Grasp Quality Measures for Transferring Objects

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Abstract. There is a lack of quality indexes to evaluate grasps that are more likely to allow a hand-to-hand transfer of an object during a manipulation task. In order to overcome it, this paper presents a proposal of grasp transfer quality measures to evaluate how easy or feasible is that an object grasped by one hand could be grasped by another hand to perform a hand-to-hand transfer. Experiments were conducted to evaluate the proposed grasp transfer quality measures using different objects and the model of a real robotic hand.

Keywords: Grasping; Grasp Quality Measures; Transfer Manipulation.

1 Introduction

The use of dual-arm robots has been increasing in the field of object manipulation due to their advantages over one-arm robots. However, using two arms simultaneously can lead to other specific problems, such as the computation of suitable grasps to hold the object with both hands or to transfer the object from one hand to the other. This, in turn, generates the need of quality measures to evaluate and choose the best grasps to perform the transfer of an object.

The evaluation of grasp quality in a general sense has been already studied, a review of different quality measures proposed for grasp planning in literature is presented in [1]. In this review, the quality measures are classified into two groups: the first group is related to the contact points on the grasped object and the second group to the hand configuration. Besides, the combination of the quality measures from the previous two groups is also discussed to obtain good grasps for specific purposes. Nevertheless, despite the list of already proposed quality measures, none of them addresses the problem of measuring how good is a grasp for an object transferring, even when this is a very frequent action.

This paper focuses on the proposal of quality measures to evaluate grasps in order to determine how good they are in order to transfer objects from one hand to another using a dual-arm robot, as shown in Fig. 1.

The rest of the paper is structured as follows: Section 2 summarizes relevant literature on grasp quality measures. Section 3 describes the grasp transfer quality measures. Section 4 describes how the grasp transfer quality measures are

* Work partially supported by the Spanish Government through the projects DPI2013-40882-P and DPI2016-80077-R. F. Soler and A. Rojas-de-Silva partially supported by the Mexican CONACyT doctoral grants 410931 and 313768.

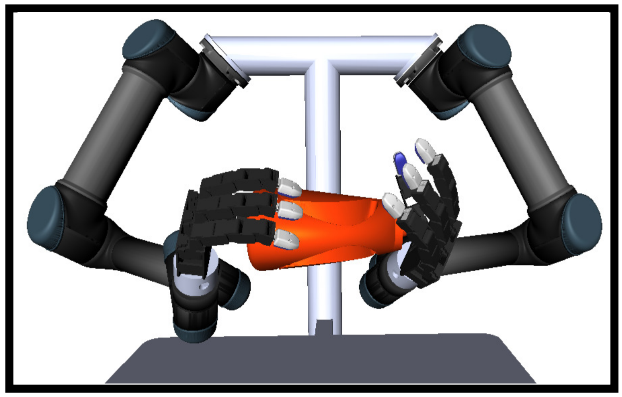

Fig. 1. Dual-arm robot (ADARS: Anthropomorphic Dual Arm Robotic System) about to perform a transfer of the object from the right to the left hand.

computed. Section 5 presents application examples of the grasp transfer quality measures and results. Section 6 presents the validation process, and Section 7 presents the summary and future work.

2 On the quality of a grasp

One of the fundamental property for grasps is force-closure (FC) [2]. A grasp is FC if the forces applied by the fingers on an object counteract any disturbance force or torque in any direction ensuring object immobility. The most common quality index is based on the FC property and was presented by Ferrari and Canny [3] and describes the largest perturbation that the grasp can resist under arbitrary disturbances or wrenches. This quality measure is directly associated with the Grasp Wrench Space (GWS), which is the set of all wrenches than can be applied on an object through unitary forces at the grasping contact points. The quality measure is defined by the radius of the largest ball centered at the origin of the wrench space and contained in the convex hull of the possible wrenches produced by unitary forces of the fingers on the object. If the origin is inside the convex hull, then the grasp is FC. To quantify the quality of a grasp, several approaches have been proposed, such as the largest sphere fitting inside the convex hull of GWS, the nearest distance from the origin to the border of the convex hull and the volume of the GWS [4]. The Object Wrench Space (OWS) [5] contains all the wrenches that can be produced by a set of unitary external disturbances forces acting on the surface of the object. The OWS is hardly used by grasp planners due to the high amount of time required for its computation which is a problem when many grasps have to be evaluated. Recently, an algorithm to speed up the computation time of a grasp quality metric based on OWS was presented in [6]. Another tool used to evaluate grasps based on wrench spaces is the Task Wrench Space (TWS) [7]. The TWS uses detailed information about the given task and incorporates all the perturbation wrenches that can be produced during a manipulation task. When the task information is not specified, such wrenches emerge from the interaction between the object and the environment, such as the gravity and object's acceleration due to arm movements.

