Optimal Grasping for Space Debris Removal

Shrinivas Prasad Kulkarni
180070057

EE 692 RnD Project
Guide - Prof. Dwaipayan Mukherjee
Dept. of Electrical Engineering, IIT Bombay
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Abstract

This project institutes a novel idea to tackle the problem of space debris removal, specifically focusing on debris that is large in size, and can interfere with functional satellites in space. Grasping the debris by a hand and maneuvering it as needed, possibly towards a graveyard orbit seems intuitive, but grasping requires a robotic hand. Since a hand is nearly impossible to deploy in space which can grasp objects, we move towards multiple finger-like objects which are not physically connected by a palm to replicate our hand. Since these are not physically connected, controlling them individually to make them work together again is infeasible, and we finally move towards multi-agent systems. The idea is to use multiple cooperative agents which interact with each other, and use them to perform the task of grasping and maneuvering the debris as desired.

1 Introduction

Space debris pose a great hazard to functional spacecrafts, and when a functional spacecraft is impacted by a debris, it not only becomes defunct, but also adds to the space debris, and contributes to the hazard which destroyed it in the first place. This problem is grave and open, with new methods emerging to tackle it. The motivation for this project was the same problem, and the idea is to use multiple agents working in coordination to displace a debris from its orbit to some other, possibly a distant orbit which is not used by satellites. The agents have to place themselves in a certain manner around the debris to maneuver it as required, and this is a problem in itself, which is posed as a grasping problem in this report (the agents are the fingertips of an imaginary robotic hand, and the object to be grasped is the debris). This report will focus mainly on this sub-problem, and once we have a satisfactory solution to it, we would know where to place the agents on a debris, after which the problem of maneuvering the debris can be posed as a formation control problem, where the agents cooperatively maintain their formation which corresponds the the optimal grasp previously calculated, and push the debris in the direction of their choice.

In section 2, relevant work done in the field of optimal grasping is discussed. Section 3 explains the fundamentals of multi-fingered robotic grasping theory, excerpts from various papers, which is essential to move forward. Section 4 formally defines the problem statement addressed in the project, with the following section introducing viable approaches to tackle the same. Section 6 selects and formalizes the main approaches as optimisation problems for general grasping, and 7 tailors them to fit our problem. Section 8 illustrates some simulations performed for robotic grasping, and along with section 9, includes future directions to completely address the problem undertaken, that of space debris removal.

2 Previous Work in Object Grasping

2.1 Work involving Machine/Deep Learning

A human baby learns to grasp objects with time and previous experience, and it also is able to extend its learnt grasps to new objects it encounters, it is quite intuitive that a grasp detection problem can be posed as a learning

problem, whose solutions implement ML/DL models. A few such papers will be briefed upon in this subsection.
[1] researches on picking objects from cluttered environments. the paper presents a robotic pick-and-place system capable of grasping and recognizing both known and new objects in a clutter. The system handles a wide range of object categories without needing any task-specific training data for novel objects. It trains a neural network on different objects for 4 basic grips, and learns to use the best from these 4. It then executes the action with the highest affordance on known or novel objects. [2] considers the problem of grasp pose detection on point clouds (of objects). Briefly, at each point on the object surface, normals are calculated, along which the axis of the hand will lie. For this axis, grasp candidates are generated, which will have 6 degrees of freedom. In this manner, a huge set of 6DOF grasp candidates are generated, and these are then classified as good or bad grasps. CNNs are used for the latter part, but to train them, we need a large amount of data consisting of grasps, and whether or not they are good. For this purpose, a lot of grasp candidates are generated for which the two fingers are closed onto each other, and then the formed grasp is evaluated based on whether it is friction-less and antipodal. The main drawback, as mentioned, is that the paper only considers 2-fingered grasps. [3] takes an approach similar to [2] with inputs to the algorithm being a point cloud and additionally the geometric parameters of the robot hand. The output is a set of hand poses that are expected to be good grasps. Their novel contributions are that they identify a set of necessary conditions on the geometry of a grasp that can be used to generate a set of grasp hypotheses. This helps to focus grasp detection away from regions where no grasp can exist. Second, they show how geometric grasp conditions can be used to generate labeled datasets for the purpose of training the machine learning algorithm. This enables generation of large amounts of training data and it grounds the training labels in grasp mechanics. But again, the paper only considers 2-fingered robotic hands. [4] employs deep learning for the problem, but with the same limitation of assuming a 2-fingered robotic hand. The reason for mentioning being that the grasp detection process is two-staged, with the first stage involving a small deep network used to exhaustively search potential rectangles, producing a small set of top-ranked rectangles. A larger deep network is then used in the second stage to find the top-ranked rectangle from these candidates, producing a single optimal grasp for the given object. This approach of using a fast but crude model to filter out large quantities of useless grasps, then employing a fine, possibly time-consuming model to search for the grasp on the reduced space is noteworthy, and, if deep learning is to be employed for multi-fingered grasping, it could be of immense use.

