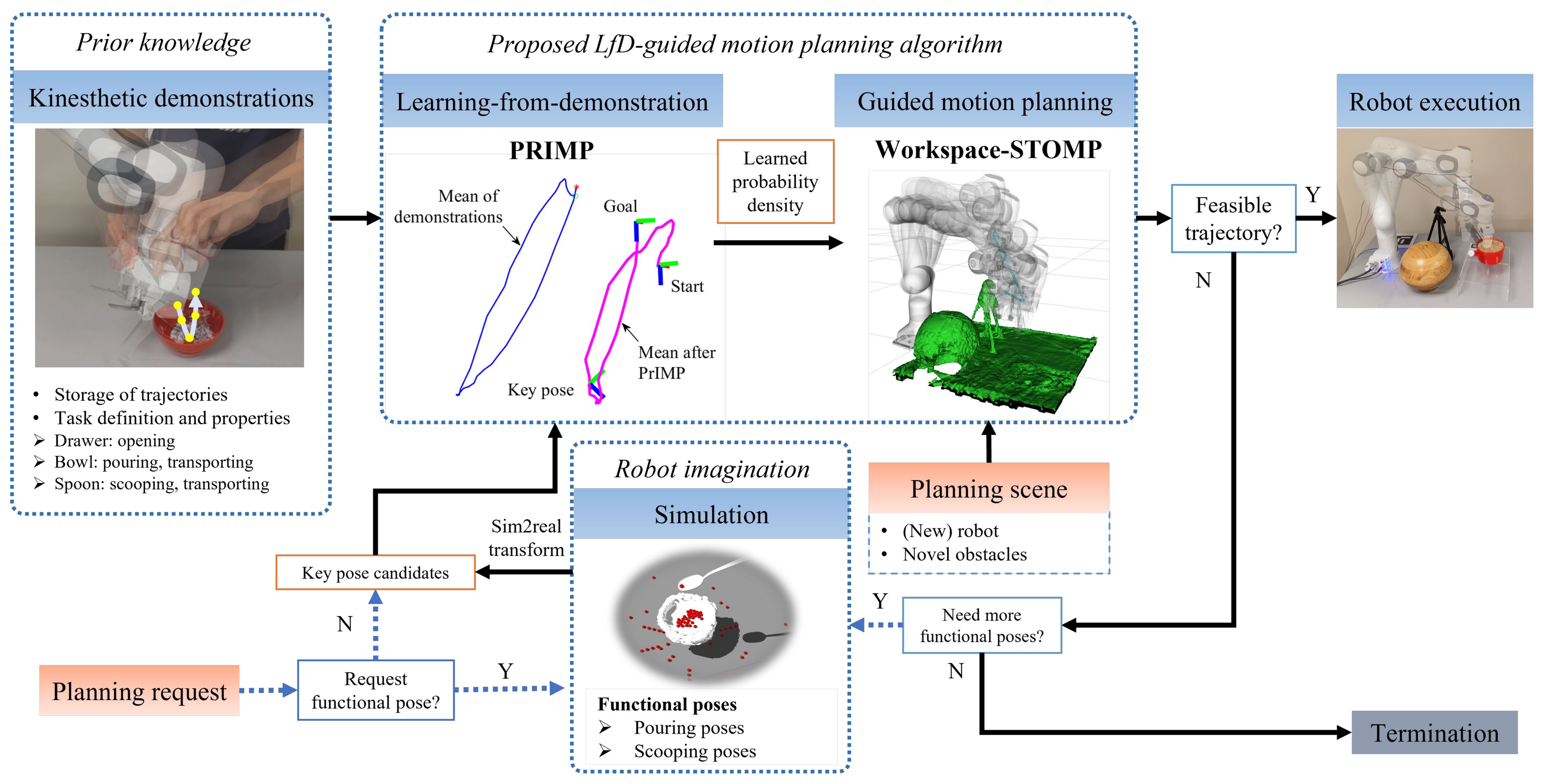


Illustration for the general idea. The robot arm is asked to use a spoon to scoop from a bowl in a household environment. With the help of human demonstrations, imagination of object affordance, learning skills from the demonstrations and motion planning, the robot fulfills the task in a novel scene with unseen obstacles.