Earlier works on grasping consider that the object being grasped is alone in the environment. An algorithm is proposed in which a grasp scoring function uses information about the environment around the object and the robot's kinematics to find feasible grasps in a cluttered environment [8]. Other quality function uses the sum of several measures to obtain grasps for each hand using a dual-arm robot [9]. The main task is to move an object from one position to another by transferring an object from one hand to another, so that at some moment of the task, a bimanual grasp is done, which is evaluated by another quality function based on the quality of each hand separately and the configuration of the robot when grasping the object at its start and goal configuration. The GWS can also be used to determine the quality of a bimanual grasp as in the case of single grasp. The computation and evaluation of grasps are done on-line as well as the search of no-collision motions which means that the search of feasible grasps is not limited to a set of pre-computed grasps since grasp poses are defined during the planning process [10]. The manipulability information is used as a quality measure [11] to find grasps that allow a high manipulability to manipulate large objects, since they limit the movement of a dual-arm robot when it is working as a closed kinematic chain.

3 Grasp transfer quality measures

The goal of the grasp transfer quality measures (TQ) is to determine how good is an initial grasp so that a second suitable grasp can be done on the same object in order to perform a hand-to-hand transfer. If the grasp being analyzed obtains a good quality for transferring, it means that: a) it allows good grasps for another hand to perform a transfer, or, b) it allows an easy finding of the grasp for the second hand. Both cases will be discussed below in this work.

It is desired that both the initial grasp before the transfer and the second grasp after the transfer are FC grasps in order to ensure object immobility during any manipulation. How good is a FC grasp in terms of the maximal perturbation it can resist in any direction is evaluated using a FC grasp quality Q [3], which is defined as

$$Q = \min_{\omega \in \partial W} \|\omega\| \tag{1}$$

where ∂W is the boundary of the convex hull of the set of wrenches produced by the applied grasping forces on the object boundary.

Some of the grasp transfer quality measures TQ introduced below in this work are based on Q.

3.1 Measure based on the individual maximum FC grasp quality reachable

This proposal is based on the maximum FC grasp quality that can be achieved on the object. The grasp transfer quality TQ_{MQ} of the initial grasp is a function of the maximum FC grasp quality that can be achieved by a second grasp when the object is already grasped by the first hand, i.e., the first hand acts an obstacle for the second hand to grasp the object and therefore not all the object surface is reachable for a second grasp. TQ_{MQ} is computed as

$$TQ_{\mathrm{MQ}} = \frac{Q_{\mathrm{p}}}{Q_{\mathrm{g}}} \tag{2}$$

where

Q_{p} is the maximum FC grasp quality that could be reachable by the second hand while the first hand is holding the object.

Q_{g} is the maximum FC grasp quality reachable on the whole object without any constraint.

$TQ_{\mathrm{MQ}} \in [0,1]$, being 1 the best case. Note that in practice the computation of TQ_{MQ} depends on the hands used, because when the first hand grasps the object its structure will make some points of the object to be unreachable by the second hand. These practical aspects and how Q_{p} and Q_{g} are computed are described below in Section 4.2.

3.2 Measure based on the grasp quality improvement

This proposal is based on the ratio of Q_{p}, previously defined, and the FC grasp quality of a initial grasp Q_{i} and is expressed as

$$TQ_{\mathrm{GQ}} = \frac{Q_{\mathrm{p}}}{Q_{\mathrm{i}}} \tag{3}$$

$TQ_{\mathrm{GQ}} \in [0,\infty]$. TQ_{GQ} has a simple interpretation: the greater the value of TQ_{GQ}, the better the chance to find grasps with the second hand that improves the quality of the initial grasp.