2.2 Analytical Treatment to Multi-fingered Grasping

Most of the work involving ML/DL considers 2-fingered grasps, which is not aligned with our purpose. Moreover, the DL models would learn to grasp at most as well as the grasps in the training data, and it can be seen that not a lot of focus on the quality of grasp is given while generating the data for training, probably because 2-fingered grasps do not provide that much freedom to do so. Lastly, training for simple objects even with 2-fingered grasps involved a lot of computational power, and it is not clear whether ML/DL is feasible for multi-fingered grasps, more so when we can have any number of fingers. We thus move to a more analytical treatment of multi-fingered grasps. [5] includes an overview of grasp kinematics, which establishes the foundation, [6] includes a formalization of the intuition for form closure, and [7] includes grasp quality metrics for multi-fingered grasps, based on force closure. These basics are explained in the next section.

3 Rudiments

This section covers the fundamentals of grasping needed to move forward.

3.1 Kinematics and Friction

We rely on screw theory to describe the motion of rigid objects. Our main concern will be the wrench. If we consider a force f applied at a point p (by a finger in contact with the body at p), the wrench is the 6-dimensional vector including both the force f and the moment m generated by f, given by (1)

$$\mathbf{w} = \begin{bmatrix} \mathbf{f} \\ \mathbf{m} \end{bmatrix} \tag{1}$$

When defining a wrench it is essential to specify the point about which the moment is defined.
For a point of contact, the total force is modelled using a friction cone, and the finger does not slip if the force it applies lies within this friction cone. Any force can be broken down into a normal force to the body, and a tangential

force. Friction needs to balance the tangential force for the body to not slip. Since the maximum frictional force is bounded by μ times the normal force, we have a cone forming. Figure 1 illustrates the same.

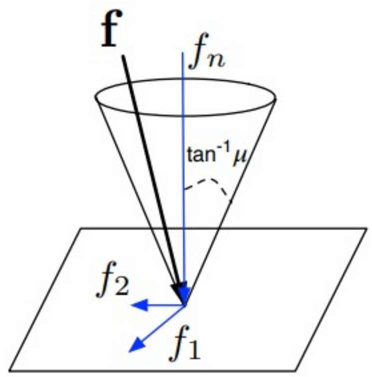

Figure 1: Friction Cone

More details available in [5]

3.2 Closure definitions

Form and Force closure are the two main characterizations of a grasp.

3.2.1 Form Closure

Form closure is obtained when the robotic hand surrounds the object to be grasped in such a way that the object cannot move without colliding with the hand. An analytical definition for the same provided in [6] is as follows. Let $\mathbf{u}$ be the configuration of the object and $\mathbf{q}$ be configuration of the hand. Assuming there are n_c contact points between the hand and the object, a gap function, $\psi_i(\mathbf{u}, \mathbf{q})$ is defined for all contact points. The gap function gives the distance between the hand and the object at the contact point. $\psi_i(\mathbf{u}, \mathbf{q}) = 0$ when contact occurs, becomes positive when contact breaks, becomes negative when there is penetration of the object by the finger. A grasp achieves form closure iff

$$\psi(\mathbf{u} + d\mathbf{u}, \mathbf{q}) \geq 0 \implies d\mathbf{u} = 0 \tag{2}$$

The intuitive meaning of the definition can be understood as follows. Suppose initially, all point of contacts have the distance measure > 0. It is obvious that some movement $d\mathbf{u} > 0$ is possible, after which all distance measures would be ≥ 0. Hence, a form closure is not possible with this initial condition. Consider a case when a few ψ are zero, and others are positive. In this case, we cannot ensure that we can move the body without causing a penetration at places with $\psi = 0$. In case there does not exist $d\mathbf{u} > 0$ which, when applied, there is no penetration, we have form closure.

