Robotics and Autonomous Systems 62 (2014) 1208–1219

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

Efficient sensory-grounded grasp pose quality mapping for gripper design and online grasp planning

Danny Eizicovits *, Sigal Berman

Department of Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel

HIGHLIGHTS

- Mapping wrist pose grasp quality supports gripper design and grasp planning.
- Quality measures are tied to the robots' perception capabilities.
- Quality measures are computed from the segmented 3D point cloud of the object.
- Scanning the object's surface results in low computation time and high map quality.
- The method is suitable for arbitrary object shapes.

ARTICLE INFO

Article history:
Received 9 December 2013
Received in revised form
18 March 2014
Accepted 24 March 2014
Available online 28 March 2014

Keywords:
Robotic manipulators
Grasping
Graspability map

ABSTRACT

The gentle grasping and manipulation of objects in dense un-structured environments, such as the agricultural, food processing, or home environments constitute a formidable challenge for robotic systems. Knowledge regarding wrist poses (wrist positions and orientations) that may lead to successful grasps is especially important in such environments for both gripper design and online grasp planning. Graspability maps store grasp quality grades at different wrist poses in object-centered coordinates. Previously graspability maps were derived based on object models in a lengthy, offline process and thus had limited usability. We have developed geometry-based grasp quality measures related to classical grasp quality measures, which can be determined directly from a 3D point cloud. This facilitates embedding agent perception capabilities within the grasp quality determination. Additionally by scanning the object's surface for finger contact points rather than scanning the volume of the bounding box about the object, and by using parallel computation, graspability map computation-time is considerably reduced, facilitating online computation of multiple measures. We validate the developed measures in a physical environment, show that computation-time can be reduced by more than 90% with very low reduction in map quality, and show the applicability of the developed methods for both simple and complex objects.

1. Introduction

Grasping an object is a fundamental part of many robotic tasks, yet it is considered among the most difficult tasks for a robot to accomplish [1]. This is due to the limitations of available robotic grippers and the inherent difficulties of grasp planning. Grasp planning is especially difficult in un-structured, dynamic environments, in which sensory perceptions are plagued with uncertainties. Various flexible grippers are now commercially available, yet the increased flexibility complicates grasp planning. Thus, in many cases the gripper is developed for the task and implementation at hand. The agriculture and food processing industries and the home environment are relatively new markets for robots, whose deployment in these sectors is expected to undergo exponential growth in the current decade [2]. The environments in these sectors are inherently difficult to structure and the shape of the manipulated objects is often variable and soft requiring gentle handling. Improving gripper design and grasp planning in such environments is of great importance [3].

The act of grasping is composed of several subtasks including, determining hand grasp configuration, determining arm grasp configuration, and finding a collision-free trajectory from the robot's current configuration to the grasp configuration. Determining hand configuration includes, determining contact points, finger configurations, and wrist pose (wrist position and orientation).

* Correspondence to: Department of Industrial Engineering and Management, Ben-Gurion University of the Negev, P.O.B 653, Beer-Sheva 84105, Israel. Tel.: +972 8 647 9785.

E-mail address: Dannyeiz@bgu.post.ac.il (D. Eizicovits).

http://dx.doi.org/10.1016/j.robot.2014.03.011
0921-8890/

Arm configuration is derived based on the wrist pose by solving the inverse kinematic (IK) problem. Traditionally, these tasks are executed serially, that is, the grasp planner computes a suitable hand configuration for which an IK solution is calculated and then a collision-free arm trajectory is planned. If the IK solution is not feasible or if a path is not found, another hand configuration is considered. Most existing literature focuses on isolated sub-tasks such as hand configuration synthesis for various objects and hands [4,5] or optimized arm trajectory planning [6,7].

Inspired by research of human grasp motion where studies indicate that hand configuration synthesis and arm trajectory planning are separate yet coordinated [8], robotics researchers are investigating methods for combining these two processes. Vahrenkamp et al. [9] suggested the Grasp-Rapidly exploring random trees (Grasp-RRT) algorithm which combines computation of reachable and feasible grasp configurations with the computation of collision-free paths. Finger contact points are found by closing the fingers at target poses for which a collision-free path is found. Grasp feasibility is determined based on the grasp wrench space. Lippiello et al. [10] suggest an iterative algorithm combining object surface reconstruction based on multiple images with grasp planning and computation of finger trajectories. Starting from an initial hand pre-shape based on a rough elliptical estimate of the object's shape, the grasp planning algorithm runs in parallel to the object shape reconstruction algorithm and uses the intermediate surface reconstruction results for local optimization of finger contact points. For expediting online grasp planning researchers have used various simplifying heuristics of both hand and object, e.g., decomposing objects into shape primitives [11], using a parameterized set of grasp motion primitives (approaching from the side or from top of the object) [12], and planning grasp configurations in a reduced configuration space, where the dimensionality reduction is achieved by using principal components of a finite set of hand postures (finger configuration) [13].

