Potential Grasp Robustness for underactuated hands: New heuristics and uncertainty considerations

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***Abstract*—The Potential Grasp Robustness (PGR) approach introduces a less conservative metric for the case of underactuated hands. By considering several states of each contact point, the PGR provides a way to evaluate manipulative finger limbs configurations for underactuated hands. This metric is computationally heavy due to its combinatorial nature, which is a shortcome for complex object shapes and multifingered hands. In this work we address this limitation, proposing two new heuristics and comparing them to the previously proposed ones. The heuristics proposed in this work consider: (i) a larger combination of states than previous heuristics and (ii) a data-driven heuristic that analyzes a large set of executed grasps and finds the most common combinations of contact points that lead to an accurate estimation of PGR. We evaluate the new heuristics in two types of underactuated hands, considering the trade-off between the accurate estimation of the heuristics and their computational complexity. In addition, the PGR metric does not consider the uncertainty in object pose, which is important for using the metric on real applications. By considering uncertainty in the computation of PGR, we show that the grasp selection differs from the maximization of the conventional PGR.**

***Index Terms*—grasp metric, underactuated hands, robustness to pose uncertainty, PGR heuristics**

I. Introduction

In the literature, many metrics that evaluate the quality of the grasp have been proposed [1], however these metrics have been developed for fully-actuated hands.

Underactuated hands [2] are becoming increasingly important due to their low-cost, intrinsic compliance and high grasping performance with unstructured objects [3], [4].

Recently, metrics have been developed that take this type of hands into account [5]. One of these metrics is the potential grasp robustness (PGR), which will be the one focused on this work.

This metric is computationally heavy because it grows exponentially with the number of contact points, and assuming that each contact point can only be in one of three states[1], there will be 3^{n_c} possible combinations for the contact point states. To make the calculation of the PGR metric less heavy, Pozzi et al. in [6] developed two heuristics that choose only a subset of these combinations. In this work two more heuristics will be proposed and their effectiveness and efficiency will be tested.

The calculations of these metrics are made in a simulation environment, so the pose of the object relative to the hand is known without any uncertainty.

To evaluate the grasp metric in realistic conditions, uncertainty in the object pose should be considered. For instance, the pose detection with respect to the hand by applying vision-based techniques suffers from intrinsic uncertainty due to noise in the sensor and also the arm and hand joints may add more uncertainty to the grasp execution. Therefore, there is always the likelihood that the grasp will not be stable for a slight change in pose. Thus, it is necessary to choose a grasp that is good not only in the ideal pose but in its surroundings, in order to overcome this uncertainty problem.

For this purpose, in this work it will be proposed one way to choose the best object's pose taking into account the index of PGR metric and maximum variation that the pose can have without compromising the quality of the grasp.

II. Potential Grasp Robustness

Contact forces are the forces applied by the hand on the contact points to prevent object movement through external wrenches.

Bicchi in [7] has defined a subspace of controllable internal forces, which can be modified by the actuators, and he also developed a method for evaluating force closure properties based on these controllable internal forces. Since the contact force distribution is indeterminate and the static equilibrium equations does not define a unique solution, Bicchi replaced the rigid body kinematic assumption for the contact points with a lumped linear elastic stiffness model.

The Potential Contact Robustness (PCR) metric relies on the elastic stiffness model and computes, for each contact point, the distance which the contact force is from violating the frictions constrains. The PCR index is the shortest distance obtained from all contact points. Even though PCR considers elastic stiffness for the contact points, in [8], Prattichizzo et al. claim that the PCR is too conservative because it considers that all contact points needs to apply a contact force to the object for a grasp to be stable. This may not be true because not every contact point needs to apply a force to the object to guarantee the grasp stability.

To obtain a more realistic metric than PCR, the PGR was developed. In [8] PGR was introduced, which affirms that each contact point can be in one of the following three states:

[1]Which hold or not some Coloumb friction cone constraints

- State 1: The constraints in (1) and (2) are satisfied, and therefore the contact force can be transmitted in any direction.
- State 2: Only the constraint (1) is satisfied. Therefore, the contact force only can be transmitted in the normal direction of the contact point.
- State 3: None of the constraints (1) and (2) are met, so the contact point is considered to be detached, and the contact force will not be transmitted.