3.2.2 Force Closure

A grasp achieves force closure if it can be maintained in spite of external forces acting on the restrained object. When force closure is achieved, for any external force acting on the body, there exists some combination of finger forces lying in their respective friction cones which can resist the force. More on Force Closure in the next subsection.

3.3 quality metrics

The space of wrenches that can be applied to an object by a grasp given limits on the contact normal forces is called the grasp wrench space (GWS). In order to construct this space, it is necessary to approximate a friction cone with a finite number m of force vectors equally spaced around the boundary of the cone (see Figure 2)
Ferrari and Canny [7] describe two methods of constructing a GWS. In both cases, a convex hull bounds the space. In one, the sum magnitude of the contact normal forces is bounded, and in the other, the maximum magnitude of the normal forces is bounded.

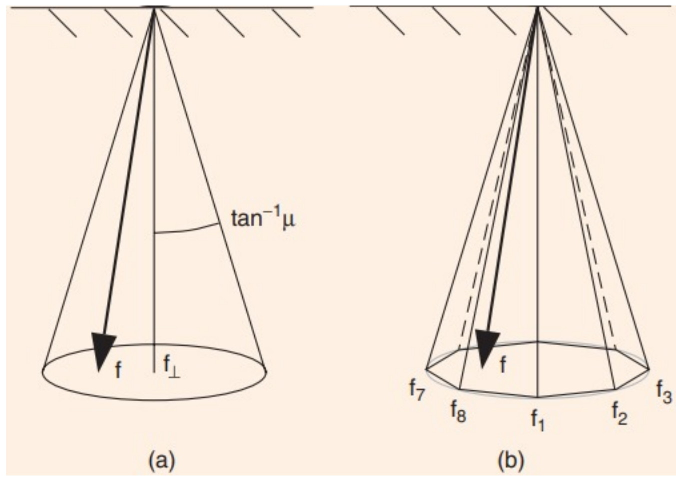

Figure 2: (a) Friction Cone (b) regular pyramid approximation

Considering the force at i-th contact, for the second case, we have:

$$f_i = \sum_{j=1}^{m} \alpha_{ij} f_{ij} \tag{3}$$

where f_{ij} are the forces at the boundary of the friction cone which generate the approximate friction cone, $\alpha_{ij} > 0$ and sum of α_{ij} over m is at most 1.
Similar equation can be written for moments, and hence for wrenches:

$$w_i = \sum_{j=1}^{m} \alpha_{ij} w_{ij} \tag{4}$$

Any wrench exerted on the body through the n_c contacts can be scaled to belong to the set:

$$W_{L_\infty} = CH(\bigoplus_{i=1}^{n_c} \{\mathbf{w}_{i1}...\mathbf{w}_{ik}\}) \tag{5}$$

where $\bigoplus$ is the Minkowski sum and CH is the convex hull. Since there are finite elements in the sets which are Minkowski-summed, the set inside CH is finite, hence the CH gives us a polytope. The quality measure is the distance of the closest face of the polytope from the origin. The idea is, the set inside CH is the set containing sums of all combinations of basis wrenches of the fingers, and all forces that the fingers in totality can apply, given the upper bound on the normal force of each finger, is the convex hull (weighted average) of these vectors. The closest face of the polytope from the origin is the direction in which the fingers can resist the least to an opposite external force, and hence it decides the grasp quality. The grasp achieves force closure iff the origin lies within this polytope. If we call this direction the weakest link of the grasp, a grasp is good when it has a strong weakest link. In other words, in a good grasp, the fingers are evenly distributed such that they can resist evenly in all directions. In the first case, where the sum magnitude of the contact normals is bounded, everything else remains the same, but we have a new set of all possible wrenches:

$$W_{L_1} = CH(\bigcup_{i=1}^{n_c} \{\mathbf{w}_{i1}...\mathbf{w}_{ik}\}) \tag{6}$$

4 Problem Statement

Covering the important basics, we will now move to writing a suitable problem statement for our purpose. We want to employ a multi-agent system to grasp and maneuver a space debris from it's orbit to a distant/graveyard orbit. In order to do this, we need to decide a formation that the agents will have which will enable them to grasp the debris. We view this problem as a robotic arm grasping problem, and try to use the developments in the field to try and tackle our problem. The problem then remains of what factors should be accounted for while choosing a grasp for our task. The quality metrics form [7] is a good step, where we want the grasp to have a good quality force closure on the debris. But there is certainly a scope of improvement, once we take into account the task to be performed by the grasp. The [7] quality metrics evaluate whether the grasp is good enough to resist disturbances in all directions, but based on a task, the disturbances/external forces can be a small set, and we can afford using all our resources to be able to counter only these. Thus, we can certainly improve once we know how exactly will the agents act on the debris to move it.