For more details, please visit:
https://chirikjianlab.github.io/primp-page/

System Pipeline



Method

PRIMP: A probabilistic learning-from-demonstration method

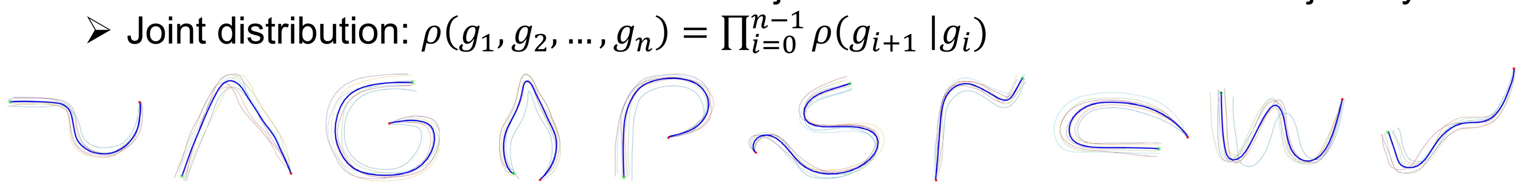
Given a set of demonstrated trajectories (**6D pose**), the goal is to compute a probability distribution of the given demonstrations as a reference to guide the future executions of the robot for a similar task.

1. Temporally align multiple trajectories using **Globally-Optimal Reparameterization Algorithm (GORA)** [2], by solving the variational calculus problem

$$\min \int_0^1 \mathrm{g}(\tau)\, \dot{\tau}^2\, d\tau\,, \text{where } \mathrm{g}(\tau) = \left\| g^{-1} \frac{\partial g}{\partial \tau} \right\|_W^2 \quad \rightarrow \quad F(\tau^*) = \frac{\int_0^{\tau^*} \mathrm{g}^{\frac{1}{2}}(\sigma)\, d\sigma}{\int_0^1 \mathrm{g}^{\frac{1}{2}}(\sigma)\, d\sigma} = t$$

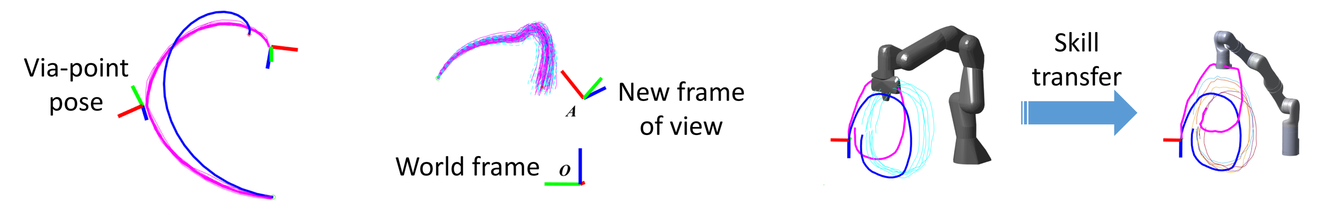
2. Approximate **relative** pose distributions using Lie-theoretic method. For m samples,
   - **Mean** μ_i satisfies $\sum_{k=1}^{m} \log\left(\mu_i^{-1} g_i^{(k)}\right) = \mathbb{O}$;
   - **Covariance**: $\Sigma_{i,i+1} = \frac{1}{m} \sum_{k=1}^{m} \log^{\vee}\left(\mu_{i,i+1}^{-1} \Delta_{i,i+1}^{(k)}\right) \log^{\vee T}\left(\mu_{i,i+1}^{-1} \Delta_{i,i+1}^{(k)}\right)$,

     where $\Delta_{i,i+1}^{(k)} = \left(g_i^{(k)}\right)^{-1} g_{i+1}^{(k)}$.
3. Encode initial mean and covariance as a joint distribution of the whole trajectory
   - Joint distribution: $\rho(g_1, g_2, \dots, g_n) = \prod_{i=0}^{n-1} \rho(g_{i+1} \mid g_i)$



