Computation of Suitable Grasp Pose for Usage of Objects Based on Predefined Training and Real-time Pose Estimation

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***Abstract*—Existing grasping mechanisms focus on executing accurate grasps which are not always suitable for the usage of objects. We developed a system that can be used to train humanoid robots with different types of grasp poses. We present a grasping mechanism using homogeneous transformation that allows a humanoid robot to grasp objects in such a way that is suitable for the usage of the objects. The system captures the relative poses of an object and a robot's wrist for training such that when the object's pose changes, the robot's gripper attached to the wrist adjusts its pose accordingly and lines up with the object. For detecting the objects and estimating their poses, we developed and used a color-based pose detection and estimation system and a homography-based planar pose detection and estimation system. We conducted experiments using a humanoid PR2 robot. We used the Robot Operating System as the primary framework of the system and MoveIt Interface for manipulation of grasps. The grasping system showed robust results for different poses of the objects using both arms of the robot. Our experiments involved human validation in which the robot successfully grasped objects such as a screwdriver, a wrench and books from human hands in different grasp poses that are appropriate for usage of the objects.**

Keywords–Robotics; Homogeneous Transformation; Pose Estimation; Grasping; Objects Usage.

I. Introduction

Grasping is an important aspect of a robot's capabilities. Since different objects come in different shapes, it is often difficult for robots to grasp objects accurately. In order to use tools, such as a screwdriver and a wrench, a robot needs to grasp them with high level of precision as they need to be grasped at specific locations and also in appropriate orientations. This is not the case for a tennis ball for which the grasp pose can be more flexible. A human grasps a screwdriver from the top of its base and this is an ideal grasp. If a robot attempts to grasp it for usage, it needs to do the same. Thus, an approach is required so that robots can grasp tools in ideal grasp poses. This requires a robust system that can train the robots to grasp objects in required poses so that regardless of the objects' orientations, robots can grasp it properly and use.

In this paper, we have designed a grasping technique for humanoid robots that will enable the humanoid robots to grasp objects of diverse shapes precisely based on predefined grasp poses. We are using a homogeneous transformation matrix to record the relative poses between the end-effector of a robot and an object so that when the position and orientation of the object changes, the end-effector follows it accordingly based on the recorded relative pose. Since this system allows users to train the initial poses of objects and robot's end-effectors, the robots can be trained with different types of grasp poses. We used a humanoid PR2 [1] robot for conducting experiments. In our experiments, we used linear shaped tools, such as a wrench and used a color-based pose detection and estimation system for these tools. We also used rectangular-shaped objects for the experiments. We used a planar pose estimation system for running experiments with such objects. During the experiments, the robot could robustly grasp objects in different grasp poses which are suitable for the usage of the objects.

The major outcomes of this research are (i) developing a system that can train a humanoid robot different types of grasps, (ii) finding predefined grasp poses that would allow a robot to use tools such as screwdrivers, hammers, etc., (iii) enabling the robot to grasp objects accurately from human hands, (iv) introducing a homography-based planar pose detection and estimation technique for objects that have complex shapes (v) implementing a color-based pose detection and estimation system using mathematical formulas for objects with linear shapes

The rest of the paper is structured as follows: Section II discusses the related works in grasping, Section III presents an analysis of the grasps for humanoid robots, Section IV elaborates the vision systems that were used for pose estimation of objects, Section V provides an overview of the system, Section VI discusses the results and Section VII draws the conclusion of the paper and discusses future works.

II. Related Work

There has been a wide range of research on robot grasping. Designing a grasping system is challenging due to the infinite nature of the shapes of objects. Kehoe et al. [2] used a candidate grasp from a set of grasps based on feasibility analysis conducted by a grasp planner and a humanoid PR2 robot was used for their experiments. For stable horizontal poses of objects, objects such as a mustard bottle is close to the width of the PR2's gripper so the grasps were not very accurate in such orientations of the object. Huebner et al. [3] also took a similar approach as they performed grasp candidate simulation. They created a sequence of grasps and then computed a random grasp evaluation for each model of objects. In both works, a grasp was chosen from a list of candidate grasps. Their research focused on finding a grasp that would be successful while we focus on training a robot to grasp objects in a way that is not only successful but also suitable for usage of the objects.

