Selecting the best grasp during post-grasp manipulation under multi-objective criterion

Tommaso Pardi, Rustam Stolkin and Amir M. Ghalamzan E.

Abstract— Consider the task of grasping an object, and then moving it along the desired trajectory. These two robotics problems (selecting a stable grasp of a hand on an object, and planning a task-oriented trajectory of the robot) have been mostly studied separately from one another. However, given a desired post-grasp trajectory of the object, different choices of grasp will strongly affect performance. We present our preliminary implementation of grasp-selection that maximise post-grasp objectives. Our method examines a number of different possible grasps on an object while exploring the resulting post-grasp motion space for each grasp. Four different criteria are computed for each grasp configuration and post-grasp trajectory, in order to evaluate the performance of a particular motion that it yields. A collision-avoidance cost based on well-known potential field methods is assigned to each grasp, based on the resulting post-grasp motion that it will yield. Then, two objectives use the “augmented” technique to assign a safety/torque cost to the motion. A fourth cost estimates the manipulability ellipse along the post-grasp trajectory. Finally, an optimisation process merges all these costs together, and the grasp selected enables the desired post-grasp object motion, while minimising the proximity of all robot parts to obstacles during that motion, yielding torque efficiency, safe motion and maximising the manipulability. In future, we will elaborate the multi-objective optimisation of grasp selection.

I. INTRODUCTION

A fundamental question in many robotics applications is how to manipulate an object to perform a task. Although robotic operations can be very different one-another, they share a common structure that was extensively studied in past years. Looking at this problem from a general point of view, three sub-problems are easily traced: 1) (pre-grasp) synthesis grasp configurations on the object’s surface, 2) (grasp) perform a form-force/closure grasp, 3) (post-grasp) move the object to perform a task. Tackle all of them together makes the problem very complex, so, despite the strong connection between all those phases, the bulk of literature has addressed them separately. The results achieved under this assumption build the state-of-art for manipulation operations. However, a full consideration of all three phases in real-world tasks is demanded to attain a grasp configuration able to perform the entire task properly. For example, a simple task of moving a sliding door in presence of obstacles poses some limitation on available grasp configurations. Indeed all grasp candidates are able to generate some motions, but just a few of them may be able to perform the entire task without collision.

In the past decades, many advanced approaches for addressing at least one phase have been proposed [1]–[3]. Some of them cope with pre-grasp, [1] (GPD) uses Convolutional Neural Networks to generate grasp configurations at high likelihood on the object’s surface from a 3-D camera sensor; [3] proposes an algorithm that generates several grasp configurations based on a high-likelihood metrics. The main downside of these methods is that they have just focused on pre-grasp stage. Thus selecting one of these grasp configurations randomly does not assure to be able to perform the entire task.

As for grasp synthesizing, force-closure [4], or form-closure analysis [5] are classical approach to compute stable grasping configurations based on a 3-D model of an object. However, building a 3-D model of all unknown objects is not easy and may not be practically feasible. In the last few years, some promising works have started to cope with more than a phase at the same time. GraspRRRT [6] simultaneously finds a feasible grasping configuration, solves inverse kinematic (IK) and searches a collision-free reach-to-grasp trajectory. Kitaev et al. [7] face the problem differently. It uses rollouts in physics-based simulation and grasps the target object in a cluttered environment by pushing objects aside. [8]. Finally, it synthesises grasps and plans a collision-free reach-to-grasp. Although these algorithms cope with pre-grasp phase and propose a method to reach it without collision, they do not care about following post-grasp trajectory.

As for the post-grasp phase, a task-oriented planning drives researcher to prioritise certain abilities along the task for improving overall execution. For example, in [9], a compliance control method is designed to reduce post-collision bouncing effects, and in [10] and [11] a manipulator’s impact ellipsoid is defined as a variation of the end-effector impact force w.r.t. variations in joint space. Moreover, [12] proposes a manipulability index along the direction of the linear velocity of a Cricket Robot’s Centre of Mass given a trajectory. Recently a bulk of papers, [13]–[15], address the post-grasp phase, sharing the idea of selecting a grasp configuration in order to minimise some specific objective demanded by the task. In [14], a method is proposed to elect a grasp configuration able to minimise the impact on external obstacles. In [13] and [15], a grasp configurations selector is proposed to enable torque-efficient manipulations, and for optimally facilitating post-grasp motions using a Task-Relevant Velocity Manipulability (TOV), respectively.

Our work shares the same line of research with these
works for designing a grasp selector algorithm. However, instead of addressing just a single problem at the time, we propose a method to minimise all objectives and provide the robot with this information, before that a grasp configuration is selected.