3.3 Measure based on the reachable area of the object surface

The area of the object surface is used to define this measure. The surface of the object that is reachable by a second hand (when the first hand is grasping the object) is used to compute the grasp transfer quality TQ_{SA} for the initial grasp. It is computed as

$$TQ_{\mathrm{SA}} = \frac{S_p}{S_g} \tag{4}$$

where

S_p is the reachable area of the grasped object surface when the first hand is grasping it.

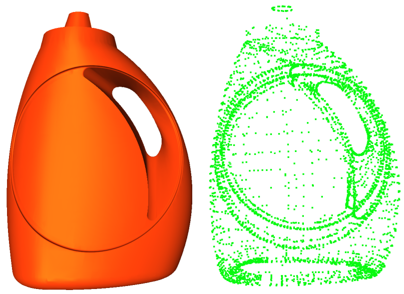

Fig. 2. Left: 3D object model. Right: Point cloud of the complete object P_g.

S_g is the whole area of the object surface.

$TQ_{\mathrm{SA}} \in [0,1]$, being 1 the best case. The computation of S_p and S_g is described in Section 4.3.

3.4 Measure based on the number of reachable points of the point cloud

This proposal is based on the number of points of the point cloud representing the object that are reachable by the second hand while the first hand is grasping the object. The grasp transfer quality TQ_{NP} is computed as

$$TQ_{\mathrm{NP}} = \frac{m}{n}, \quad n > m \tag{5}$$

where

m are the number of points reachable by the second hand when the first hand is grasping the object.

n are the number of points of the whole object model.

$TQ_{\mathrm{NP}} \in [0,1]$, being 1 the best case.

4 Implementation

This section describes how the grasp transfer quality measures are computed in practice. The object model is represented by a point cloud $P_g = \{p_i, i = 1, \ldots, n\}$ (Fig. 2), with high enough density, i.e. n must be large enough. The point clouds have been manipulated using The Point Cloud Library (PCL), which is a large scale open project for 2D/3D image and point cloud processing [12].

4.1 Obtaining the reachable part of the object

Given the point cloud P_g representing the whole object boundary, and an initial grasp for a given hand, the reachable part of the object is determined by the points of P_g that are not in contact nor enveloped by the hand and therefore could be considered as grasp points for the second hand. In practice, this set of points, denoted as P_p, is obtained as follows:

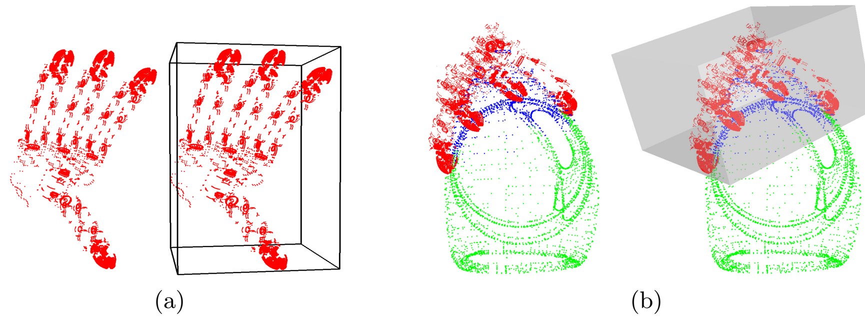

Fig. 3. (a) Left: P_h representing the grasping configuration of the Allegro Hand. Right: MBB-P_h obtained for a point cloud of the Allegro Hand representing the grasping configuration. (b) Left: P_h and P_g. The red points represent the Allegro hand, the green points represent P_p and the blue points are in contact or enveloped by the hand. Right: MBB-P_h is shown in solid to show its dimension.

1. The 3D hand model for a given grasp configuration is represented by a point cloud denoted as P_h (see Fig. 3a-Left).
2. Compute the *Oriented Minimum Volume Bounding Box* of P_h (for simplicity denoted as MBB-P_h henceforth) as shown in Fig. 3a-Right.
3. The reachable part of the object boundary is considered to be the set of points $P_p = \{p \in P_p \mid p \notin \text{MBB-}P_h\}$.

Fig. 3b shows an example of the resulting reachable part of an object.