The unilateral constraint is given by (1) and the Coulomb friction constraint by (2), where $\lambda_{i,n}$ is the normal component of the contact force (λ_i), $\lambda_{i,t}$ and $\lambda_{i,o}$ are the its tangential components and μ_i is the friction coefficient of the contact point.

$$\lambda_{i,n} \geq 0 \tag{1}$$

$$\sqrt{\lambda_{i,t}^2 + \lambda_{i,o}^2} \leq \mu_i \lambda_{i,n} \tag{2}$$

A. Heuristic H2

H2 is based on the theoretical result on the minimum number of contact points that satisfy constraints (1) and (2) (State 1 - Single Point with Friction (SPwF) [9]). Since it was shown in [10] that three SPwF points achieve a force closure grasp, the heuristic H2 assume that the hand can only transmit force through three contact points to the object. Thus, three contact points are considered as attached (set in State 1), and the rest of them are considered as detached (set in state 3). This assumption disregard all the possible combinations with State 2, reducing largely the computational complexity.

The number of combinations performed in this heuristic becomes $\binom{n_c}{3}$ instead of 3^{n_c}.

III. New heuristics for PGR

A. Heuristic H3

The heuristic 3 was developed based on the heuristic H2, but considering the state 2 as well on the set of combinations. As in H2, H3 has a fixed number of points on state 1. The remaining points are considered to be either in state 2 or 3 (as opposed to H2, that only consider the state 3). By considering states 2 and 3 in the remaining points, it is expect to obtain more accurate values, i.e., more identical to those obtained by brute force (BF). In subsection V-A, the accuracy of this heuristic indices is discussed.

The number of combinations evaluated by this heuristic is $\binom{n_c}{3} \cdot 2^{n_c-3}$, which is bigger than the combinations evaluated by H2.

B. Heuristic H4

The idea behind Heuristic H4 is to analyze a large set of grasps executed in simulation, and counting the total sum of contact points at each state, using the underactuated hand of the robot Vizzy [11]. Thus, it was noted that the majority of the executed grasps had (2,2) or (2,3) contact points in state (1,2), respectively. The rest of the remaining contact points were in state 3.

The number of combinations evaluated by this heuristic is $\binom{n_c}{2} \cdot \left(\binom{n_c-2}{2} + \binom{n_c-2}{3} \right)$.

IV. Robustness to the uncertainty object's pose

Grasp quality metrics are computed by taking into account the characteristics of well-defined contact points between the object and the hand. When the best-simulated grasp is chosen and is applied to an object in the real-world, the experimental grasp is rarely the same as the one simulated. This is due to the object pose uncertainty obtained by vision-based systems and therefore the object is always grasped in the vicinity of the object pose chosen in simulation, thus the utility of metric evaluation is reduced because the grasp may be inadequate in the surrounding of the simulated object's pose.

Current research into the uncertainty of an object's pose has made several advances. Some ways to reduce/eliminate this uncertainty include developing grasp control methods, grasp quality evaluation, pose error estimation and grasp task space [12].

There are some methods to more accurately estimate the pose of the object. Chalon et al. [13] used a particle filter to estimate the object's pose. Zhang and Trinkle [14] also used a particle filter to estimate the pose even when the object was hidden, not only with the help of vision-based system but also integrating tactile sensor data. Moreover this filter also estimates physical parameters such as the friction's coefficient. Weisz and Allen [15] have developed an indicator that assesses if the grasp likelihood respects the force closure property, considering a certain uncertainty in the pose. The estimation of the likelihood is done in an empirical way, counting the number of grasp that succeeded over the number of trials. Kim et al. [16] [17] considers the effects of objects dynamic and pose uncertainty on the performance of estimating grasps success through real experiments on a robotic hand.

This work proposes a new metric that combines the index obtained by PGR and the the maximum pose difference (between the deterministic one and the pose with uncertainty) that maintains the same value of PGR. This can be seen as the robustness of PGR with respect to pose uncertainty.

Let the position axes be defined as follows: Z-axis is the axis parallel to the normal of the palm, and X and Y axes are perpendicular to each other and to the Z-axis.

To compute the maximum robustness of PGR to position uncertainty for an object that can move on a three dimensional space (e.g. precision grasps), first, one should find the maximum variation on each axis (X, Y, Z-axis). Then, with the maximum variation in each axis computed, the maximum robustness of PGR to position uncertainty can be given by:

$$PosVar = \sqrt{PosVarX^2 + PosVarY^2 + PosVarZ^2} \tag{3}$$

where $PosVarX$, $PosVarY$ and $PosVarZ$ are the maximum variation that the grasp can resist on the X, Y and Z position axis, respectively, without compromising the grasp quality.

