Grasp sequence generation for planning robotic in-hand manipulation

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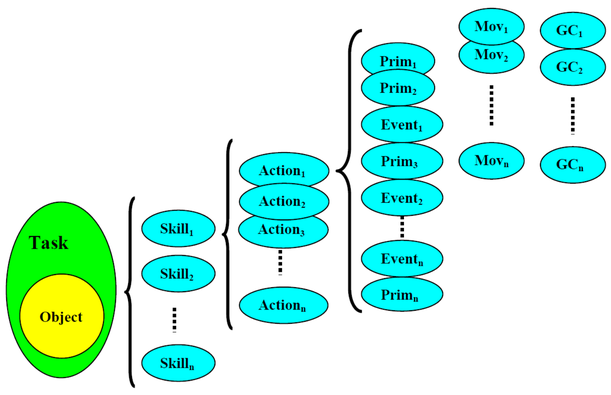
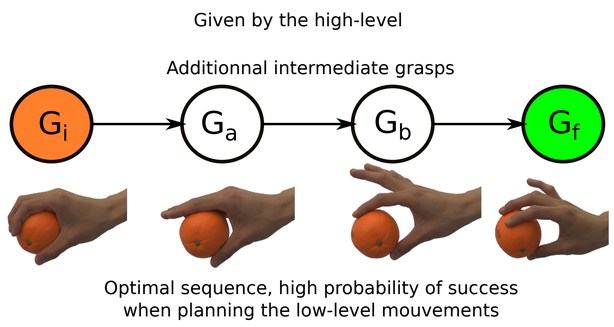
1. Introduction

The work presented here concerns the planning of movements to make a robotic hand execute in-hand manipulation. In-hand manipulation is a complex activity that is decomposed into several hierarchical levels (see Fig. (1), taken from [1]).

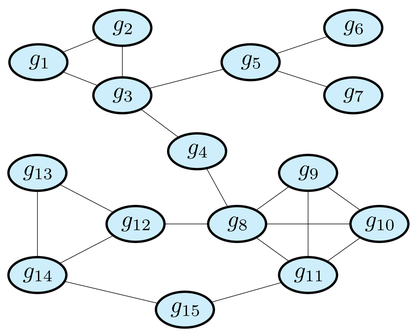


Most of the work on manipulation planning uses graph search techniques: a path is searched in a graph of configurations, that can be either a state inked to the hand, the object, or a combination of the two, such as grasps in [2].
We aim at introducing an intermediate layer of planning that generates grasp sequences. This solution is also based on a graphical model (Fig. (3)), nodes are simple canonical grasps. Transitions are described by a probability of success.

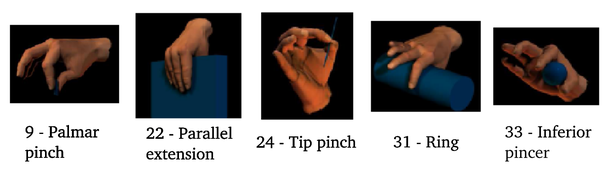


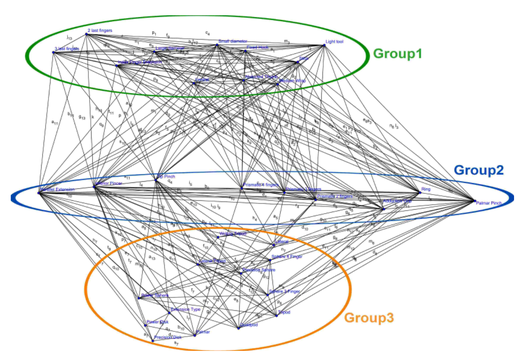
2. Modeling the grasp sequence

We assume that a manipulation action is made of a sequence of grasp configurations. Let a_j^i be the action driving the transition from grasp i to grasp j. This action has a probability of success.
We use a set of 33 predefined canonical grasps, and a 34th: "no grasp", the failure state. These grasps are enlisted in [3], identified as the most frequently observed grasp in human in-hand manipulation movements. We aim at finding the grasp sequence that leads optimally from the initial grasp to the final grasp $g_{init}, g_{final} \in G$, using intermediate grasps (Fig. (2)).



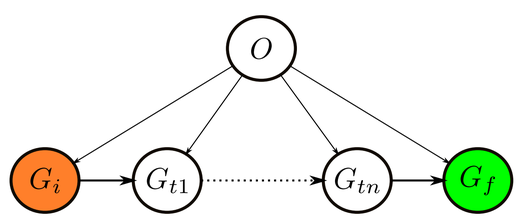
The probability of success of $g_i \rightarrow g_j$ depends on intrinsic factors: biomechanical constraints, hand geometry, the object parameters, the comfort criteria (low energy); and extrinsic factors such as obstacles and task constraints. These values are here empirically estimated through a methodic analysis. This analysis has enlighted 5 key grasps, likely to be used very often during manipulation, shown on Fig. (4), and 3 groups of grasps, shown on Fig. (5).

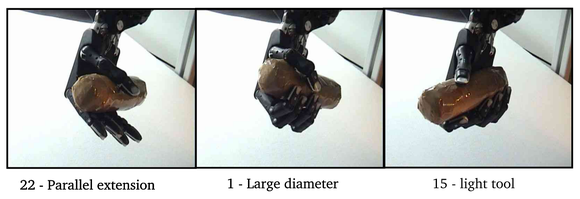




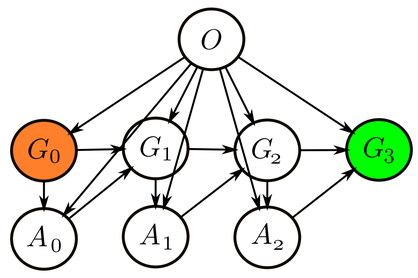
We are testing different algorithms for modeling and generating the grasp sequence.

Bayesian network A Bayesian network of the sequence is represented in Fig. 6. G_t to represent the grasp type at stage t in the sequence, and O the object.
This has been implemented without the object influence on the Shadow hand (see Fig. (7)).

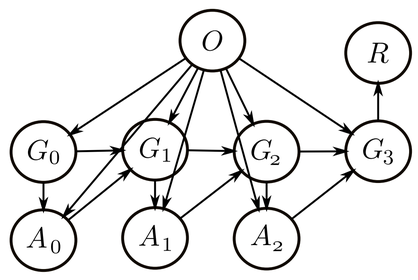




Hidden Markov Model (HMM) The actions attempted can be considered as variables in the network, forming a HMM.



Markov Decision Process (MDP) The agent is the robot, and it chooses which actions to take at each step. A positive reward is obtained if the last grasp is the goal grasp. The sequence of actions to take maximizes the expected reward.



References

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[2] H. Zhang, K. Tanie, and H. Maekawa, "Dexterous manipulation planning by grasp transformation." IEEE International Conference on Robotics and Automation, 1996.

[3] T. Feix and O. Block, "The generation of a comprhensive grasp taxonomy," KTH Royal Institute of Technology, Tech. Rep., 2009.

Acknowledgments

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Conclusion

A useful robotic hand should autonomously decide what to do with a given object, provided the high level objective (task) is known, and execute human-like movements, while adapting to the world context in real time. That is what our grasp sequence generator aims at, when completed by a lower level of planning and control. Different models will be compared, and the most efficient will be chosen.