4.2 Obtaining Q_{g} and Q_{p} using OWS

As stated above, OWS includes the wrenches that can be generated by normalized forces acting anywhere on the surface of the object. The general form of OWS is defined as

$$\boldsymbol{\omega} = \sum_{i=1}^{n} \alpha_i \omega_i \ \wedge \ \alpha_i \geq 0 \ \wedge \ \sum_{i=1}^{n} \alpha_i = 1 \tag{6}$$

where ω_i denotes the wrench that can be applied on the object at contact point $p_i \in P_g$.

This is equivalent to the convex hull given by

$$OWS = ConvexHull(\bigcup_{i=1}^{n} \{\omega_i, ..., \omega_n) \tag{7}$$

The metric used to evaluate the grasp FC grasp quality Q is given by Eq. (1). Therefore, Q obtained from OWS represents the maximum FC grasp quality that a grasp can achieve on the whole object, i.e., Q_{g}. Similarly, Q_{p} represents the

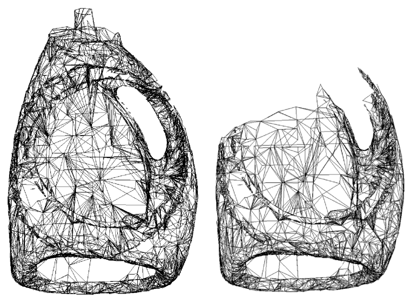

Fig. 4. Triangular mesh models M_g and M_p of a detergent bottle computed from P_g and P_p respectively

maximum FC grasp quality that a grasp could achieve on the reachable part of the object while the first hand is holding the object.

4.3 Defining S_g and S_p

Since the representation of the objects is given by point clouds, and there is no guarantee of a uniform distribution of the points, it is used the Greedy Projection Algorithm (GPA) [13] to create triangular mesh models representing the object surfaces from unorganized point clouds. The area of a triangular mesh model (M) is computed by

$$S = \sum_{j=1}^{n_t} \mathcal{A}_j \tag{8}$$

where
$\mathcal{A}_j$ is the area of the j-th triangle of M.
n_t is the total number of triangles.
$\mathcal{A}_j$ is obtained by the Heron's formula considering the lengths of its three sides

$$\mathcal{A}_j = \sqrt{s(s-a)(s-b)(s-c)} \tag{9}$$

where
a, b, c are the lengths of the triangle edges.
$s = \frac{a+b+c}{2}$ is the semiperimeter of the triangle.

From the point clouds P_g and P_p of the object, their respective triangular mesh models M_g and M_p are obtained. Fig. 4 shows an example of the triangular mesh model computation of a detergent bottle considering the grasp shown in Fig 3b.

Once M_g and M_p have been created, their respective areas S_g and S_p are computed using Eq. (8).

(a) (b)

Fig. 5. (a)Allegro Hands. (b) Objects used for experimentation: a detergent bottle, a cookie box, a feeding bottle, a coffee mug and a milk box.

5 Application Examples

The experimental verification of the four proposed TQ was done using two robotic Allegro Hands from Simlab (Fig.5a) which have 16 degrees of freedom (DOF), 4 fingers and 4 independent joints per finger.

Five objects with different sizes and shapes have been used for the evaluation of the proposed TQ (Fig 5b). The object models were obtained from GrabCAD and Autodesk 123D repositories [14,15], which offer a large variety of CAD models of object with different shapes and sizes. All the selected objects can be grasped and handled by one hand.

The computation of the grasps for each object was done using the robotic simulation toolbox Simox [16] that allows the generation of random grasps around free-flying objects satisfying the FC property. Eq. 1 was used for the FC grasp quality computation for each individual grasp.

The values of each TQ for each object are obtained as follows:

1. Compute a set of 30 grasps using the right hand, $\mathcal{G}^r = \{g_1^r, \ldots, g_j^r\}$ $j = 1, \ldots, 30$. Fig. 6 shows an example of a random grasp for each object used in this work.
2. Compute a set of point clouds, $\mathcal{P}_p = \{{P_p}^1, \ldots, {P_p}^j\}$ $j = 1, \ldots, 30$, representing the reachable part of the object for each grasp g_j^r.
3. Compute OWS.