For power grasps, the hand wraps around the object against the

palm, and therefore the position uncertainty on the Z-axis is not very relevant. Thus, to compute the maximum robustness of PGR to position uncertainty, it is only worth considering the maximum variation on the X and Y-axis. The formula for this computation can be expressed as

$$PosVar = \sqrt{PosVarX^2 + PosVarY^2} \tag{4}$$

The computation of the maximum variation on an axis can be done as follows: First, it is defined a $VarStep$ (in this work, it is set to 3mm). Then two new positions are computed, which are the initial position displaced by $VarStep$ in the positive and negative axis direction. After that, the PGR metric for these new positions is calculated, and it is checked if any of them is less than a minimum value that depends on the initial PGR (stopping condition): if so, it is found the variation the axis can tolerate and the algorithm ends; otherwise the algorithm computes new positions that are shifted by $\pm\ k\ \cdot\ VarStep$ of the initial position (k is the number of the current iteration) and continues until the stopping condition is verified. The stoping condition is given in (5).

$$PGR_{curr_+} < PGR_{init} - \psi \quad || \quad PGR_{curr_-} < PGR_{init} - \psi \tag{5}$$

Where PGR_{curr_+} and PGR_{curr_-} are the PGR index computed when the object position on the axis is displaced by $k\ \cdot\ VarStep$ along the positive and negative direction, respectively. The PGR_{init} is the PGR index for the initial object position, where there isn't any pose uncertainty in any axes.

In the experiments of this work, the threshold (ψ) was set to 3. This value was chosen in order to consider only the most stable grasps, therefore a stable grasp is the one that had at least a PGR close to the initial PGR (PGR_{init}), grasps with significantly lower PGR values are not considered. Values close to this threshold could eventually be chosen.

The pseudo-code to compute the maximum variation in a generalized A-axis can be seen in algorithm 1. Where $InitPos$ is the initial 3D position of the object and $InitPosA$ is the initial position of the object in A-axis, $VarStep$ is the sampling interval at which the object position is shifted in A-axis, thus obtaining $CurrPosA_+$ and $CurrPosA_-$ position if this shift is done along the positive or negative axis direction, respectively. The current object position in 3D is given by $CurrPos_+$ and $CurrPos_-$ when it is shifted along the A-axis to the $CurrPosA_+$ and $CurrPosA_-$ position, respectively. The maximum variation in the A-axis is then given by $PosVarA$.

The computation of the maximum variation in the object's rotation is identical to the one of the position although no difference exists for power grasps, i.e., for all grasps the maximum variation of rotation is represented by:

$$RotVar = \sqrt{RollVar^2 + PitchVar^2 + YawVar^2} \tag{6}$$

where $RollVar$, $PitchVar$ and $YawVar$ are the maximum variation that the grasp can resist on the Roll, Pitch and Yaw angles, respectively, without compromising the grasp quality. Similar to the computation of the maximum position variation of each axis, the same idea was applied to the maximum rotation variation for each angle. This means that algorithm 1 was applied, but instead of varying the position, the rotation angles were varied (in this case, a $VarStep$ is defined to 1.6 degrees).

Thus, to choose the best grasp for a given object, it is proposed an index that takes into account the PGR index and the maximum variation of position and rotation. This index is given by:

$$PGR_{PoseVar} = PGR \cdot PosVar \cdot RotVar \tag{7}$$

V. Experiments and discussion

All experiments were developed in the MATLAB toolbox for Underactuated and Compliant Hands called Syngrasp [18].

A. New heuristics for PGR

1) Vizzy Hand: To test whether these new heuristics are capable of reproducing identical results to those obtained with brute force or at least for most grasps, these new heuristics were tested on a set of 138 grasps for Vizzy's hand [11] and compared to brute force and Pozzi et.al. heuristic H2 [6].

To evaluate the most adequate heuristic, we should consider the trade-off between accuracy (when compared to ground-truth values obtained by brute force computation) and computation time. On one hand, in the case of brute force, the PGR value is very accurate but requires a long time to be computed. On the other hand, the PGR values computed by the heuristic H2 are not accurate but the computation time is low. There are two ways to compare and analyze the performance of these new heuristics. One of them evaluates if the PGR indices are the same or similar (showing the same tendency) to the values obtained by brute force.