Modern satellites, like Meteosat-7 which became defunct in 2017, have reserved fuel to take them to the graveyard orbit. The "graveyard orbit" is not an actual orbit but, rather, a region, where old satellites will not pose a threat to those still in service. This protected region has been set at geostationary altitude (36,000km) plus 200km. Anything above this altitude belongs to the graveyard. Figure 3 illustrates how a satellite increases it's altitude to enter the graveyard orbit. More details at [8].

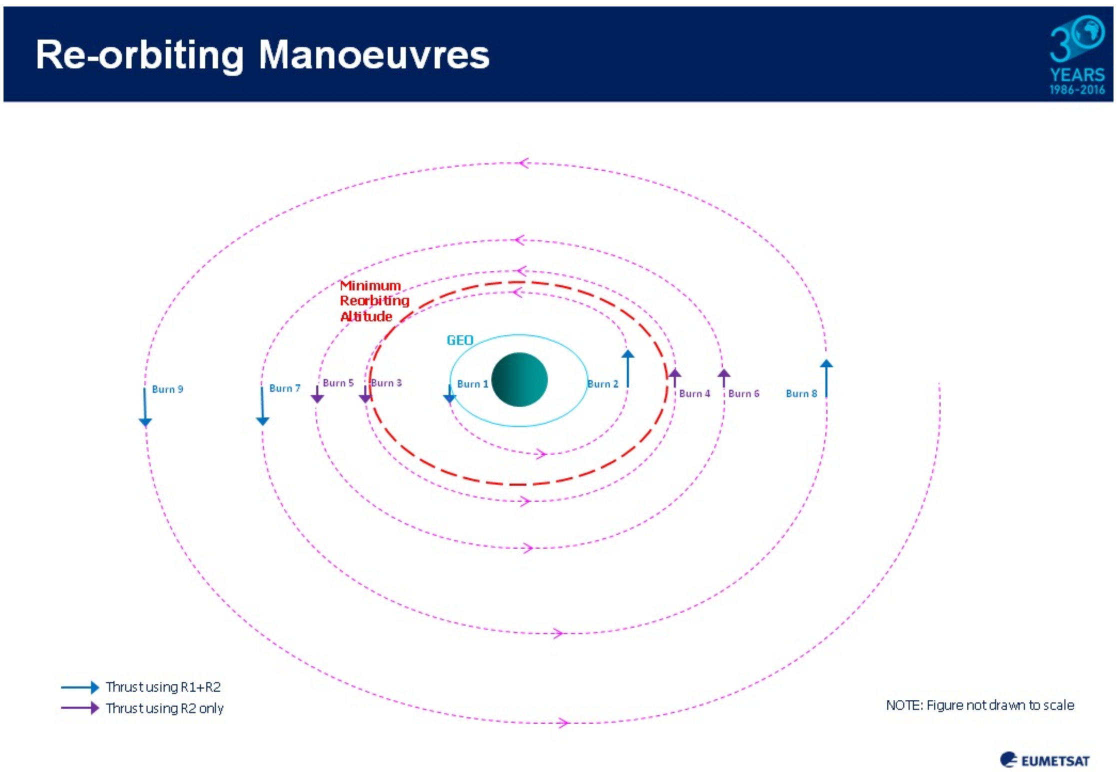

Figure 3: The burn manoeuvres necessary to re-orbit Meteosat-7 to the graveyard orbit

Since the thrusts are in the direction of the tangent at the current point on the orbit, we can assume that the external disturbance forces would lie in the plane of the orbit, also considering the centrifugal force. Thus, our problem boils down to the following.

Problem - *Given an object (space debris) and the task to be performed on it (increasing its orbit size to lead it to the graveyard orbit), find the optimal grasp (formation) to be undertaken by a robotic hand (the multi-agent system), maintaining which it will perform the task on the object (debris).*

Note that our method is valid even after the modern satellites having the ability to thrust themselves away into the graveyard because we still need methods to remove the existing debris. Now that we know the task to be performed on the object by the agents, we will proceed to discussing possible solutions.