Demonstrations from LASA dataset [3]. Bolded blue curves are the encoded mean trajectory

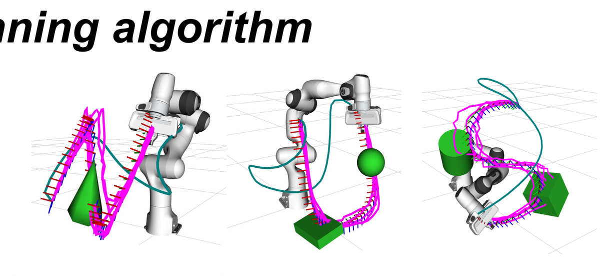
4. Adaptation to novel situations



Via-point poses | *Change of a viewing frame* | *Skill transfer among different robots*

Workspace-STOMP: A guided motion planning algorithm

The learned trajectory distribution is used to guide STOMP, an optimization-based motion planner, for collision avoidance. A novel cost function based on $SE(3)$ metric for the end-effector pose is proposed:

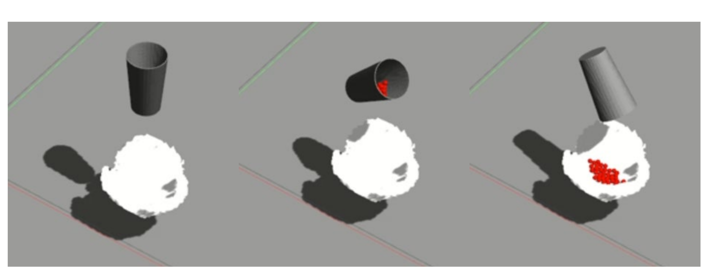


- m_r reference trajectories are sampled from the learned distribution;
- For each time step i of each joint-space trajectory rollout $\boldsymbol{q}$, the cost is defined as

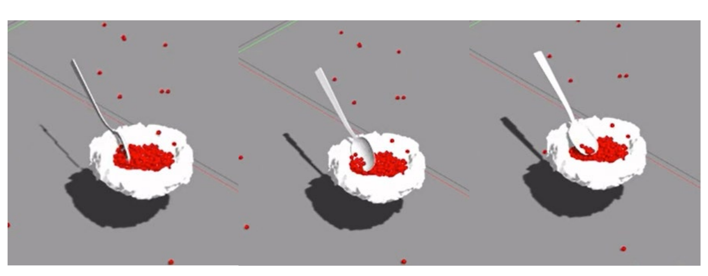
$$\boldsymbol{c}(\boldsymbol{q}_i, t_i) = \frac{1}{m_r} \sum_{k=1}^{m_r} \left(w_{\mathrm{rot}} \left\| \log^{\vee}\left(R^T(\boldsymbol{q}_i, t_i) R_r^{(k)}(t_i) \right) \right\| + w_{\mathrm{tran}} \left\| \boldsymbol{t}(\boldsymbol{q}_i, t_i) - \boldsymbol{t}_r^{(k)}(t_i) \right\| \right)$$

Affordance learning using physics-based simulation

Object affordance is learned to obtain the **key poses** for each task. The key poses are treated as the via-point poses for PRIMP.