The four TQ described by Eq. 2, 3, 4 and 5 were computed for each $g_j^r \in \mathcal{G}^r$ using P_g, OWS and $\mathcal{P}_p$.

Table 1 shows the results of the grasp transfer quality measures of 10 randomly chosen grasps of one particular object.

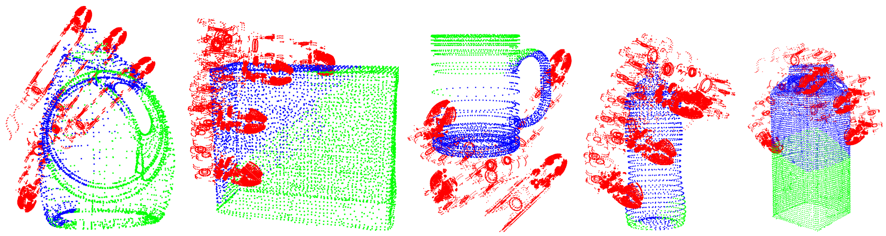

Fig. 6. Example of a random grasp for each object. Red points represent the grasping hand pose P_h. Green points compose the point cloud that represents the reachable part of the object P_p. Blue points are the points that are in contact or enveloped by MBB-P_h.

Table 1. Results of TQ for 10 grasps computed on a detergent bottle and the indices TQ^* used for the correlation analysis.

Detergent Bottle	TQ				TQ^*		
Grasp	TQ_{MQ}	TQ_{GQ}	TQ_{SA}	TQ_{NP}	TQ^*_{MQ}	TQ^*_{GQ}	TQ^*_{RS}
1	0.991	3.901	0.767	0.761	0.91	3.28	0.76
2	0.986	3.772	0.705	0.743	0.9	3.48	0.73
3	0.984	3.168	0.69	0.719	0.93	2.99	0.71
4	0.983	3.57	0.662	0.495	0.9	3.52	0.608
5	0.976	3.549	0.644	0.601	0.9	3.49	0.73
6	0.975	3.294	0.639	0.675	0.85	3.19	0.51
7	0.975	2.944	0.633	0.617	0.78	2.792	0.708
8	0.973	3.6	0.631	0.566	0.68	3.546	0.756
9	0.973	2.438	0.629	0.394	0.83	3.25	0.704
10	0.972	3.122	0.628	0.61	0.73	2.21	0.706

6 Validation

An auxiliary index TQ^* for each proposed grasp transfer quality TQ will be computed in order to perform a correlation analysis between the values of TQ obtained for the right hand and the values of TQ^* obtained for the left hand (shown in Table 1). The indices TQ^* were computed as follows:

1. Compute a set of 500 grasps using the left hand, $\mathcal{G}^l = \{g_1^l, \ldots, g_i^l\}$ $i = 1, \ldots, 500$, in the same way as the set $\mathcal{G}^r$ around the whole object.
2. Select the grasp g_i^l with the best quality $Q^l_{g_{max}}$.
3. For each grasp g_j^r:
   (a) Remove the grasps in $\mathcal{G}^l$ that are in collision with MBB-P_h in order to obtaining another set of grasps $\mathcal{G}_j^l = \{g_i^l \in \mathcal{G}^l \mid g_i^l \text{ compatible with } g_j^r\}$.
   (b) Select the grasp $g_i^l \in \mathcal{G}_j^l$ with the best quality $Q^l_{p_{max}}$.

Table 2. Correlations between TQ and TQ^*

	Correlations %			
Object	TQ_{MQ}-TQ^*_{MQ}	TQ_{GQ}-TQ^*_{GQ}	TQ_{SA}-TQ^*_{RS}	TQ_{NP}-TQ^*_{RS}
Detergent Bottle	76.09	80	81.86	81.31
Coffee Mug	85.81	72.52	66.98	64.50
Cookies Box	55.39	95.69	77.52	78.34
Feeding Bottle	97.94	91.16	60.47	57.57
Milk Box	80.66	81.70	76.01	77.21

(c) Compute the TQ^* as
- For TQ_{MQ}

$$TQ^*_{\mathrm{MQ}} = \frac{Q^l_{p_{max}}}{Q^l_{g_{max}}} \tag{10}$$

- For TQ_{GQ}

$$TQ^*_{\mathrm{GQ}} = \frac{Q^l_{p_{max}}}{Q^r_j} \tag{11}$$

where Q^r_j is the FC grasp quality of g^r_j.
- For TQ_{SA} and TQ_{NP}

$$TQ^*_{\mathrm{RS}} = \frac{c}{m} \tag{12}$$

where c is the number of grasps in $\mathcal{G}^l_j$ and m is the number of grasps in $\mathcal{G}^l$.