5 Viable Approaches

The main idea that follows from the aforementioned theory is to set up our problem as an optimization problem where the objective function would be the quality metric under various constraints for the grasps. This would require us to write a formal optimization problem for the same. This section introduces a few feasible approaches, but covers only the main ideas behind them. The optimization problems would follow in the next section for the approaches chosen from the ones discussed here.

5.1 Optimal Force Closure grasp

The starting point could be finding an optimal grasp based on the quality metrics defined by [7], which would give us an optimal force closure grasp on the object. This would be the best approach in case we do not know the task performed by the agents on the debris, or if the task is too complex; the reason being the metrics maximise the worst case resistance. But since we have information about the task, this method will result in suboptimal grasps In [9], the authors describe an interactive simulator they have created which implements these metrics to evaluate grasps for different objects using different multi-fingered hand models.

5.2 Task-Oriented Grasping

Li and Sastry in [10] introduce a new quality measure called the task oriented quality measure in order to utilize the additional information about the task to be performed on the object, and score the grasp better. Before introducing the idea, the stage is set for it in the following paragraph.
In general, a grasp exists to perform some task, which can be described by the space of wrenches that must be applied to an object to carry out that task. This space is called the task wrench space. If the task wrench space is a subspace of the grasp wrench space, then the grasp is valid for that task. However, it is not necessarily the most efficient grasp that can accomplish the task, since the internal forces on the object may be much larger than necessary. The most general quality measures assume nothing is known about the task wrench space. If we assume that disturbance wrenches could come from any direction, the task wrench space will be a 6-D ball. The quality would then vary directly with how large a ball we can fit in in our unit grasp wrench space, since that would be the largest worst case resistance provided by our grasp. Note that this quality measure is the same as the least distance of a face from the origin.
The main idea in [10] is to model our task as ellipsoids, or encoding the information we have about it by changing the 6-D ball that we had initially. The quality would then depend on how large an ellipsoid we can fit in our unit grasp wrench space. The paper illustrates this idea with two simple examples, but also mentions that finding the right ellipsoid which encodes the task is a complicated task, and requires a lot of experience on similar tasks.
The paper can be referred for details, but the main idea while forming the ellipse is to choose a body coordinate system, then stretch the axes of the ellipse such that the directions of maximum expected collision forces have longer axes. The intuition is, the UGWS should be longer in these directions to accommodate the larger disturbances.

5.3 Grasp Evaluation Based on Disturbance Force Rejection

Another method to evaluate grasps based on tasks was proposed by [11]. The paper incorporates the force directions that together form the task to be performed. Consider a matrix $\mathbf{G}$ of dimension $6 \times mn_c$, whose columns are the wrenches formed by the forces at the boundaries of the friction cones at the n_c contact points, m being the number of vectors on the boundary of each FC. This matrix is called the grasp matrix. Summing up the contributions from all contacts, the total wrench exerted by the grasp on the object, $\mathbf{W}$, can be written as:

$$\mathbf{W}{=}\mathbf{G}\mathbf{x} \tag{7}$$

where $\mathbf{x}$ consists of mn_c elements, each element of it being a weight it gives to the basis wrenches (α_j for all contacts). Since $\Sigma x_j = 1$, RHS is the convex hull of $\mathbf{G}$. The grasp has force closure if (7) has a solution for all $\mathbf{W}$. The procedure to evaluate the grasp as described is,

- Consider a unit vector $\mathbf{e}$, representing a fixed direction for the disturbance force so that the disturbance force can be written as $f\mathbf{e}$, where f is a dimensionless scalar
- Sweep this disturbance force over the surface of the object, finding the smallest, positive f that results in a wrench that is exactly on the border of the UGWS. Let us denote this value by f^*.

