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Grasp quality measures based on point-cloud input

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Abstract

Developing robotic systems for selective harvesting is an important but challenging task due to the complicated nature of the task and the environment. Robotic selective harvesting comprises three major components: detection, grasping and manipulation. It is important in such a task is to embed perception capabilities within grasp planning and execution. To this end we have developed grasp quality measures that can be determined based on a 3D point-cloud. The grasp quality measures were integrated into a graspability map representation, which is an efficient method for representing grasp quality of various wrist poses about the object. To test measure validity, a physical and a matched virtual environment were developed. Grasp quality in both environments was measured and compared, and results show a high correlation between them (above 90%). This asserts the validity of the developed measures. An additional measure based on empirical analysis of human harvesting motion was integrated in the grasp quality measure to form a correspondence between computed graspability map and graspability maps based on the empirical study.

Keywords: automation, robotics, grasp quality measures, graspability maps

1. Introduction

Automation of selective harvesting, i.e., harvesting of ripe fruits, is a major research challenge due to the complexity of the environment, the high degree of perception uncertainty, and due to the need for soft handling of the harvested fruit. A robotic system for selective harvesting must have advanced perception capabilities along with multiple degrees of freedom and advanced motion control along with high precision, speed, and compliance. Additionally flexibility and adaptability to the needs of the different cultivars are required.

One of the major challenges in developing robotic harvesting systems is determining how to grasp, detach, and manipulate the fruit efficiently without causing damage to either the fruit or the plant (Muscato, 2005). Thus, grasp quality measures that can reflect the effect of the grasp pose (position and orientation of robotic endpoint) are important for both system design and online path planning of reach-to-grasp motion. Such measures that can be determined based on 3D sensory perceptions are important for online implementations and for encoring the measurements to the perception capabilities of the robotic system, i.e., the mechanical and geometrical properties of the grasp quality should be calculated directly from the point-cloud data.

Two classical grasp quality notions are the force closure and stability. A grasp is a force closure grasp when it immobilizes the object for forces or torques from arbitrary directions (Dizioğlu and Lakshiminarayana, 1984). The force closure quality can be measured based on the grasp wrench space which takes into account the set of all wrenches applied by the grasp contact points on the object (Nguyen, 1986). Grasp stability portrays the ability of the system to maintain its original state under external disturbances (Chinellato et al., 2003), i.e., if position and force errors caused by an external disturbance disappear after the disturbance disappears. One classical way of measuring grasp stability based on geometrical input, is by minimizing the distance between the object's center of mass, and the centroid of the polyhedron formed by the contact points (Kamon et al., 1996).

Grasp quality measures can be represented using graspability maps. Graspability maps offer an efficient representation of grasp quality, by storing wrist poses (position and orientation) that lead to successful grasps, about the object. The graspability maps are gripper and object specific. Different grasp quality measures can be integrated to form an adapted measure suitable for different grasp tasks. The process of computing graspability map is typically time-consuming, requiring several hours for a single object and gripper (Roa et al., 2011; Zacharias et al., 2007). Models of the object and hand used for grasp quality computation may be difficult to acquire or are based on various simplifying assumptions. Graspability maps have been suggested for the improvement of online grasp and path planning and as a tool for comparing, evaluating and designing grippers (Roa et al., 2011). An efficient method for graspability map generation based on point-cloud object representation has been suggested (Eizicovits and Berman, 2014). This method both encored the grasp quality measures in the agent's sensory perceptions and greatly expedites map generation increasing its utilization to both online and offline applications.

Two measures adapted from classical grasp quality measures and suitable for computation based on a point-cloud model were suggested: force closure angle (FCA) and the stability distance (SD)). This paper presents the validation process of these grasp quality measures. In addition we present an additional measured for graspability map adaptation to the task of apple harvesting. The remainder of the paper is organized as follows: section two presents the developed quality measures, section three details the validation process, and section four presents the results, section five presents graspability maps adapted for of apple harvesting and conclusions are presented in section six.

2. Grasp quality measures based on point-cloud data

The force closure angle (FCA) quantifies the force closure quality for two soft contacts p_i and p_j (Eq.   .), and is defined as:

$$FCA = \begin{cases} \dfrac{\vartheta - \max\left[\theta_j, \theta_i\right]}{\vartheta} & \theta_j, \theta_i > 0 \\ 0 & else \end{cases} \qquad (\ )$$

Where ϑ is the friction angle and θ_j, θ_i define the angle between the line connecting both contact points and the friction cone. The stability distance (SD) is defined as the 3D distance between the center of mass (c_m) and both contact points p_i and p_j , (Eq.   ). While the FCA depends only object shape and curvatures the SD is highly affected by the object dimensions and thus the SD measure should be normalized. Two normalization methods were suggested (Eq.), one with respect to the largest object feature (SDL) and the second with respect to the finger width (SDW_f).