To evaluate whether the PGR values of the new heuristics are equal/similar to those of the brute force, the average percentage errors between the brute force value and each heuristic of the set was calculated.

The average percentage errors for heuristic H2, H3 and H4 are, respectively, 78.86%, 52.94% and 6.68%, on the other hand, 6.06%, 9.09% and 89.39% of H2, H3 and H4 indices are equal to those of BF .

Thus, by analyzing these results it can be concluded that the best heuristic to predict the quality of the grasps is H4, being able to successfully predict approximately 90% of the brute force indices of the set. For heuristic H3, although there are few indices equal to those obtained by brute force, it can still predict with some certainty the quality of the grasp. Regarding H2 heuristic, it is possible to conclude that this heuristic can rarely obtain indices equal or similar to those obtained by the brute force.

In Fig. 1 it is possible to see the PGR indices for the brute force and for each of the heuristics. Only a set of 60 grasps is shown so that the graphic is more noticeable.

Algorithm 1 Algorithm to compute the maximum position variation in a generalized axis A

procedure MAXPOSVARA($InitPos$)
  Compute: PGR_{init}
  Define a variation step: $VarStep$
  Define a threshold: ψ
  Define the iteration number: $k = 1$
  $CurrPosA_{+} \leftarrow InitPosA + VarStep$
  $CurrPosA_{-} \leftarrow InitPosA - VarStep$
  Compute: $PGR_{curr_{+}}$ ▷ in $CurrPos_{+}$ object position
  Compute: $PGR_{curr_{-}}$ ▷ in $CurrPos_{-}$ object position
  while $PGR_{curr_{+}} < PGR_{init} - \psi \quad || \quad PGR_{curr_{-}} < PGR_{init} - \psi$ **do**
    $k \leftarrow k + 1$
    $CurrPosA_{+} \leftarrow InitPosA + k \cdot VarStep$
    $CurrPosA_{-} \leftarrow InitPosA - k \cdot VarStep$
    Compute: $PGR_{curr_{+}}$
    Compute: $PGR_{curr_{-}}$
  $PosVarA \leftarrow 2 \cdot (k - 1) \cdot VarStep$

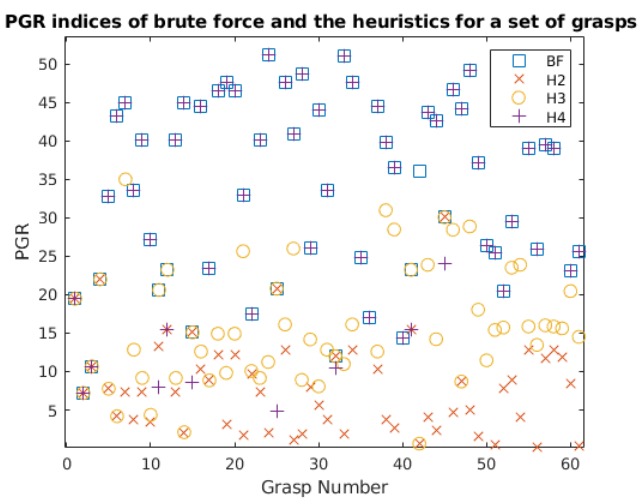

Fig. 1. BF and Heuristics indices for a set of 60 grasps

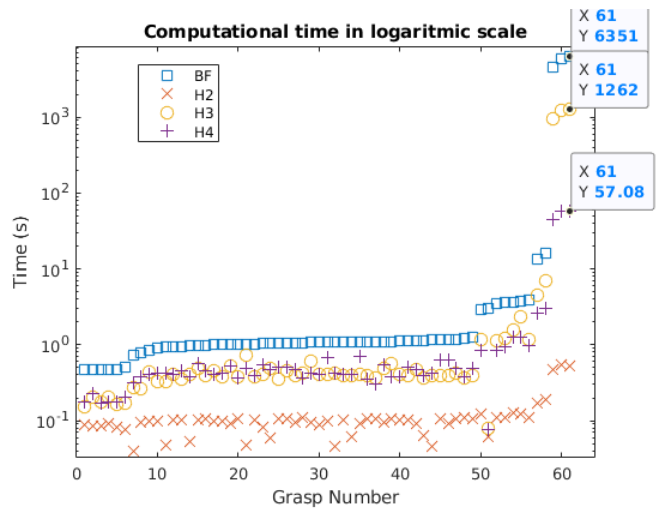

Fig. 2. Time that BF and Heuristics indices took to be computed for each grasp

As explained in section III, only a few combinations of the contact point's states are considered in heuristics H3 and H4, thus taking less time to be computed than brute force.