- Repeat this process for all directions of the disturbance force to end up with a closed surface S in force space

The interpretation of this surface is straightforward. If a disturbance force is inside it, a unit grasp will be able to resist the resulting wrench, no matter where the force is applied.

f^* computation is the key component of the procedure, which is done by solving the following minimax problem:

$$f^* = \min_{\mathbf{a}} \max_{\mathbf{x}} \left\{ f \in \mathbb{R}^+ : \quad -\mathbf{W}_0 - f \begin{bmatrix} \hat{\mathbf{e}} \\ \mathbf{a} \times \hat{\mathbf{e}} \end{bmatrix} = \mathbf{G}\mathbf{x}, \right.$$
$$\left. \hat{\mathbf{e}} \in \mathrm{FC}_{\mathbf{a}}, \quad \mathbf{a} \in \partial D, \quad x_i \geq 0, \quad \sum_{i=1}^{mn} x_i = 1 \right\}.$$

Figure 4:

where δD is the object surface, FC_a the friction cone at a. W_0 is the offset wrench representing forces like gravity. Apart from the force directions, we include the task information by limiting the object surface which is swept to find f^*. Expecting the resistance to work for a force direction irrespective of where it is applied is suboptimal. An excellent example for this is the task of writing. When a human hand writes, the disturbance/external force acting on the pen is upward on the tip, and the hand grips the pen accordingly. But the grip is not at all good if we find f^* value searching the entire body of the pen, since the grip fails when the upward force is applied at the top part of the pen when holding.

6 The Optimisation Problems (Main Direction)

This section establishes the optimisation problems built on the foundations discussed before. Solving these would lead to finding the optimal grasp on an object. The number of fingers, or the number of contact points is kept out of the problem, and can be chosen based on other constraints, or can be considered a parameter which can be tuned to extract the most for a specific purpose.

6.1 Task-Oriented Grasping Optimisation problem

The task is modeled by the ellipsoid given in (8), where Q is a positive definite symmetric matrix, and $a \in R^6$ reflects the asymmetry properties of the task. This definition is quite general, and would work for any arbitrary task.

$$A_\beta = \{y \in R^6, \langle y, Qy \rangle + \langle a, y \rangle \leq \beta^2\} \tag{8}$$

For a task, we will decide an appropriate A_β. For any grasp G, the quality measure for that specific task would be

$$\mu(G) = sup\{\beta \geq 0 | A_\beta \subset UGWS(G)\} \tag{9}$$

where UGWS is the unit grasp wrench space.
Since we have to maximise the quality measure over grasps, the optimisation problem becomes,

$$max_{\beta \geq 0} \beta \tag{10}$$

such that

$$A_\beta \subset UGWS(G), \text{ and G is a feasible grasp} \tag{11}$$

In words, we are given a task/task ellipsoid, and a quality calculator given a grasp and the task ellipsoid. We now want to traverse the set of all feasible grasps, and find the one that maximises the quality metric. A feasible grasp is a formation of points on the surface of the object which the agents/fingers can take.

6.2 Disturbance Force Rejection

Building on the theory discussed in section 5.3, for a given task(set of force directions), we would have the information about the preference order of the force directions, or the order in which the forces are expected to be higher in magnitude. Using this, the optimisation problem would be,

$$max \ w^T \mathbf{f}^* \tag{12}$$

$$f^\star = \min_{\mathbf{a}} \max_{\mathbf{x}} \left\{ f \in \mathbb{R}^+ : \quad -\mathbf{W}_0 - f \begin{bmatrix} \hat{\mathbf{e}} \\ \mathbf{a} \times \hat{\mathbf{e}} \end{bmatrix} = \mathbf{G}\mathbf{x}, \right.$$
$$\left. \hat{\mathbf{e}} \in \mathrm{FC}_{\mathbf{a}}, \quad \mathbf{a} \in \partial D, \quad x_i \geq 0, \quad \sum_{i=1}^{mn} x_i = 1 \right\}.$$

Figure 5:

with the above constraint where G is the grasp matrix as defined before, of a feasible grasp.
The w^T is the weight vector multiplied with the vector of f^*s from all directions, which decides the preference to be given to the force directions while optimizing for the best grasp. This weight vector would be chosen based on the the order in which the forces are expected to be higher in magnitude, and possibly other factors. When this objective function is maximised, we would have a grasp which offers good resistance to the task forces, and it does so with a desired preference among them. For a given w^T and the force directions for the object, we will optimise over feasible grasps, based on the quality of them.

7 Specializing the optimisation problems for our purpose

In this section, the problems established would be further fine-tuned according to the problem at hand, space debris removal. See Figure 3, the disturbance forces act along the tangential direction (acceleration by the agents), and along the radial direction (centripetal force). These are the only two external disturbance forces.