II. PROBLEM FORMULATION

We consider reference frame $x_r \in SE(3)$ (the black frame in Fig. 1). Frame $x_g \in SE(3)$ is attached to the end-effector at each time (shown with blue thick frames). We use operational space trajectory to refer to successive poses of this frame that correspond with a sequence of poses attached to the centre of mass of the object $x_c = \{o_c, x_c, y_c, z_c\}$. $x_c(t) = \{^tR_c(t), ^tR_c(0) \forall 0 \leq t \leq T\}$ defines a desired trajectory for the object, $t$ denotes a time and $t_f$ is time-to-completion for the manipulative movements, $^tR_c(t)$ is rotation matrix from $x_c(t)$ to $x_r$, and $^tR_c(t)$ represents translation of $x_c(t)$ expressed in $x_r$. We assume the object is non-deformable. Hence, when the robot comes into contact with the object, a trajectory of the corresponding end effector pose at grasping configuration can be expressed based on $x_c$ and a fixed transformation from $x_g$ into $x_c$, as follows:

$$^tR_g(t) = ^tR_c(t)^tR_g$$
$$^tR_t(t) = ^tR_c(t) + ^tR_c(t)^tR_g$$

where $x_g = \{^t\alpha_g, ^t\beta_g\}$ are rotation and translation from $x_g$ to $x_c$, respectively. We consider the trajectory for object movements, namely $^tR_c(t)$, is known, e.g., moving/opening a sliding door. Hence, for each grasping configuration, namely $x_g(t)$, the operational space trajectory of the end-effector, namely $x_g(t) = \{^tR_g(t), ^tR_g(t)\}$, is fixed and can be computed using eq. (1). An IK algorithm [11] is then utilised to compute the corresponding joint space trajectory of the manipulator as follow:

$$q(t)|_{x_g, x_c} = IK(x_g(t)),$$

where $q(t) = \{q_1(t), ..., q_n(q)\}, q \in \mathbb{R}$ at each time stamp and $n_q$ is the number of joints.

A. Collision Avoidance Objective

We define a set of body points attached to manipulator’s links and joints. Therefore, the trajectory of each body point is:

$$b_j(t) = FK_j(q(t)), j = 1, ..., n_{bp}$$

where $FK_j$ is the forward kinematics corresponding with the $jth$ body point, namely $b_j \in \mathbb{R}^1$. A group of trajectories expressing the movements of the body points for a known grasping candidate $x_g$ is

$$X_b(t) = \{b_1(t), b_2(t), ..., b_{n_{bp}}(t)\}$$

where $n_{bp}$ is the number of body points, $X_b \in \mathbb{R}^{n_{bp} \times T}$, and $T$ represent the discrete time.

We specify an obstacle by a set of linear constraints as follows, [17]:

$$g_h(x) \leq 0, g_h \in L^m, m \in \mathbb{R}^3$$

A collision cost is defined as:

$$J_c = |C + 1|_1$$

where $C$ is the matrix containing costs based on the distance between body points and obstacles, $\delta^{-1}$ is a fixed value for setting the maximum available cost, $1$ is a matrix whose elements are equal to 1, and $/$ is the element-wise division operator. $J_c$ yields maximum costs on and inside the convex region representing an obstacle.

B. Torque Objective

We assume that the dynamic model of the robot is known, and we have the whole motion equations of the manipulator. To find a grasp at minimum effort, the “augmented” equation of motion is used. Thanks to this formulation, we obtain a set of motion equations describing dynamics of the robot with the object attached to its end-effector, [13]. The effort metrics are computed in terms of the $L_2$ norm of the joint torques, as follows:

$$J_T = \frac{1}{T} \sum_{i=1}^{T} \left( \frac{\tau(t_i) + \tau(t_{i+1})}{2} \Delta t \right)^2$$

C. Safe Objective

Assuming, as in [11-13] to know the model of both robot, and the object we want to manipulate. Using the “augmented” equation of motion, the inertia matrix of the robot plus object is retrieved.

$$\Delta_{TOT} = \Delta_{Robot} + \Delta_{Obj}$$

To obtain a safe grasp, the robot has to select the grasp configuration that yields minimum kinetic energy, [14] proposes to minimise the total mass along all the trajectory.

$$J_S = \frac{1}{v^2 \Delta TOT(x)}$$

where $v$ is the unity vector in the direction of motion.
\[ u^T (JJ^T)^{-1} u = 1 \] (6)

where \( u \) is the end-effector twist, and \( J \) the robot’s Jacobian. In order to maximise the manipulability ellipse along all robot post-grasp movement, we can minimise such quantity, \[ J_M = \int_{t_0}^{T} \frac{1}{a^2(t)} dt \] (7)

where \( a(t) \) is the average ellipsoid radius at time \( t \).

