Predicted Composite Signed-Distance Fields for Real-Time Motion Planning in Dynamic Environments

Oxford Robotics Institute, University of Oxford

Mark Nicholas Finean, Wolfgang Merkt, Ioannis Havoutis

{mfinean, wolfgang, ioannis}@robots.ox.ac.uk

UNIVERSITY OF OXFORD

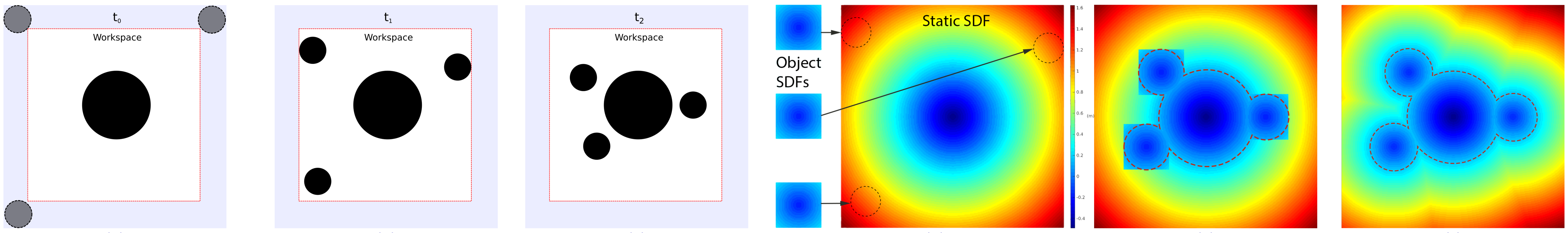
Motion Planning in Dynamic Environments

- Optimisation-based motion planners can provide the fast planning needed for use in dynamic environments, with many using Euclidean distance fields to represent the environment.
- Euclidean distance fields are commonly considered to have CPU compute times that are not fast enough for real-time performance, thus are pre-computed and assumed to be static.

Our proposed framework integrates a dynamic receding-horizon version of the GPMP2 motion planner with our novel technique of using 'predicted composite signed distance fields' and provides fast re-planning using predicted obstacle trajectories.

Predicted Composite Signed-Distance Fields (SDFs)

- We exploit the speed of the `min` operation and composite obstacle SDFs onto a maintained SDF of the static environment.
- Signed-distance field calculations are only required to be accurate up to a specified ϵ for motion planning problems, enabling us to compute and maintain relatively small SDFs for the obstacles.
- By tracking and predicting the future location of an obstacle, we can predict the SDF of the environment at later times. The motion planner can then plan to avoid the predicted paths of moving obstacles.
- We compare the time to perform full SDF calculations with our predicted composite approach — our approach typically exhibits an 81–97% reduction in time for subsequent predictions.



(a) (b) (c) (d) (e) (f)

Figure: 1a, 1b and 1c depict a toy example of three moving spheres entering the workspace in which a static obstacle (large central sphere) is present. 1d shows an SDF of the static environment, with the tracked objects in 1b overlaid for illustration purposes. For each of the tracked objects in the scene, an SDF is calculated and associated with them. By tracking the positions of the moving objects, we infer their velocities in order to make predictions of their future positions. At these future positions, we can superpose the object SDFs onto the static SDF using a `min` operation—the result is a composite SDF. 1e shows a composite SDF for t_2. 1f shows the corresponding exact SDF — critically for motion planning, the two are identical for distances up to ϵ away from the obstacle surface boundaries, as indicated by the red dashed line.

