Towards Bayesian Grasp Optimization with Wrench Space Analysis

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Grasp planning and optimization have been hot topics in the last decade. Due to the complexity of generating good grasps in analytic form for arbitrary objects, most of the proposed approaches rely on sampling strategies: candidate grasps are generated according to some criteria and then ranked with some quality metric. Uniform sampling around heuristic pre-grasps [1], [2], simulated annealing [3], randomized trees [4] and active learning [5] are state-of-the-art techniques to generate grasp candidates. In this work we propose the use of Bayesian Optimization methods [6] to tackle the problem. Our work exploits a sequential sampling strategy, where the results from previous trials convey information to guide the next samples. We show experimentally that, depending on object's shape properties, sequential decision may reduce significantly the number of trials necessary to achieve quasi-optimal grasps with respect to random search.

We use the OpenRave Simulation Environment [7] to develop our methods. The simulation environment consists of a manipulator arm, the Barrett hand, and a few objects of different complexities (Fig. 1). A grasp is parameterized by the x and y positions with respect to an object-centered reference frame. A trial consists in placing the open robot hand at the chosen configuration (x,y), then close the fingers until they contact with the object surface, and finally compute the grasp quality metric. The objective is to optimize the grasp parameters x and y such as to obtain the highest quality value. We use a wrench space based metric as in [3] able to evaluate both force-closure and non-force-closure grasps. Each trial feeds a Gaussian Process Regression model [8] that estimates the expected value and variance of the quality metric. These measures can be evaluated easily at any point on the state space. To decide the next point to try, we maximize at each time step a form of Expected Improvement function (EI) with exploitation-vs-exploitation control [9]. This function is derived from the Gaussian process in a straightforward manner. To search for its global maximum we use the DIRECT algorithm [10]. This is a global optimization method that works by partitioning the space in intervals (DIRECT stands for DIvide RECTangles), evaluating the EI in their center, and choosing, at each time step, the interval where the EI can be maximal for any bound on the function derivative (Lipschitz constant). We performed experiments in simulation to evaluate our approach with the objects shown in Fig. 1. The initial trial is chosen randomly around the object. Then the algorithm runs autonomously and

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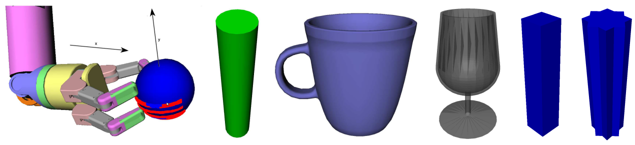

Fig. 1. The hand and objects used in the evaluation.

we compute the number of trials needed to achieve a grasp quality metric at 5%, 10% and 20% away from the global optimum. The results are summarized in the following Table. One can observe that smooth objects are learned in less than

	Sphere	Glass	Cylinder	Mug	Cuboid	Star Prism
20%	14	19	20	1	59	31
10%	14	19	20	55	59	105
5%	14	31	39	55	59	105

20 trials. Then the mug, a bit more complex object, requires about 50 trials. Objects with edges require a bigger number of trials, but still at a tractable level. Even the star-like shaped object, with multiple discontinuities, can obtain good grasps with a few tens of trials. We also compared our approach with random sampling and the conclusions are similar. Our method is better for smooth objects, whereas the performance of the two methods become similar as the objects present more edges (plots not presented here for lack of space). We expect that, with a higher number of dimensions, the advantages of the Bayesian Optimization method become more evident. This will be the subject of future work.

References

[1] A. Miller, S. Knoop, H. Christensen, and P. Allen, "Automatic grasp planning using shape primitives," in *Proc. of ICRA 2003*, 2003.

[2] A. Morales, T. Asfour, P. Azad, S. Knoop, and R. Dillmann, "Integrated grasp planning and visual object localization for a humanoid robot with five-fingered hands," in *Proc. of IROS 2006*, 2006.

[3] M. Ciocarlie, C. Goldfeder, and P. Allen, "Dimensionality reduction for hand-independent dexterous robotic grasping," in *Proc. of IROS 2007*, 2007.

[4] N. Vahrenkamp, T. Asfour, and R. Dillmann, "Simultaneous grasp and motion planning: humanoid robot ARMAR-III," *IEEE Robotics and Automation Magazine*, vol. 19, no. 2, pp. 43–57, 2012.

[5] O. B. Kroemer, R. Detry, J. Piater, and J. Peters, "Combining active learning and reactive control for robot grasping," *Robot. Auton. Syst.*, vol. 58, no. 9, pp. 1105–1116, 2010.

[6] E. Brochu, V. M. Cora, and N. de Freitas, "A tutorial on Bayesian optimization of expensive cost functions," University of British Columbia, Tech. Rep. TR-2009-23, November 2009.

[7] R. Diankov, "Openrave: A planning architecture for autonomous robotics," *Robotics Institute, Pittsburgh, PA, Tech. Rep.*, no. July, 2008.

[8] C. E. Rasmussen and C. K. I. Williams, *Gaussian Processes for Machine Learning*. The MIT Press, 2006.

[9] D. Lizotte, "Practical bayesian optimization," university of Alberta, Edmonton, Alberta, Canada, Tech. Rep. PhD Thesis, November 2008.

[10] D. E. Finkel, "DIRECT Optimization Algorithm User Guide," 2003.