7.1 Writing the task ellipse

Assume the body coordinate is set as illustrated in Figure 6. Following the method described in [10], the task requirements are,

- Large magnitude of force acting in the y direction
- Balancing out the disturbances in the x direction
- Avoiding rotation along z axis, as this would require rearrangement of the formation
- Avoiding rotation along the other two axes
- Avoiding movement in the z direction

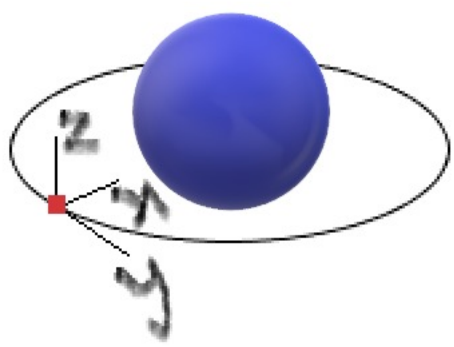

Figure 6: Chosen debris body coordinate

If we use $(r_i)_{i=1}^6$ to denote the ratio of maximum required resistance forces in each force direction, we obtain a task ellipsoid in the wrench space as,

$$A_\beta = \{(f_x, ..., \tau_z) \in R^6, \frac{f_y^2}{r_1^2} + \frac{f_x^2}{r_2^2} + \frac{\tau_z^2}{r_3^2} + \frac{\tau_x^2}{r_4^2} + \frac{\tau_y^2}{r_5^2} + \frac{f_z^2}{r_6^2} \leq \beta^2\} \tag{13}$$

The values for r_is would need to be set appropriately, perhaps with some experience as mentioned in the paper, but we can comment on which values need to to be large, and which don't in most tasks. Here, r_1, r_2 need to be large, as they are key to the task performed. If the grasp is such that it does not generate torque/rotate the body, we would not need high values for others, and for r_6, the grasp needs to apply force in the right direction. *In fact*, the rotations as well as drifting in the z direction are caused due to grasping itself, and the only external disturbances would be in y and x directions.

7.2 Disturbance Force Rejection

Since the external disturbances are only 2, w is a 2-D vector. Also, both these forces act on the centre of mass, hence the area of the object surface over which we sweep to find f^* can be reduced considerably as well. Also, as shown in [11], even though traversing the whole object surface can be computationally expensive, for polyhedral objects, it is sufficient to traverse only the vertices. This makes solving this optimisation problem computationally faster than the former, since is we explore $O(G)$ grasps in both cases, and the time required to compute the UGWS is $O(UGWS)$, the time complexity for the former problem is $O(G * UGWS)$, whereas for the latter, it is $O(G * n_{vertices})$.

8 Simulations

[9] provides a grasp simulator, GraspIt!, which has various multi-fingered hands as well as objects. This software has been set up and used to visualize some of the theory discussed above. The software implements section 3.3, and has the ability to compute the quality of a grasp using the same. The limitations are it works for a few predefined multi-fingered hands only, and there is not much flexibility in terms of the object to be grasped as well, but it is an excellent starting point to further specialize the software for a specific purpose.
Using W_{L_1} as the UGWS, and the QM as the distance of the closest face from the origin, Figure 7 illustrates the simulator-computed quality metric value for the corresponding grasp (bottom left).