Pouring task

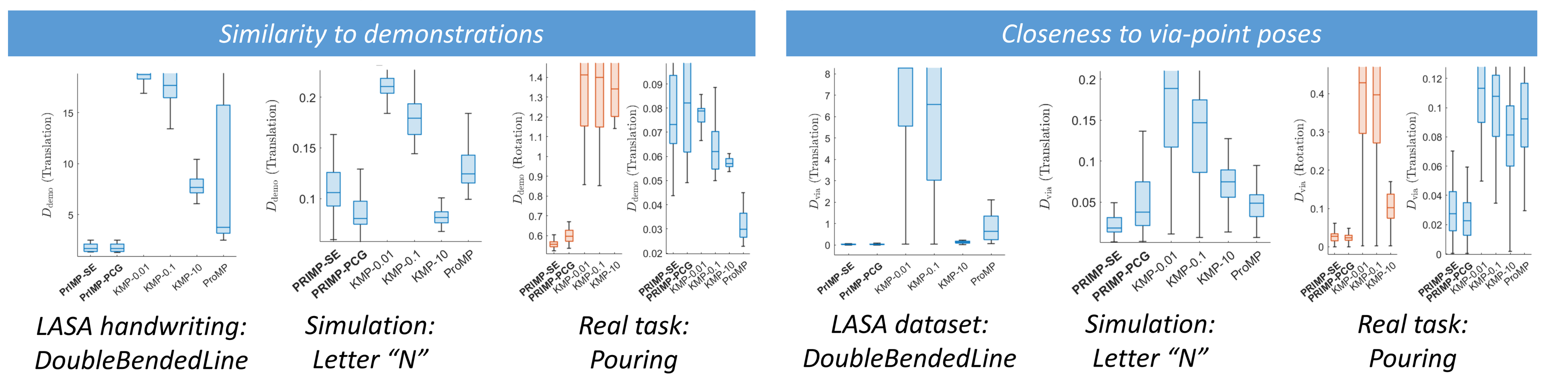


Scooping task

Benchmarks

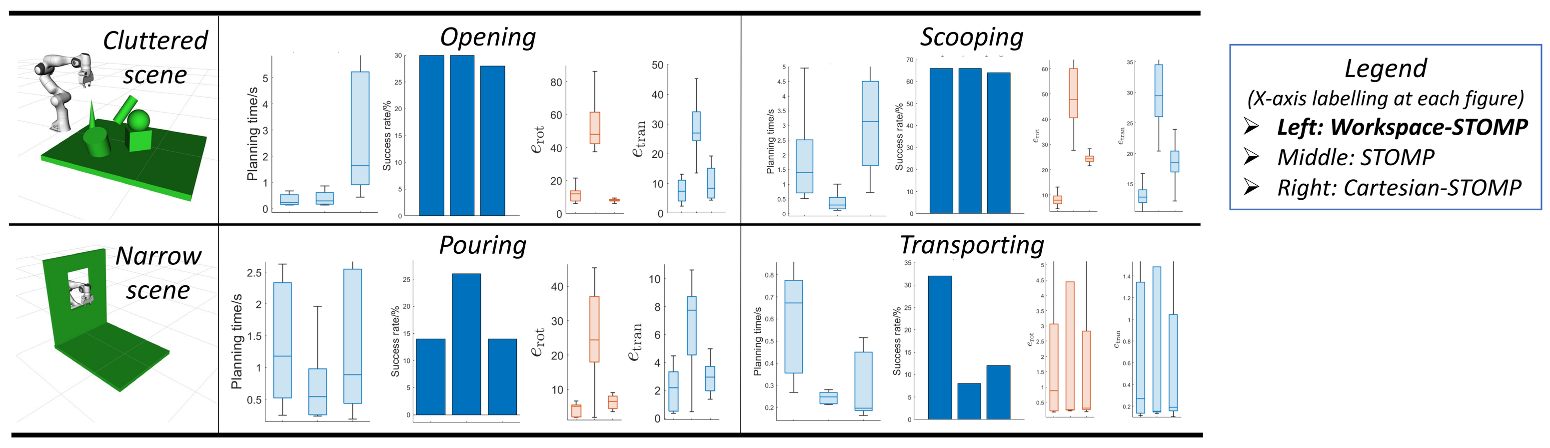
Learning from demonstration

Baseline methods: (1) ProMP [4], (2) KMP [5]
Dataset: (1) LASA handwriting, (2) Simulated motions, (3) Real-world tasks (6D pose)
Metrics: (1) Similarity with demonstrations, (2) Closeness to the desired via-point poses