In Fig. 2 is visible the time that each of the indices took to be calculated. Where it can be observed that for times when BF takes about 1 second, H3 and H4 takes about half that time. Also, it can be seen that for a 13 contact points grasp, BF takes 6351 seconds while H3 takes 1262 seconds (19.87% of BF time) and H4 takes 57.08 seconds (0.90% of BF time).

In Fig. 3 it is shown the ratio between each heuristic computational time and BF time. It is observed that the heuristic that takes on average less time is H2. For few contact points, heuristics H3 and H4 take almost the same time, but as the number of contact points increases, H4 becomes faster than H3.

2) Human Hand: In order to see if these new heuristics are able to predict with success the indices obtained through brute force, the average percentage errors and standard deviation where computed. For heuristic H2, H3 and H4, the average percentage errors are, respectively, 16.3%, 9.4% and 14.0%, and the standard deviation are 18.7%, 17.7% and 10.0%. The heuristic H3 was the best one to identify the grasp quality, but it still takes some considerable time to be computed. Although the heuristic H4 is less accurate than H3, still takes less time to compute than H3.

B. Robustness to the uncertainty object's pose

In this section, we will choose the best power grasp for a 60 mm edge cube to be grasped by Vizzy's robotic hand. This choice will be made by the index introduced in section IV, which takes into account the greatest variation in the pose that the grasp can have and yet be considered stable.

To find out the position of the object that leads to the best grasp, we decided to make a grid with values from the

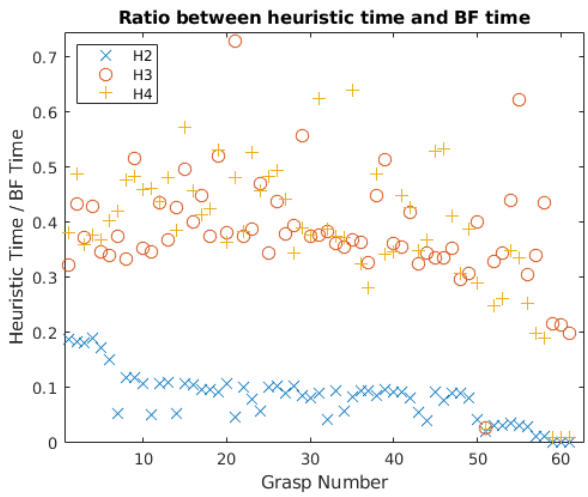

Fig. 3. Ratio between heuristic time and BF time

object's center where its position on the X and Y axis is varied. For each of these positions, the grasp was executed and then evaluated with the $PGR_{PoseVar}$ index. The best position of the object's center is one that maximizes the PGR index and the variation in the position and rotation, i.e., the $PGR_{PoseVar}$ index.

It is important to note that we are talking about a power grasp, so the object's position on the Z-axis remains constant to keep one face of the cube in contact with the palm.

In Fig. 4 is shown the PGR index as a function of the position (X and Y) of the center of the object. Where it can be seen that the position (71, -5) maximizes the PGR index and the maximum variation the pose can have and therefore it is the best choice for the object's position to be grasped. Adjacent positions of the X-axis position ((68, -5) and (74,-5)) also show good PGR index and good variation robustness, where, eventually could also be chosen.

