Learning A Real-Time Grasping Strategy

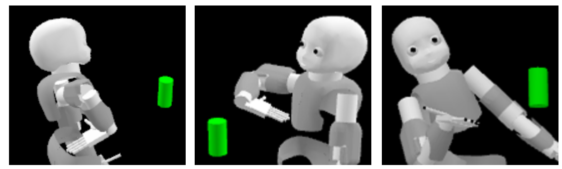
Bidan Huang[2,1], Sahar El-Khoury[1], Miao Li[1], Joanna Bryson[2] and Aude Billard[1]

ABSTRACT

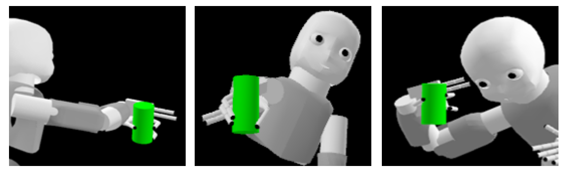
When reaching out to grasp an object, a robust grasping strategy should be able to adapt rapidly to external perturbations that can modify the initial object position or orientation. We achieve this goal by taking a two-step approach. In the first step, we compute a variety of stable grasps on a given object. In the second step, we propose a strategy that learns, from the computed grasps, a statistical model allowing the robot to adapt its grasp in real time to object displacement. We have implemented the system on the 9 degrees of freedom hand of the iCub humanoid robot.

Objects can be grasped in many different ways not only according to the task to accomplish but also according to the configuration of the object relative to the initial hand pose which can favor one grasp over the other. In order to find such a variety of grasps, we formulate grasp synthesis as an optimization problem by taking into account the position (h) and orientation (o) of the hand as well as the finger joint angles (θ). The resulting grasps are thus feasible for the hand kinematics and optimal according to a force-related quality measure. We tested our algorithm on a cylindrical object and obtained 612 grasps that we categorized into 20 groups [1]. These grasps were used for teaching robots to grasp through a user friendly interface [2]. The average computation time is 2.65 *sec*. This time is too long when a robot needs to grasp a moving object in a human-robot interaction scenario. For example, in an application such as catching a flying object, the grasp decision needs to be taken in a time in the order of milliseconds [3]. Thus, in order to adapt rapidly to object displacement, the computed grasps are used for learning a real-time grasping strategy.

Here we achieve real time by modelling data from the different grasps as a Gaussian Mixture Model (GMM), producing a density distribution of the feasible grasping region. The learned model, Ω, described as a sum of 40 Gaussian components, gives a probabilistic encoding of the joint distribution of the variables, i.e. $p(h,o,\theta \mid \Omega)$. Once a model is learned, it is used to generate feasible grasps through Gaussian Mixture Regression (GMR) which provides a solution to compute the conditional $p(\theta \mid h,o,\Omega)$ of a GMM. This allows us, given a current hand configuration $q=\{h,o\}$, to predict a desired finger posture θ guaranteeing a good quality of the grasp. When the query point q lies outside the regions covered by the training data, inference can be unreliable. That is, when the hand location is far away from the object, inference using the probabilistic encoding of GMM/GMR can be poor, leading to an unfeasible grasp. Thus, during the execution of the grasp strategy, we first check whether the likelihood of the initial query point with respect to the model is sufficiently high. If this is not the case, a projection $q^\star$ is computed such as $q^\star$ is the closet point to q with a sufficient likelihood under the model. This projection is then used as a new query point in the prediction of the desired joint configuration. We tested our model by randomly generating 3000 initial hand configurations and computing their corresponding final grasps (Fig. 1). The average computation time obtained for generating one grasp is 8.6 *msec* with a standard deviation of 0.37 *msec*. The experiments were run in Matlab on a machine with 4GB RAM and a CPU at 2.8GHz.



(a) Initial pose 1 (b) Initial pose 2 (c) Initial pose 3



(d) Final grasp 1 (e) Final grasp 2 (f) Final grasp 3

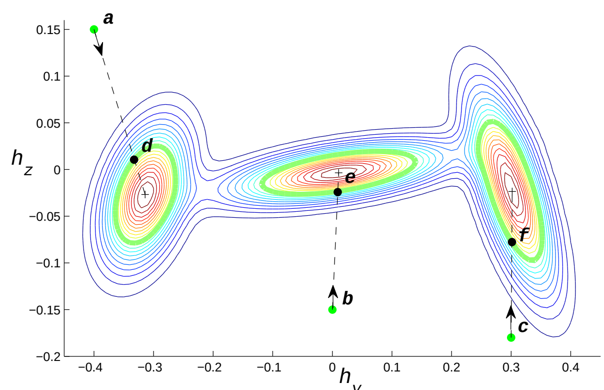


Fig. 1: Two-dimensional illustration of the learned model. h_y and h_z correspond to the hand position along the y and z axis of the object reference frame. a, b and c are the initial query points, while d, e and f are their corresponding computed grasps.

[1]Learning Algorithms and Systems Laboratory (LASA), Swiss Federal Institute of Technology Lausanne (EPFL), Switzerland

[2]Intelligent Systems Group (IS), Computer Science Department, University of Bath, UK

REFERENCES

[1] S. El Khoury, M. Li, and A. Billard, *Bridging the Gap: One Shot Grasp Synthesis Approach*, IEEE/RSJ International Conference on Intelligent Robots and Systems, 2012

[2] S. El Khoury, M. Li, , A.L. Păiş, and A. Billard, *Teaching Robots to Grasp through a User Friendly Interface*, submitted to Beyond Robot Grasping - Modern Approaches for Dynamic Manipulation Workshop, IEEE/RSJ International Conference on Intelligent Robots and Systems, 2012

[3] S. Kim and A. Billard, *Estimating the non-linear dynamics of free-flying objects*, in Robotics and Autonomous Systems, 2012.