### III. Objectives Optimisation

By construction, each objective depends on the grasp configuration and yields best results with lower values. We therefore define a matrix \( J \in \mathbb{R}^{4 \times n_{gc}} \) with 4 rows and \( n_{gc} \) columns, number of grasp configurations, as follows:

\[ J = [J_C J_T J_S J_M]^T \] (8)

Then, we want to select the best \( c_{x_g} \) over the set of available grasp configurations:

\[ c_{x_g} = \text{argmin}_{g_{x_m}} W J \] (9)

where \( W \in \mathbb{R}^{4} \) is a matrix of coefficients for scaling objectives priority depending on the task, and normalise all magnitudes.

### IV. Experiments

The proposed approach is tested on two experimental setups. A simulated model of a Panda Robot, manufactured by Franka Emika, has been used in both experiments. It has 7 Degree of Freedom (DOF), and its kinematic model is provided directly by the manufacturer. In the first experiment, the robot is tasked with a pick and place operation of a cylindrical object, and all grasping configurations are hard-coded upon the surface of the object; the task in the second experiment is again a pick and place operation, but the robot has to grasp a cylindrical object and move it along a predefined post-grasp trajectory. A collection of 25 grasp configurations, upon the surface of the object, is given, Fig.2(a). They describe the end-effector’s pose (cartesian position and quaternion) to reach for performing a good grasp. The goal of the algorithm is to select the one grasping configuration for maximizing all objective together. In Fig.3(a), 3(b), 3(c), 3(d) are showed the objectives’ cost for each single grasping configuration; collision avoidance, manipulability, torque and safety respectively. The red color in the graphs represents the best grasping configuration when a single objective is taken into consideration. However, as a result of a lower value in the global optimisation process, the selected grasping configuration is the 21th, Fig.3(e).

#### B. Second Experiment

The second experiment aims to show how this technique can be successfully extended to different grasping configurations generator. In the first stage, the neural network based GPD algorithm generates a bunch of grasping candidates upon the surface of an orange mug made of plastic. Then, these configurations are passed to our optimisation algorithm which selects the best candidate according to the objectives’ values.

Fig.2(b) shows few of the 43 grasping configurations generated by GPD, and, like for the previous experiment, costs for all objectives are reported in Fig.4. Moreover, in Fig.4(e) the resulting best grasp selected by the optimisation process is shown in red.

### V. Conclusion and Discussion

This paper presents a novel predictive grasping approach that mixes four objective functions. The approach selects a grasping configuration from a set of feasible ones. This grasp yields the best values for collision-free, subsequent manipulative movements, manipulability, safety, and torque-efficiency.
Grasping Configurations

(a)
(b)
(c)
(d)
(e)

Fig. 3. In these pictures, the object’s cost for moving the object from an initial pose to a final goal is depicted for each objective. The normalisation technique poses average values at zero, assigns positive numbers for worst results, and negative numbers to minor costs. The red bar in all graphs shows the winning grasping configuration, when a single objective is taken into consideration Collision Avoidance, Manipulability, Torque, and Safety consecutively. Fig. 3(e) shows the result of the optimisation and the red bar is the global winning grasping configuration.

Grasping an object and manipulating it, typically, were studied in isolation in the previous works. For instance, [1] studied only how to form stable contacts between a robot’s hand and object surface. Although this approach is proper for laboratory purpose, it cannot be applied to real-world scenarios or can lead to very poor results. For example, the robot may collide with obstacles during manipulative movements because of the chosen grasp, or perform high-torque trajectory to perform the task. Our novel grasp selection approach foresees such situations and selects the best grasp among a set of given grasp configurations, which yields a collision-free movement, a torque-efficient trajectory, low impact on outside object and maximise manipulability ellipse.

We propose a methodology for merging all objectives together, and we provide some coefficients for tuning the optimisation process and weight more a specific objective.

Here, we assume the trajectory for collision-free movements of an object is planned regardless of the manipulator kinematics. In many real-world problems, this assumption is very useful and yields reduced complexities. For instance, a book trajectory can be provided by a learn from demonstration approach, or it can be assigned because of structural constraints (e.g. a sliding door). Hence, we built our approach based on the given object trajectory. Here, we considered the case where the set of grasp configuration is composed of a discrete amount of candidates. In future works, we will relax this assumption and we will make a continuous manifold around the grasp configurations. Last but not least, more sophisticated optimisation processes will be considered in the future to improve results.

REFERENCES


Fig. 4. The costs for moving the target object from its initial position to the goal are depicted in the first four figures. The object follows a predefined collision-free trajectory toward the obstacle without yielding any collision with it. However, depending on the grasping configuration, the robot can collide with an obstacle performing the predefined post motion. Left grasping configurations in Fig. 4(a) show this behavior, and they yield high-cost value. Of the 43 grasp candidates, the best solution is the 18th.