Now, the correlation between TQ and TQ^* was computed using the Pearson correlation coefficient which is a regression measure that quantifies the variation between two variables and is obtained as:

$$CORR(\%) = \frac{\sum xy}{\sqrt{(\sum x^2)(\sum y^2)}} \tag{13}$$

where x represents the value of TQ and y represents the value of TQ^*.

Table 2 shows the correlation percentage between the theoretical values obtained with TQ and the real values obtained with TQ^* for different objects.

The results show a high correlation between TQ_{MQ} and TQ^*_{MQ} for most of the objects used and only one object shows a moderate correlation (coffee mug).

The correlation between TQ_{GQ} and TQ^*_{GQ} shows the best results obtaining correlations above 80% for most objects.

The correlation between TQ_{SA} and TQ^*_{RS}, which is similar to the correlation between TQ_{NP} and TQ^*_{RS}, shows the lowest correlation (under 80% for most

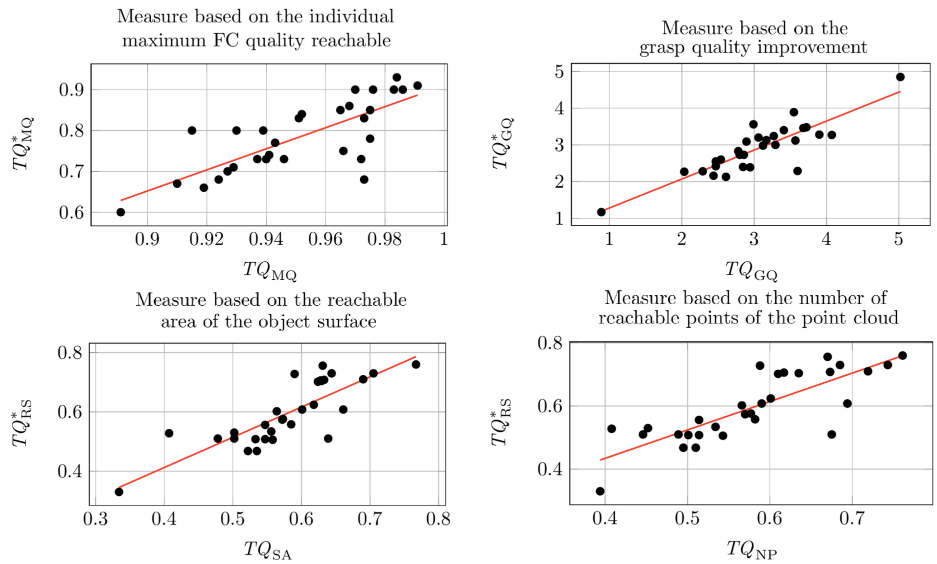

Fig. 7. Scatter diagram for each grasp transfer quality measure for 30 grasps using the detergent bottle (Fig. 2).

objects), three objects (detergent bottle, cookie box and milk box) have high correlation and two objects (coffee mug and feeding bottle) have moderate correlation. Fig. 7 shows the scatter diagram of the correlation analysis for each TQ for 30 grasps using the detergent bottle.

7 Summary and future work

This work proposes different grasp transfer quality measures to evaluate grasps with the purpose of transferring objects from one hand to another using a dual-arm robot or more than one single-arm robot. These grasp transfer quality measures can determine whether a initial grasp on an object is good enough so that another hand can easily find a good grasp on the same object. This may help to choose grasps that are more likely to allow transfer of objects. The validation results showed a high correlation between TQ and TQ^* for most objects.

The results validated in this paper were obtained for one particular hand. Future work includes the validation of the grasp transfer quality measures using more objects with different shapes and sizes and other different robotics hands.

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