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Efficient models for grasp planning with a multi-fingered hand

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ABSTRACT

This paper presents a simple grasp planning method for a multi-fingered hand. Its purpose is to compute a context-independent and dense set or list of grasps, instead of just a small set of grasps regarded as optimal with respect to a given criterion. By context-independent, we mean that only the robot hand and the object to grasp are considered. The environment and the position of the robot base with respect to the object are considered in a further stage. Such a dense set can be computed offline and then used to let the robot quickly choose a grasp adapted to a specific situation. This can be useful for manipulation planning of pick-and-place tasks. Another application is human–robot interaction when the human and robot have to hand over objects to each other. If human and robot have to work together with a predefined set of objects, grasp lists can be employed to allow a fast interaction.

The proposed method uses a dense sampling of the possible hand approaches based on a simple but efficient shape feature. As this leads to many finger inverse kinematics tests, hierarchical data structures are employed to reduce the computation times. The data structures allow a fast determination of the points where the fingers can realize a contact with the object surface. The grasps are ranked according to a grasp quality criterion so that the robot will first parse the list from best to worse quality grasps, until it finds a grasp that is valid for a particular situation.

1. Introduction

Mobile manipulators are now common in robotics research laboratories, but planning the manipulation of objects with complex shapes is still a challenging task. Among the sub-tasks involved in manipulation planning, grasp planning is of first importance as grasping is the starting point of any manipulation task.

Grasp planning basically consists in finding where to place the fingers on the object the robot must grasp. If we consider a complete robotic platform, not only the grasp configuration is needed but also the configuration of the robot base and arm. Several aspects must be taken into account in order to find a configuration for the whole robot that is suitable for picking up the object:

- the configuration must be accessible to the robot, *i.e.* it must be compatible with its inverse kinematics (base, arm and finger kinematics);
- the grasp associated to the configuration must be stable according to a chosen relevant stability criterion;
- the grasp configuration must not lead to robot self-collision or collision against the environment.

The paper proposes a method to find such configurations and it is presented as follows.

Section 2 gives an overview of the existing works related to grasp planning. Section 3 presents the proposed method. Section 3.1 explains how relative hand/object poses (referred later as *grasp frame*) are computed. Section 3.2 details how a grasp configuration is computed from a grasp frame. Such a computation is based upon an approximation of the intersection between the object surface and the finger workspace. Section 3.5 explains how to compute the intersection from the models of object surface and finger workspace detailed in Sections 3.3 and 3.4. The obtained grasps are then evaluated and sorted according to the quality score described in Section 3.6.

2. Related work

Most of the early grasp planning methods did not take into account finger or arm kinematics and are often referred as contact-level techniques [1–3]. The contacts are regarded as freely-moving points with no link to any mechanical chain. Many grasp stability criteria have been introduced for this model of point/surface contact, the most common being certainly the force closure criterion [2,4]. Force closure criterion is verified if a grasp can resist arbitrary force/torque perturbation exerted on the grasped

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object and is tested for a specific set of contacts (positions and normals). To integrate the notion of robustness of the grasp stability with respect to the contact positions, the concept of independent regions of contact has been introduced [1]. These regions are such that a grasp always verifies force closure as long as the contacts stay within the region. The computation of these regions has been solved for different object surface modelization (2D discrete surface [5], 2D polygonal surface [6], 3D polyhedral surface [7–9]).

All these contact-level techniques were not very well-suited for real applications. Therefore, many new methods appeared that integrate considerations on finger and/or arm kinematics. Miller et al. [10] proposed to decompose the object into a set of primitives (spheres, cylinders, cones and boxes). A pregrasp configuration of the hand is associated to each primitive. A set of parameters is sampled in order to test the different directions of approach of the hand. Then, for each pose, the fingers are closed on the object until collision. The quality of the obtained grasp is then computed according to the measure described in [2]. The idea of object decomposition was widely used and is still the base of many grasp planners. It provides a heuristic to reduce the possible relative palm/object poses to test. In [11], the authors decompose the object model into a superquadric *decomposition tree* employing a nonlinear fitting technique. Grasps are then planned for each superquadric using a heuristic approach close to the one in [10]. The grasps are then simulated on the original object model using the GraspIt! dynamics simulator [12], to sort them by quality. Huebner et al. [13] proposed a technique to build a hierarchy of minimum volume bounding boxes from 3D data points of the object envelop. This method offers an interesting robustness with respect to the quality of the object's 3D model, acquired from sensors (here laser scan). In [14], the object is decomposed into a set of boxes called *OCP* (Object Convex Polygon). Each box of the OCP is compared to a *GRC* (Grasping Rectangular Convex), which gives an estimation of the maximum size of the object that the hand can grasp. Different GRCs are defined corresponding to different grasping styles. Xue et al. [15] presented a method to optimize the quality of the grasp that takes into account the kinematics of the fingers during the optimization phase. They use a swept volume precomputation associated with a continuous collision detection technique to compute, for a given hand/object relative pose, all the possible contacts of each finger on the object surface. After obtaining an initial grasp provided by the GraspIt! software [12], they locally optimize the quality of the grasp in the finger configuration space.