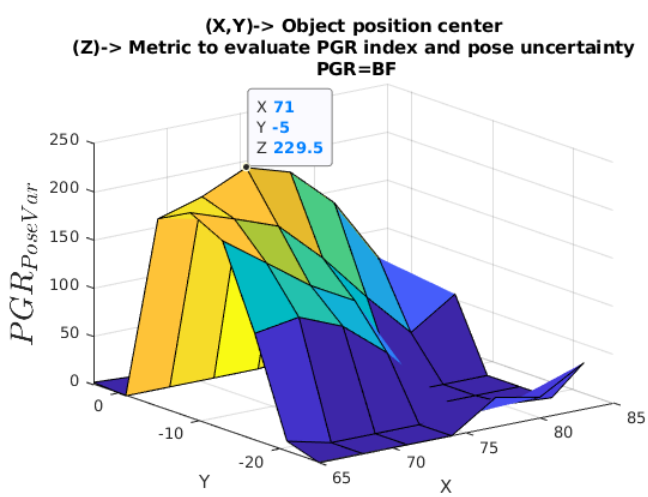

Fig. 4. $PGR_{PoseVar}$

In Figs. 5,6 and 7, it can be seen that the position (83, -5) holds the highest PGR index (49.56) of all positions tested, but the robustness concerning pose's uncertainty is not very large (6.7 mm for position and 0.19 radians for rotation). At position (83, -9) the robustness to pose's uncertainty is sufficient (18.25 mm in position and 0.24 radians) but the PGR index is a little low (around 16.16).

Thus, the choice of the best object's position to be grasped passes through a tradeoff between the best PGR index with the largest variation that the pose can have. Therefore the position (71, -5) turns out to be the one with the best PGR (40.22) and the largest variation in pose (18.97 mm in position and 0.30 radians in rotation).

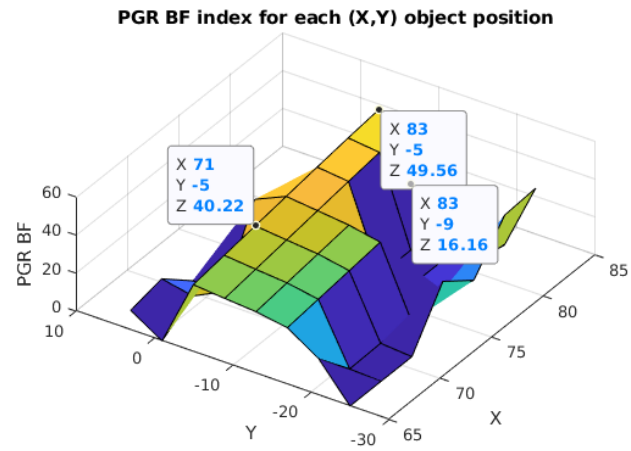

Fig. 5. PGR index for each (X,Y) object's position

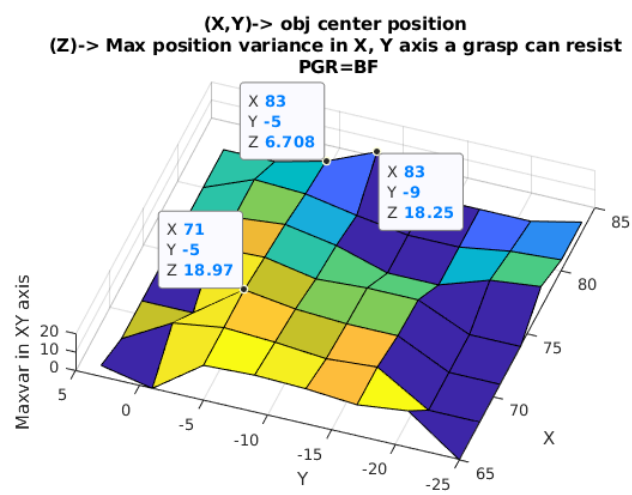

Fig. 6. Maximum position variation for each (X,Y) object's position

In Fig. 8 is presented the best grasp chosen according to the PGR index while in Fig. 9 is presented the one chosen according to the $PGR_{PoseVar}$ index.