Aleotti et al. [4] proposed a grasping model that involves programming by demonstration for teaching proper grasps with automatic 3D shape segmentation for object recognition and semantic modeling. They developed a virtual grasping algorithm for object picking and computing the part of the object which is grasped. Pinto et al. [5] trained a Convolutional Neural Network (CNN) for predicting grasp locations without vast overfitting. Graspit was used as a grasp simulator [6][7] to predict grasping. Supervised learning was used [8][9] to predict grasp locations from RGB images. These works emphasised on developing and using learning models for obtaining accurate grasps. In our work, we designed a training mechanism based on mathematical concepts which not only generated accurate grasps but also the grasps could follow a predefined training.

Related methods were also developed on autonomous grasping [10] based on estimated shapes and poses of the segmented objects. Weng et al. [11] proposed a system which recognizes objects and estimates the pose of the objects using deep neural network and then allows grasping objects using the centers of their defined pose classes. Robots were also trained to choose optimum grasp from a set of grasps using machine learning models based on human demonstration [12]. In order to ensure robust grasp of unknown objects, a new algorithm using Bayesian optimization was developed for simulation [13]. Their work did not focus on the usage of the objects but rather focused on finding a grasp that enabled the robots to appropriately hold the objects.

III. Analysis of Grasps

When a human works with a screwdriver, the ideal grasp is to grasp it from the top of its base. We classify this type of grasp as top grasp. There are also objects, such as a hammer and a wrench for which it is necessary to grasp them from side. We classify it as side grasp. Figure 1 illustrates top grasp and side grasp.

Figure 1. Top Grasp and Side Grasp.

For a 7-DOF robot such as the PR2, a robot's planner could successfully plan in various complex poses of the objects in our experiments with redundancy. Planning is inherently more challenging to plan for a top grasp. Some poses of the linear shaped tools are only suitable for grasp using the right arm while some other poses are only suitable for grasp using the left arm. Although our system is capable of recording the relative poses of objects and the robot's gripper in any relative pose, we used top grasp and side grasp in our experiments as these are the most suitable grasps for the usage of the objects.

IV. Pose Estimation

In order for robots to operate effectively, it needs to be aware of its surrounding environment. One aspect of this awareness is the knowledge of the 3D positions and orientations of the objects in the scene in real-time. In order to achieve this we need to locate the objects and find their orientations so that robots can interact with these objects seamlessly. While object classification, detection, and segmentation have become relatively easier, pose estimation remains a challenging problem as the large number of complex shapes of objects found in real life makes it hard to come up with a general pose estimation technique. Although, some recent pose estimation methods, named PoseCNN [14] and DOPE [15], show promising results in terms of accuracy; generating synthetic data for each newly introduced object requires additional preprocessing tasks that may require other expertise and can take a lot of time. Moreover, as these methods utilize neural networks, training and running these models necessitate high computing resources. Keeping these difficulties in mind, we applied directional cosines to estimate the pose for objects with simple linear shapes that extend along a straight or nearly straight line using color cues, and introduced a homography-based planar pose estimation technique for other objects that have more complex shapes.

A. Color-based Pose Detection and Estimation

We used two different colors such as yellow and green on the two edges of the linear objects. This method can be applied to any linear shaped tools. We computed the position of the object with respect to one of the edges of the objects. We calculated the roll, pitch and yaw rotational angles of the pose using directional cosine equations shown below.

$$\begin{cases} \gamma = \cos^{-1}(\dfrac{\vec{u_x}}{|\vec{u}|}) \\ \beta = \cos^{-1}(\dfrac{\vec{u_y}}{|\vec{u}|}) \\ \alpha = \cos^{-1}(\dfrac{\vec{u_z}}{|\vec{u}|}) \end{cases} \tag{1}$$

Figure 2 shows the directional cosine in 3D space

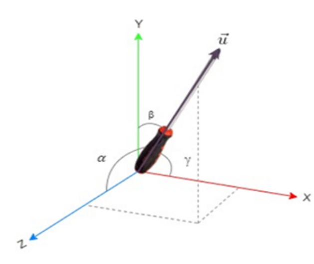

Figure 2. Directional Cosine.

B. Planar Pose Estimation Using Homography

For more complex shapes, we used a descriptor based detection system that utilizes homography and the depth data to estimate the pose of the plane of an object. First, for each object, we acquired an undistorted image of the object's plane that we wanted to detect and take as a reference for homography computation. Then we applied feature detector to find keypoints [16] and used descriptor to retrieve the feature vectors. Then, we did the same for the image frames received from the camera and find the matches using FLANN [17] and compute the homography using RANSAC [18]. We applied a perspective transform to find the corresponding points on the frame using the homography matrix and approximate the location of the two axes on the plane on the object. Finally, we used depth information to estimate the third orthogonal axis by taking the cross product and recover the pose. Figure 3 demonstrates the planar based pose estimation system and Figure 4 shows the pose detection and visualization.