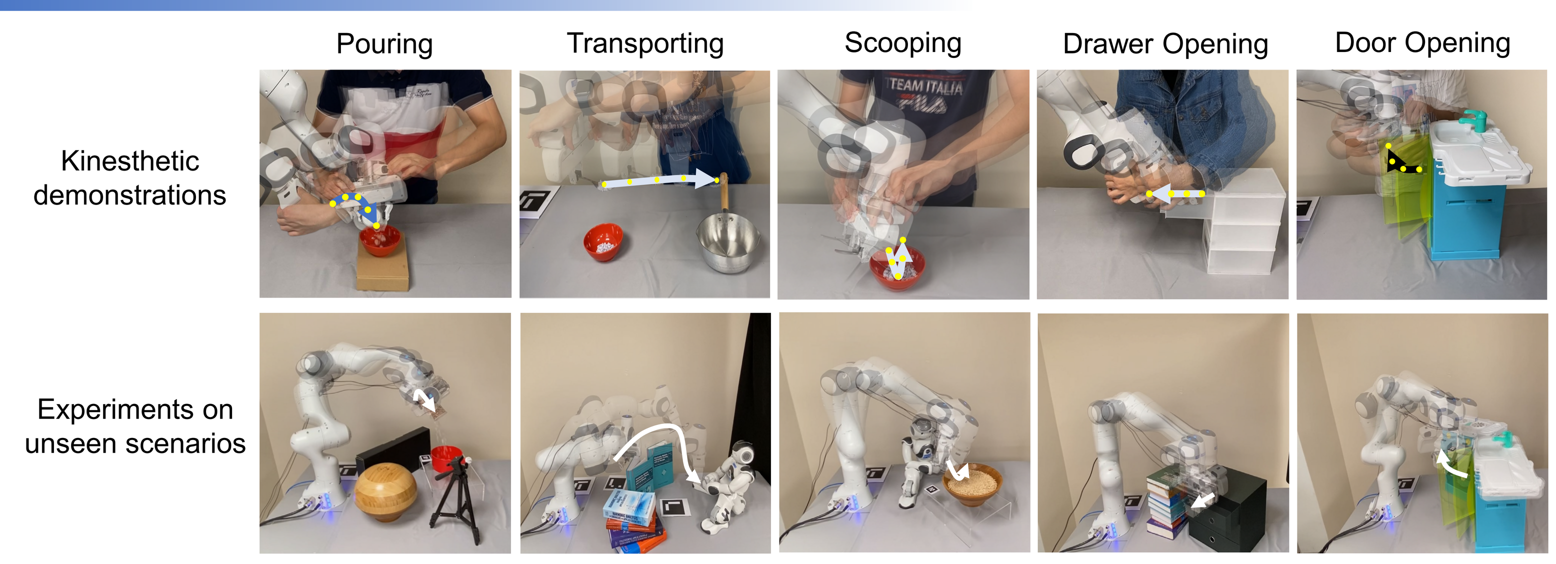


Guided motion planning

Baseline methods: (1) STOMP [6], (2) Cartesian-STOMP [7]
Dataset: Real-world tasks
Metrics: (1) Planning time, (2) Success rate, (3) Similarity with reference trajectory



Physical Experiments



Conclusion

1. PRIMP only requires a few or even a single demonstration, and is able to adapt to:
   - novel via-point poses (*i.e.*, start, goal and any point in between);
   - a change of viewing frame;
   - robot-specific workspace density.
2. Workspace-STOMP avoids unseen obstacles, guided by the learned workspace trajectory distribution.
3. A novel robotic system is proposed with the study of object affordance.
4. Future work:
   - Fuse demonstrations into the robot imagination module;
   - Add velocity and/or acceleration into the state vector;
   - Integrate force information in the probabilistic model.

Reference

[1] Ruan, S., Liu, W., Wang, X., Meng, X. and Chirikjian, G.S., 2023. PRIMP: PRobabilistically-Informed Motion Primitives for Efficient Affordance Learning from Demonstration. *arXiv preprint arXiv:2305.15761*.

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