$$SD = \frac{\left\| (c_m - p_i) \times (c_m - p_j) \right\|}{\left\| p_i - p_j \right\|} \qquad (\;)$$

where *cm* is the center of mass and × denotes the cross operation.

$$SDW_f = \begin{cases} \dfrac{abs\left(W_f / 2 - SD\right)}{W_f / 2} & SD \le W_f / 2 \\ 0 & else \end{cases} \; ; \; SDL = \frac{abs\left(L/2 - SD\right)}{L/2}$$

Grasp quality can be represented as a cropped average of the FCA and the SDL measures, (Eq.4).

$$Q_{FS} = \begin{cases} 0.5 \cdot FCA + 0.5 \cdot SDL & FCA > 0, SDL > 0 \\ 0 & else \end{cases}$$

3. Quality measure validation for apple harvesting

A physical and a virtual environment were constructed for validating the grasp quality measures. The physical environment included two objects a plastic apple and a cube, two tables, and a jaw gripper (HGPL-25-60-A, FESTO, Germany) mounted on a six degree-of-freedom (DOF) manipulator (UP6, MOTOMAN, Japan) (Figure 1). The cube was used to represent fruit that are not uniformly symmetrical. The virtual environment was developed in MATLAB (Version R2010B, Mathworks, USA) based on the exact dimensions of the physical environment, the objects, and the gripper. The task tested was to move the object from one table and place on another table, while maintaining grasp stability and minimizing damage to the object.

Figure 1: The physical environment, the robot, the gripper and the objects (plastic apple, cube).

Four graspability maps were developed, two for each object, one using only the FCA measure and another using the Q_{FS} measure. For each map, 10-15 wrist posed were manually selected such that different pose regions about the objects were represented. The grasp quality of these poses was tested in the physical environment using two different air pressures (10, 40 psi), to examine possible damage to the plastic apple.

The grasp quality in the physical environment was measured by augmenting four quality notions. If the task was successfully completed (Q_B) and motion was stable (Q_S) then two subjective grades (with discrete values from 1…5) quantified the damage caused to the apple (Q_{DMG}) and grasp appearance (Q_{EST}). The subjective grades were given by three robotic experts. The final quality (Q_{PHYS}) is given in Eq. 5:

$$Q_{PHYS} = \begin{cases} 0.1 \cdot \left(Q_{DMG} + Q_{EST}\right) & Q_B = 1, Q_S = 1 \\ 0 & else \end{cases}$$

The comparison between the final values in each environment (Q_{PHYS} and Q_{FS}) is conducted by summarizing the amount of trials in which the absolute value difference was smaller than 0.1 divided by the total amount of trials, Eq. 6.

$$Correlated\left(\%\right) = \frac{\sum_{i=1}^{trials} \begin{Bmatrix} 1 & abs\left(Q_{PHYS} - Q_{FS}\right) \le 0.1 \\ 0 & else \end{Bmatrix}}{\#trials} \cdot 100$$

4. Results

For apples the graspability maps based on the Q_{FS} and the FCA quality measures were similar due to the apple's symmetrical shape (Figure 2 (a)). Correlation (based on Eq. 6) between the physical (Q_{PHYS}) and virtual (Q_{FS}) environment was high (90%) for the low pressure value (Figure 2(b)). In case of the high pressure, the correlation was lower due to the damage caused to the plastic apple. Example of a grasp which caused damage to the fruit is given in Figure 2 (c and d).

