Toward Real-Time Object Manipulation in Dynamic Environment

Computer Graphics Lab

Xiaoxi Jiang Marcelo Kallmann

University of California Merced - http://graphics.ucmerced.edu

Introduction

The ability to plan realistic object manipulations in real-time is important for many applications, such as robotics, computer animation, and computer games. This work proposes a method designed to learn grasps from demonstrations and to learn reaching motions by executing tasks in realistic dynamic environments:

(1) It automatically detects various goal hand grasp postures for an object from human demonstrations, and employs active learning to generate grasps for new scenarios.

(2) The Attractor-Guided Planner (AGP) [1] is used to learn necessary reaching skills from previously successful solutions. Meaningful landmarks are selected along previous solution paths as attractor points, which are then reused to guide subsequent planning of new similar tasks.

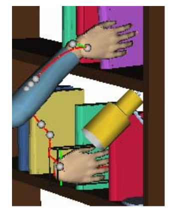
Grasping

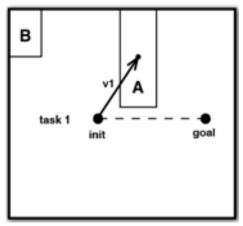
Multiple grasps are detected from real-time demonstrations*. One or more goal configurations are determined using a grasp metric* for the reaching planning phase.

*under development

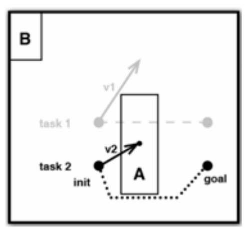
Reaching

We extract a set of attractors from a successful previously executed path, and use them to guide the planning for a new similar task: the sampling strategy of the motion planner will be then biased toward regions around the attractors.

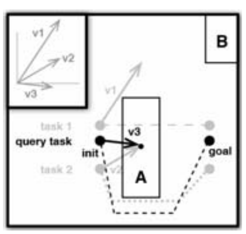




Example: task 1 is solved from scratch. We store in the database: the solution path, the initial and goal configurations, and the local coordinates of nearby obstacles ($\mathbf{v}_1$), in respect to the initial and goal configurations.

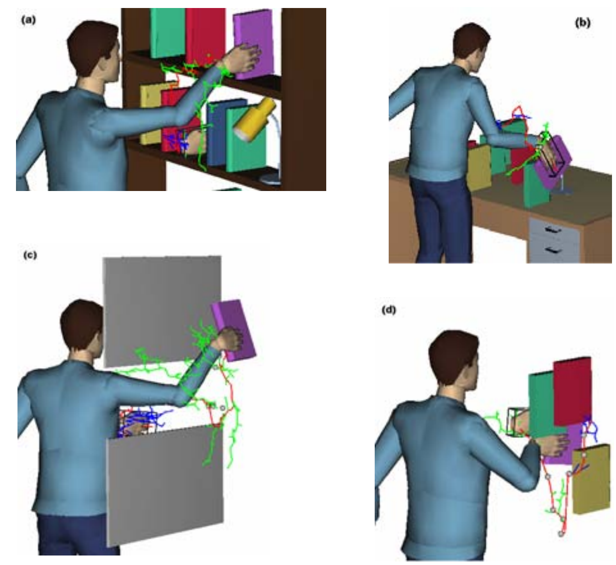


Here the environment has been modified before task 2 is queried. Task 2 is then solved from scratch. The solution path, initial/goal configurations, and the local coordinates of nearby obstacles ($\mathbf{v}_2$) are also stored in database.



Now the planning of task 3 reuses the solution of task 2 as an example. The task comparison metric depends on both the initial/goal configurations and the environmental features ($\mathbf{v}_1$, $\mathbf{v}_2$ and $\mathbf{v}_3$).

Results



The table below shows accumulated computation times of AGP (first row) and RRT (second row) in seconds for solving 200 consecutive tasks randomly generated in four different changing environments (shown above). The third row in the table shows the number of entries created in the AGP task database.

(a)	(b)	(c)	(d)
226.879	153.342	341.754	274.058
302.501	221.329	671.404	518.133
13	13	11	11

References

[1] Xiaoxi Jiang and Marcelo Kallmann, "Learning Humanoid Reaching Tasks in Dynamic Environments", IROS, San Diego CA, 2007, to appear.