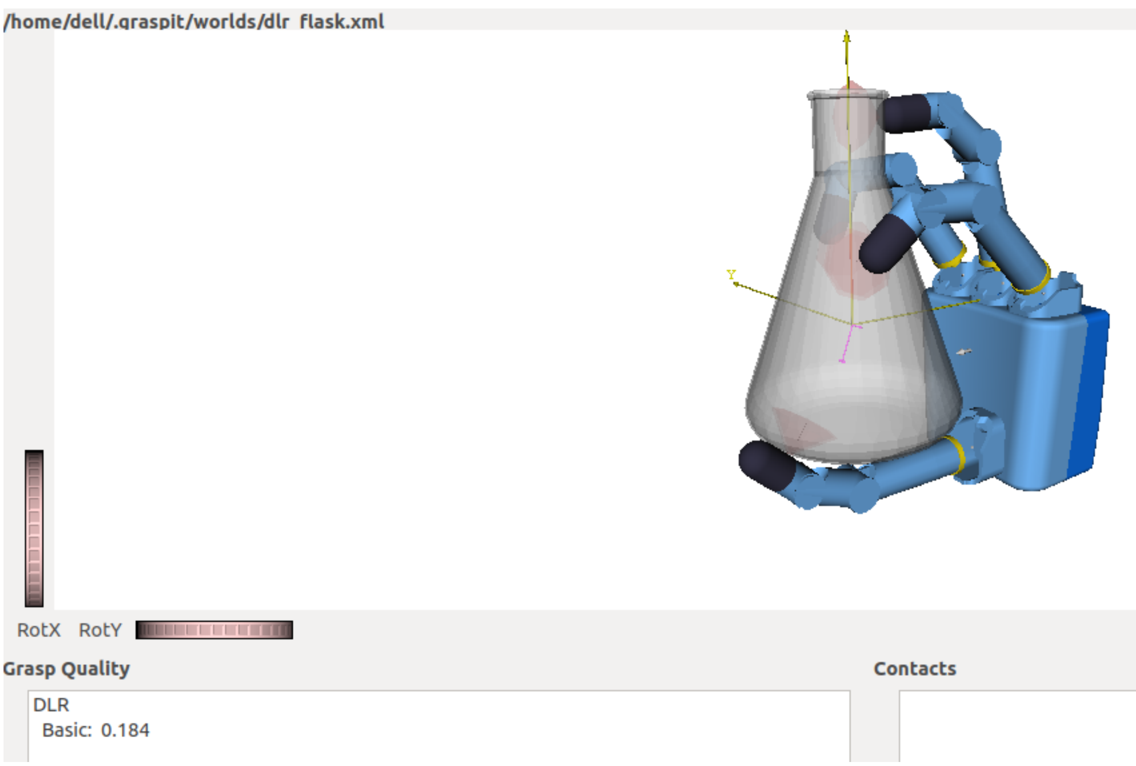

Figure 7: Grasp and it's Quality

Interestingly, the simulator also provides a grasp planner that finds a near-optimal grasp for an object and a hand for the same quality metric. It does so by first generating pre-grasps for a simplified version of the object, then tries them out one by one for the original object, calculating the quality along the way. In the end, it returns the grasp with the best quality. The only limitation is that the quality metric it uses (closest face distance from the origin) essentially assumes a unit ball as the task wrench space (general case disturbance force), and does not have an option to modify it. If we could incorporate the task ellipse discussed in section 7.1 instead of the unit ball, we can achieve a task-specific near-optimal grasp! Additionally, the incorporation does not seem to increase the computational needs for grasp planning, and since it is fast for a unit ball, it will be fast for task-specific case as well. This could be a **future direction** which can lead to acceptable solutions for our problem. The grasp planned by GraspIt! for holding a cup using a Barrett hand (a famous robotic hand) is illustrated in Figure 8.

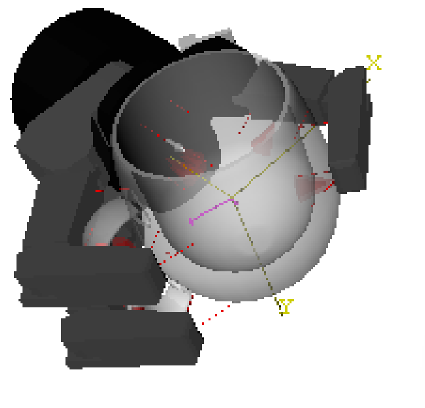

Figure 8: Near-optimal grasp planned by GraspIt!

9 Concluding Remarks

This report starts off with the approaches explored in literature for robot grasping and studies them in the context of space debris removal. It then proceeds towards formal theory for multi-fingered grasping, and discusses them in detail. A problem statement is then decided upon, and viable approaches are discussed, each of them scrutinized later with an aim to find a solution to the problem statement. In the end, grasping for a general task wrench space is simulated on GraspIt!, with both quality computation and grasp planning performed. As mentioned previously, if the task ellipse is incorporated in a new GraspIt! quality measure, using grasp planning feature of the software we will be able to find the optimal grasp for our purpose of debris removal using a multi-agent system. Essentially, the software will solve the optimisation problem stated in section 6.1 to reach an optimal grasp. The method used by GraspIt! for grasp planning can be improved upon next, and also, newer ways to solve the optimisation problems can be researched in the future to address the problem statement. The second method, disturbance for rejection based optimisation problem can be explored.

Once we have an optimal grasp for the space debris, we can move towards the next sub-problem, that of achieving and maintaining the formation cooperatively by the agents in the system, and executing the maneuver successfully. Once this is solved, we would have a complete and a novel solution to the problem of space debris removal.

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