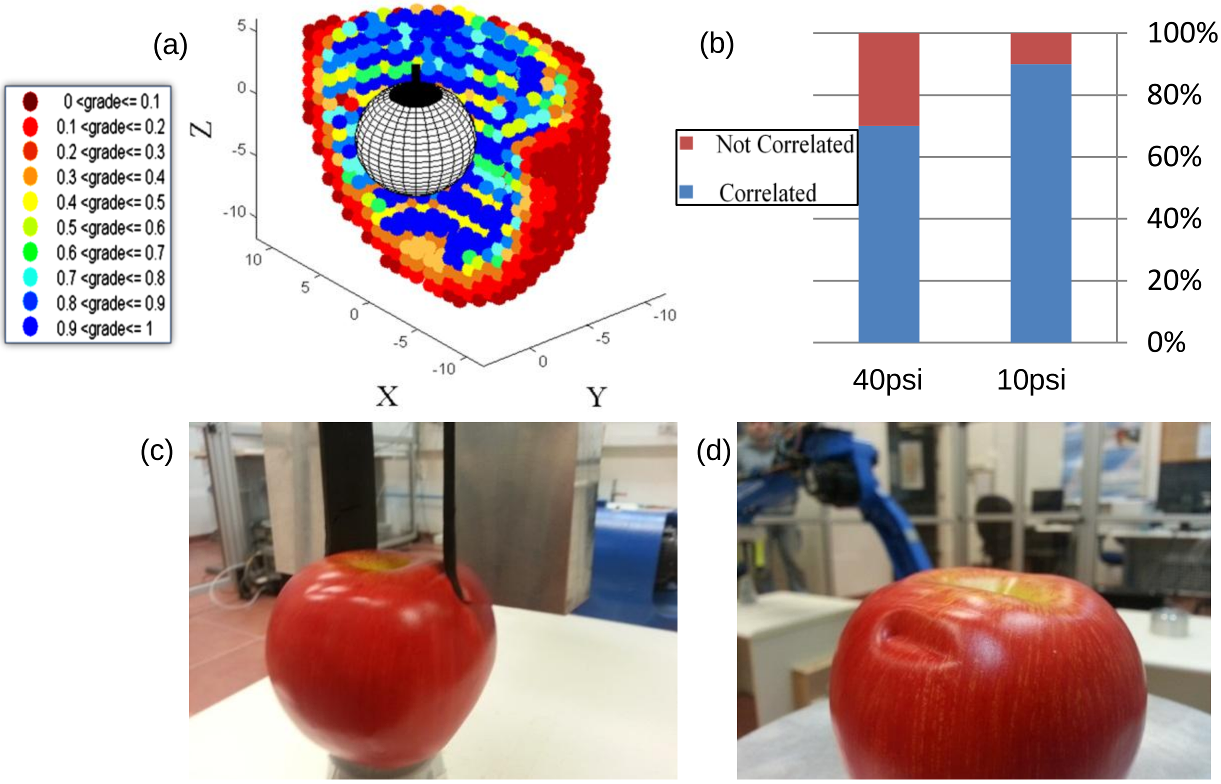

Figure 2: (a) Q_{FS} graspability map, values range from 0...1, where 0 indicates bad grasp and 1 good grasp. Only half the map is plotted for presentation clarity. (b) Correlation between Q_{PHYS} and Q_{FS} (c) Execution of a problematic grasp (d) Damage caused by the grasp.

The graspability map for the cube, based on the FCA measure, is symmetrical due to the symmetrical nature of the object (Figure 3(a)). The graspability map for based on the Q_{FS} measure, shows that grasps which are distant from the object's center-of-mass receive a lower quality (Figure 3(b)), as expected due to the addition of the SDL measure. For the Q_{FS} results were 100% correlated with Q_{PHYS}. For FCA results there was only 50% correlation with Q_{PHYS} (Figure 3(c)). This validated the need for the additional measure of stability for objects that are not uniformly symmetrical. An Example of grasp execution is given in Figure 3(d). No damage was caused to the cube since it is made of solid wood.