Integration and Experiments

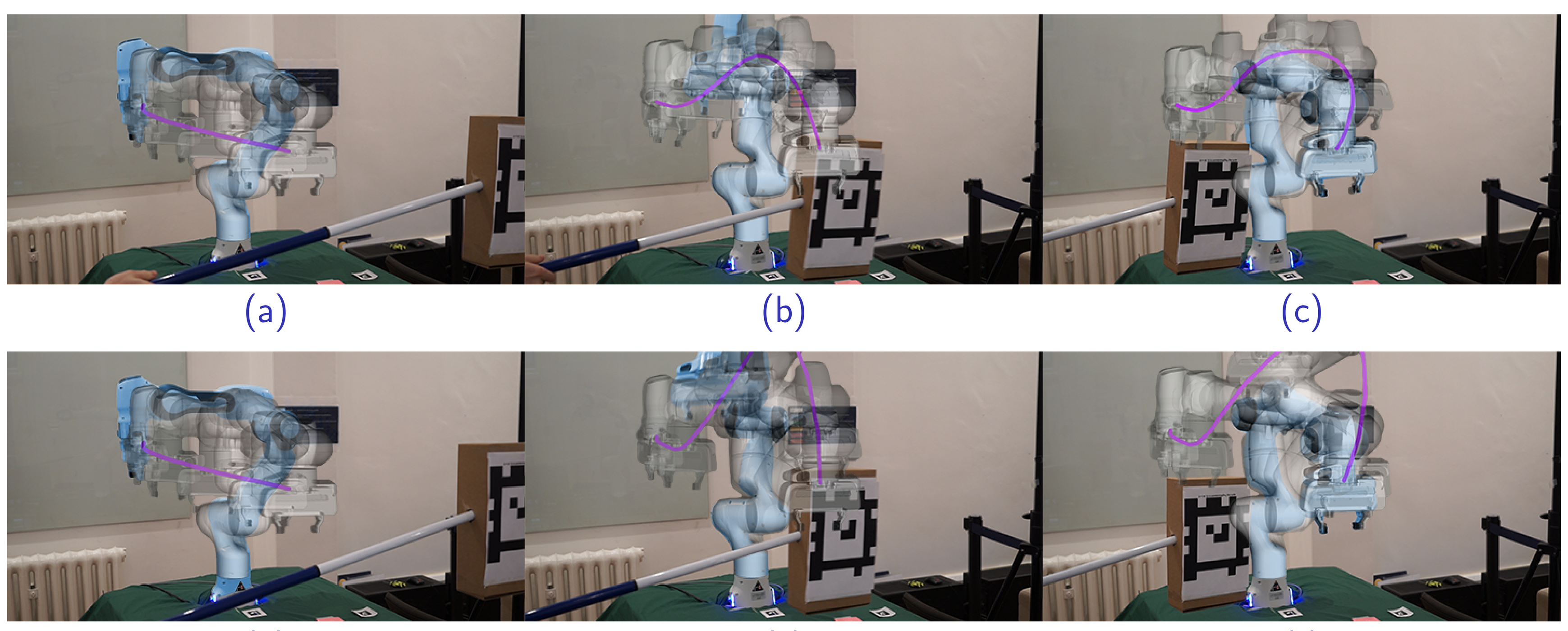
Dynamic GPMP2:

- We adapt the original GPMP2 implementation [1] to enable rapid updates of the SDF associated with each obstacle factor independently.
- The process of quickly updating obstacle factors facilitates a motion planner that can re-optimise and adapt planned trajectories to a changing environment.
- We conduct simulation experiments in the presence of dynamic obstacles of varying speeds and show that by accounting for predicted obstacle trajectories, we can generate smoother trajectories with a greater success rate of being collision-free.
- In our full pipeline, we generate composite SDFs for future times and the motion planner is run in a receding-horizon manner.

Planning in Dynamic Environments:

- We perform experiments in simulation and on hardware whereby dynamic obstacles are tracked online. A constant-velocity model is applied to each of the moving objects, enabling us to generate predicted composite SDFs for future times.
- In simulation, our approach enables a Panda 7-DoF robotic arm reaches across a gap while avoiding a moving robot.
- On hardware, the robot is tasked with avoiding a human-operated moving obstacle.
- Our method produced re-planned trajectories on a real robot arm which successfully avoided dynamic obstacles.

Results



(a) (b) (c) (d) (e) (f)

Figure: *Top row* - online motion planning using our approach of composite signed distance fields and prediction. *Bottom row* - using composite signed distance fields without prediction. From left to right, the images show the planned trajectory for times $t = 0\,\text{s}$, $t = 2.5\,\text{s}$ and $t = 5.0\,\text{s}$ (resultant trajectory). The predictive component of our framework enables a smoother resultant trajectory.

Conclusions

- Composite SDFs can be used to provide significant speed-up for generating SDFs when accounting for moving obstacles.
- By incorporating predicted obstacle trajectories, we can significantly reduce the smoothness cost of trajectories and the rate of collisions.
- Our approach can plan trajectories in dynamic environments and successfully avoid moving obstacles on a real 7-DoF Panda arm with obstacle tracking.

References

1. Mukadam, M., Dong, J., Yan, X., Dellaert, F., and Boots, B. 2018. "Continuous-time Gaussian process motion planning via probabilistic inference". *The Int. J. of Rob. Research* 37(11): 1319–1340.

ICAPS 2021

DYNAMIC ROBOT SYSTEMS GROUP
OXFORD ROBOTICS INSTITUTE