Some works gave more focus on arm and/or robot base inverse kinematics issues. Berenson et al. [16] were interested in finding grasp configurations in cluttered environments, for a given robot base position in the object area. From different object approaches, the authors precompute a set of grasps, all verifying the force closure property. Instead of trying to solve the arm inverse kinematics and checking for collisions for each grasp of the set in an arbitrary order, the authors propose to compute a *grasp scoring* function for each grasp. The function is used to evaluate the grasps that are more likely to succeed the inverse kinematics and collision tests. It is based upon a force closure score, a relative object–robot position score and an environment clearance score. The authors of [17] focused on path planning for the robot base (or body) and arm and presented a planning algorithm called *BiSpace*. Like in [16], they first compute a set of grasp configurations for the hand alone. Once one or more collision free configurations for the hand are found, they become the start nodes of several RRTs (Rapidly Random-exploring Tree [18]) that will explore the hand workspace while another RRT is grown from the robot base start configuration, that explores the robot configuration space.

Some recent works were inspired by results in neuroscience [19,20] which have shown that humans mainly realize grasping movement that are restricted in a configuration space of highly reduced dimensionality. From a large data set of human pregrasp configurations, Santello et al. [19] performed a principal component analysis revealing that the first two principal components account for more than 80% of the variance. Ciocarlie et al. [21] called the components *eigengrasps* and use them as a base to represent the reduced configuration space of the hand. They also add the six DOFs of the wrist pose. Then, they use a simulated-annealing-based optimization method, in eigengrasp space, to find the best grasp according to an energy function. The energy function takes into account two parameters. First, the distance between specified points on the hand and the object surface. Second, a quality metric based on the one in [2].

Other neuroscience results suggest a very close connection between visual perception and the choice of the hand approach to grasp the object. According to Goodale and Milner [22], the human visual system is organized into two separate parallel pathways: The ventral and dorsal streams, where the ventral stream plays a major role in perceptual identification of objects, while the dorsal stream plays a major role in visually-guided action. Although some recent studies [23] revealed that there is no evidence of the existence of two distinct pathways on healthy subjects, contrary to what the previous studies have suggested, nice results were obtained in robotics by combining vision and grasping action. In these vision-based grasping techniques [24,25], the grasping points are directly extracted from image features, instead of using images to build or localize a 3D model and work with it. Once an image is divided into square patches, descriptors (*e.g.* the *shape context* descriptor [25] and the ones based on edge, texture, and color filters [24]) are computed on each patch, and a classifier trained by a supervised-learning method is used to identify patches that contain grasping points. The 3D poses of the grasping points are then computed from images obtained from different camera positions.

3. Grasp list computation

Grasp planning of a complex object has been so far too computationally expensive to consider it can be performed in real-time. Therefore, in a real application, it is preferable to use precomputations as much as possible. In the proposed framework, a grasp list is computed off-line for the considered object in order to capture the best possible the variety of the possible grasps. This list will then be used to select, in an online application, the grasps that are currently reachable and, from them, the best one according to a scoring function described further.

In this paper, we consider only precision grasps *i.e.* contacts are made with fingertips only. This allows to reason with point contact only, that is the most common case in the literature. It also gives more grasping possibilities as smaller parts can be grasped, at the cost of a weaker stability compared to power grasps and a bigger contact pressure, due to smaller contact regions.

In the following, we illustrate the method mostly with the Schunk Anthropomorphic Hand (SAH hand), depicted in Fig. 4. It has four fingers. Each finger has four joints. Only the first three joints are actuated, the last one being coupled with the third one. The thumb has an additional actuated joint to place it in opposition to the other fingers. Some results are also shown with the Shadow hand that has five fingers. The implementation was done using general inverse kinematics [26] so that no adaptation to finger kinematics is required, at the cost of longer computation times.

For some applications, precomputing a reduced set of good grasps is of no interest because it is mainly the situation (positions of the environment obstacles) that will constrain the way the object can be grasped by the robot.