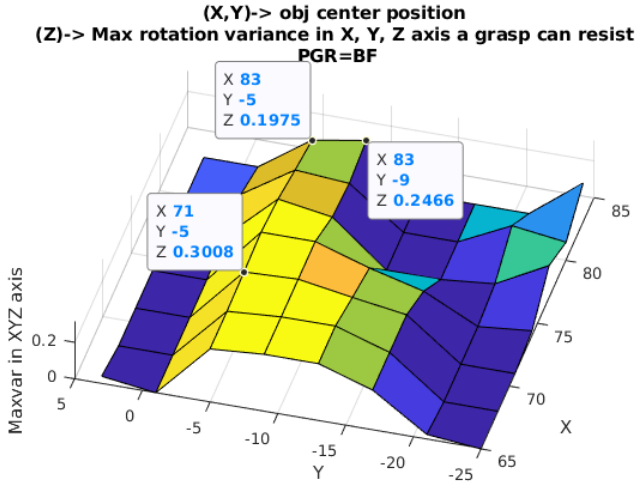

Fig. 7. Maximum rotation variation for each (X,Y) object's position

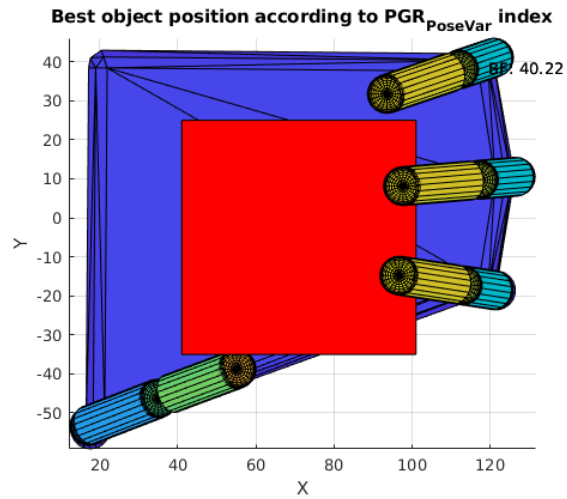

Fig. 9. The best grasp chosen according to the $PGR_{PoseVar}$ index

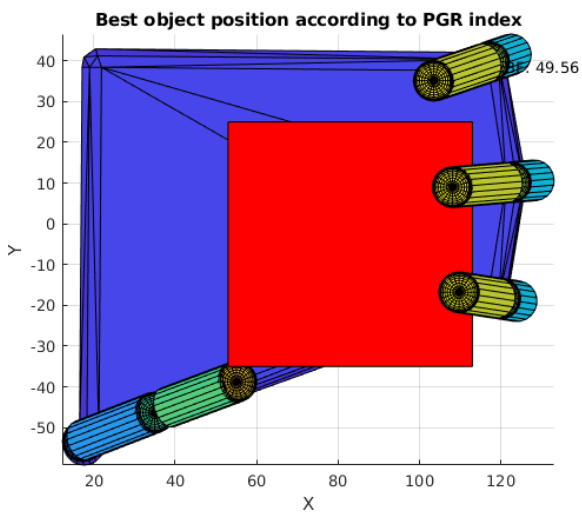

Fig. 8. The best grasp chosen according to the PGR index

VI. Conclusions

One of the problems with Pozzi et al. heuristics is that they score poorly in predicting the actual PGR indexes obtained through the brute force. The heuristics developed can predict the way better the actual PGR values; however, the computational time is higher than previous heuristics, but it is still faster than the BF.

For the Vizzy's hand, the heuristic that can most successfully predict the PGR values obtained without heuristic (BF) is H4, where about 90% of the values obtained by the H4 heuristic are the same as those obtained by BF. In terms of time performance, the time saved from heuristic H4 over BF is more significant for grasps with more contact points, whereas for a 13 contact point grasp, the heuristic H4 takes only 0.90% of the time taken by BF. The H3 heuristic cannot predict so well the PGR values obtained by BF as the heuristic H4 does, but still can identify how good a grasp is. For the human hand, the heuristic that can predict better the PGR indices is H3, with an average percentage error of 9.4%, while H2 has 18.7% and H4 has 14.0%. The index $PGR_{PoseVar}$ (that is proposed in section IV) can choose the object pose such that in its surroundings poses, any grasp (in these poses) is stable, thus the object pose chosen is robust to the pose uncertainty. This index is useful because, in the real world, the robot has some uncertainty about the object pose, and the object most likely will be grasped in a neighbourhood of the pose chosen by that index. With the optimal object pose chosen through $PGR_{PoseVar}$ index, the real-world grasp will be more likely to succeed than the pose chosen by the PGR index.

As can be seen from Fig. 8, the $PGR_{PoseVar}$ index chooses an object pose that maximizes both the PGR index and the maximum variation of the pose relative to the initial pose. In Fig. 9, the object pose of the PGR index only maximizes the PGR index, where for the chosen grasp, the thumb only touches the edge of the cube, and therefore, any variation from the initial cube pose most likely makes the real-world grasp unviable. Therefore, the $PGR_{PoseVar}$ index is useful for choosing more stable grasps to be performed in the real world.

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