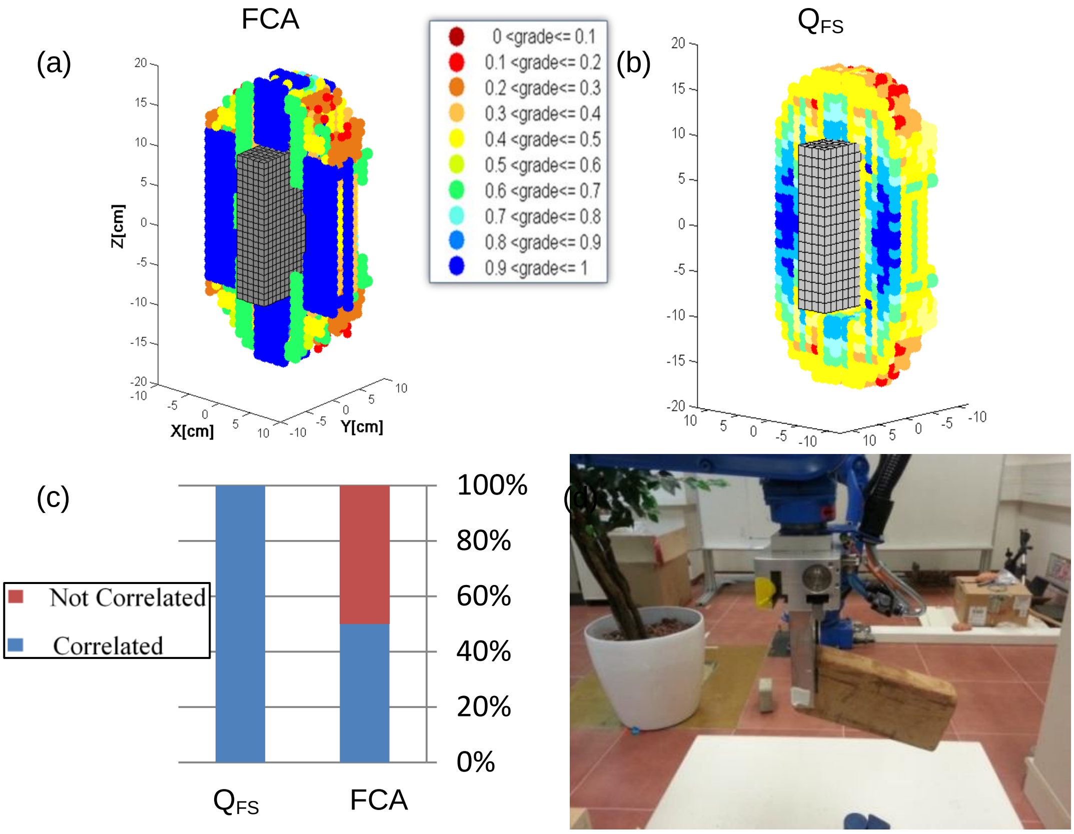

Figure 3: (a) FCA graspability map. (b) Q_{FS} graspability map, values (both a and b) range from 0...1, where 0 indicates bad grasp and 1 good grasp (c) Grade comparison between Q_{PHYS} and Q_{FS} (d) Grasp Demonstration.

5. Adaptation of the grasp quality measures for apple harvesting

Insights from graspability maps of human harvesting based on empirical measurements of human harvesting motion (Yaacobovich et al., 2012; Eizicovits et al., 2012) suggested that poses in the middle belt (equatorial belt, when the top located at the peduncle) and forward facing areas of the apples received high quality grades, and regions that could not be reached, e.g., those obscured by obstacles and the back side of the apple, received very low grades. Therefore a third quality measure was developed. The additional measure assigns high quality grades to Parallel Approach Orientations (PAO), i.e., when the gripper's fingers are in a plane perpendicular to the peduncle, and an augmented quality grade was calculated as a cropped average of all three measures, (Eq. 7).

$$Q_{FSP} = \frac{SDW_f + FCA + PAO}{3}$$

The PAO measure was added to account for the possibility of a third, passive finger, orthogonal to the two existing fingers for pressing against the peduncle mimicking the human harvesting grasp. SDW_f was preferred over SDL because the target manipulation (i.e., apple picking) requires that grasp stability be maintained throughout the motion, in which object orientation with respect to gravity changes. A graspability map based on empirical measurements and a map calculated based on Q_{FSP} are shown in Figure 4. The resemblance between the two maps is visually apparent.

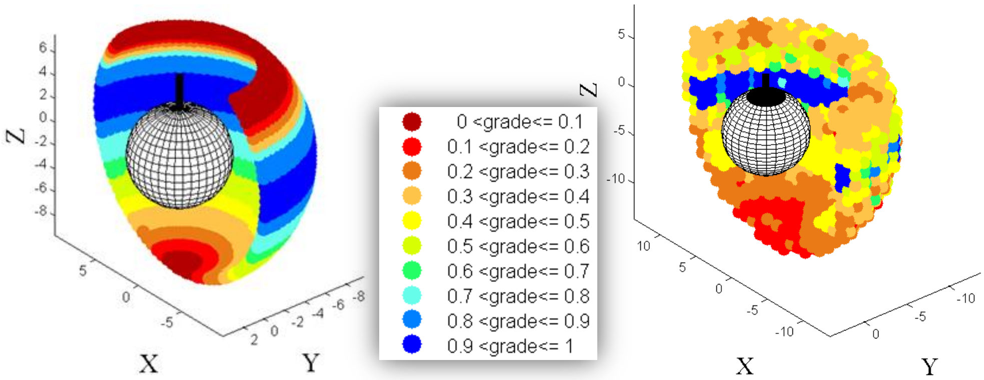

Figure 4: (a) Map based on empirical measurements. (b) Map based on FCA, (c) Map based on FCA and SDW_f, (d) Map based on all three measures (FCA, SDW_f and PAO).

6. Conclusions

This work presents the development and validation of grasp quality measures derived from 3D point-cloud data. The measures are based on mechanical and geometrical properties of the object, the gripper and in correspondence to the task and the environment. The quality measures were integrated in graspability maps and validated based on two different objects and a physical experiment. Results showed a high correlation between the maps developed in the simulation and the physical experiment (above 90%), which asserts the validity of the used quality measures. The grasp quality measures are then adapted to suit to the task of apple harvesting based on insights gained from an empirical study of human harvesting.

7. Acknowledgements

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