Offline computation and *a priori* knowledge about objects and corresponding feasible hand configurations can be harnessed to reduce the computational time of online grasp planners. One method, especially suitable for known objects in unknown environments, is to pre-compute and store hand configurations of successful grasps. In this case only the IK solution and path need to be planned during run-time. The largest and most extensive hand configuration database is the Columbia grasp database [14], which includes thousands of hand configurations for various hands and objects, calculated using the GraspIt! simulation software [15]. These samples can also be used for adapting grasps to previously unknown objects [16]. Alternatively wrist poses, rather than the complete hand configurations, that lead to successful grasps can be stored alleviating the difficulty of finding a suitable hand configuration during run-time and facilitating parallelization of online hand and arm configuration planning. This method is especially suitable when there are uncertainties regarding object shape due to object variants or sensor uncertainty. An additional advantage of storing wrist poses rather than hand configuration samples is that it is simpler to define high-quality pose regions. Using target wrist pose regions rather than samples is required for ensuring probabilistic completeness of sampling-based path planning algorithms, e.g. RRT [7].

Graspability maps store quality grades of wrist poses that lead to successful grasps for a given object and hand. The poses are stored in object-centered coordinates to isolate the representation from the object configuration within the environment. Graspability maps have been suggested for supporting both gripper design evaluation and online grasp planning [17]. The graspability map is built by enveloping the object within a bounding box, dividing the bounding box into voxels, and defining a set of orientations (within each voxels). An exhaustive search is conducted, usually using simulation, for grasp configurations in each orientation in each voxel. This process is time consuming, typically requiring several hours for a single object and gripper [17,18]. Computation is based on models of the object and hand which may be difficult to acquire or be based on various simplifying assumptions.

Task maps are sampled version of graspability maps suggested for online grasp planning [19,20]. In order to reduce map computation time task maps are generated using the RRT algorithm by sampling along a path in the six degree-of-freedom (DOF) wrist pose space. This method is suitable only for objects with a single region of grasp wrist poses, as the tested poses must all lie along a connected path. A notion similar to the graspability map is the grasp affordance density. It is defined as grasp success probability for a given hand configuration (for a specific object and hand within an environment). Grasp affordance density is the spatial probability density function of grasp affordances for a specific hand shape (finger configuration) in the wrist pose space [21,22]. Grasp affordance density functions for different hand shapes can be amalgamated. The main incentive for use of grasp affordance densities is to bind grasp success assessment to the agents' physical embodiment, i.e., to its sensory perceptions and motor capabilities. Thus the affordance density is estimated based on experimental data (simulation and hardware) and image-analysis based grasp configuration planning is typically applied [23,24]. Yet whereas the graspability map stores a quality grade (which can be based on several quality measures), the grasp affordance density stores only grasp success probability. Similar to graspability maps generation of grasp affordance densities is a lengthy, offline process which limits their applicability during run-time to previously known objects.

We address the gaps in the current grasp wrist pose quality mapping methods, i.e., efficiently creating grasp quality maps anchored in the agent's sensory perceptions that are suitable for run-time computation. To this end we have defined theoretically grounded grasp quality measures based on a point-cloud object representation, and efficient methods for graspability map generation based on such measures for objects with arbitrarily complex shapes. The remainder of the paper is organized as follows: Section 2 presents the grasp quality measures used for the computation of graspability maps based on point cloud data. Section 3 presents the methodology of the map generation process. Section 4 presents the graspability map analysis and Section 5 presents the results and discussion of the analysis. Conclusions are presented in Section 6.

2. Grasp quality measures

Classical grasp synthesis algorithms require as input a 3D geometrical model of the analyzed object. Grasp quality characteristics are then calculated using the object model coupled with finger contact models [25]. Although such object models offer high computation accuracies, they are object-specific, incur heavy computation costs, and are commonly difficult to create since the shape of natural objects is not typically characterized by basic geometric shapes. Using shape primitives rather than exact models was suggested as one way to reduce computation time without considerably affecting the quality of the synthesized grasps [26]. However, using such methods requires that the primitive-shape based model, typically based on the complete 3D model of the object, be carefully constructed. The construction of either an exact or primitive-shape based 3D model from visual data is difficult at best, and depending on the object and its environmental characteristics, the task can be prohibitively challenging. Indeed, missing data, obstacles, and/or specularities must often be dealt with during such reconstruction tasks. Thus far, graspability maps have been computed using 3D object models. The current use in both indoor and outdoor robotics applications of state-of-the-art depth sensors, such as stereo cameras or RGB-D sensors facilitates the adoption of model construction methods that exploit 3D point cloud representations. While