Figure 3. (a) Homography for Different Planar Rotation. (b) Computed Third Directional Axis Projected onto Image Plane.

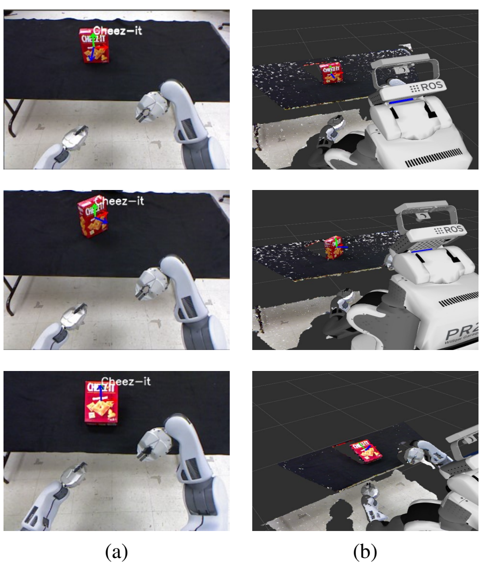

Figure 4. (a) Pose Detection in Robot's Camera (b) Visualization of Corresponding Poses in Rviz.

V. System Overview

We used Robot Operating System (ROS) [19] as the primary framework for the system as it is used by humanoid robots such as PR2 and Baxter. We also used MoveIt Interface [20] for manipulation of the arms and the grippers of the robot. We had two different phases: the training phase and the testing phase. During the training phase, we placed the object and the robot's gripper close to each other in our desired training poses. We got the poses of the objects from our vision systems while we recorded the pose of the robots' wrist to which the gripper is attached using a wrist pose recording system for the PR2 robot. Then we computed the transformation matrix using the two poses and used the matrix in testing phase. We used the ROS Python API for developing the functionality of the transformation matrix. The transformation matrix captures the relative poses of the object and the wrist. During testing phase, we placed the objects in different poses and our system used mathematical equations to generate a new grasp pose for the robot's end-effector. The 3D coordinate frame for the vision system and the robot's wrist during the training and testing phase need to be the same. Once a grasp pose was computed, we used the C++ API of the MoveIt Interface for the manipulation of the robot's arm and the wrist to grasp objects. Figure 5 shows the high level system architecture.

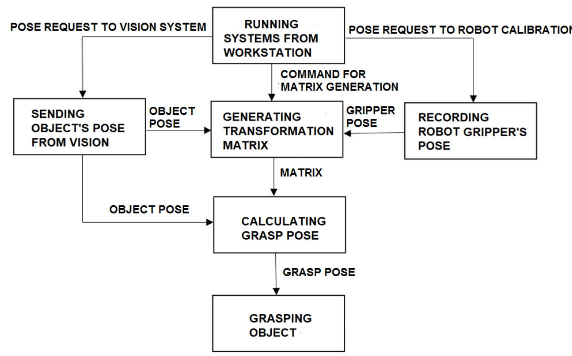

Figure 5. System Architecture.

A. Training

The system allows us to train a wide range of grasp poses, allowing the robot to use various grasps for different object uses. During the training phase, we placed the object and the robot's gripper close to each other and recorded the relative pose. Figure 6 illustrates the training process in which the robot's gripper and a screwdriver were placed in close proximity and the relative poses were recorded for grasping the objects from top which is the general grasping approach for a screwdriver. Figure 6 shows a training scenario.

Figure 6. Recording Relative Pose for Top Grasp.

B. Matrix Calculation

We used the following homogeneous transformation matrix [21]:

$$^{A}T_{B} = \begin{bmatrix} ^{A}R_{B} & ^{A}P_{B} \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & x_t \\ c_{21} & c_{22} & c_{23} & y_t \\ c_{31} & c_{32} & c_{33} & z_t \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

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${}^{A}T_{B}$ refers to the transformation of the coordinate frame B with respect to the coordinate frame A. ${}^{A}R_{B}$ and ${}^{A}P_{B}$ refer to the rotation and translation respectively of the coordinate frame B with respect to the coordinate frame A. We then used (3) to record the relative pose.

$$ {}^{O}T_{G} = {}^{O}T_{B} \times {}^{B}T_{G} \text{ where } {}^{O}T_{B} = ({}^{B}T_{O})^{-1} \tag{3}$$

In the equation, O refers to the object, B refers to the robot's base and G refers to the wrist of the robot to which the gripper is attached.

C. Pose Calculation

Once we have a training matrix saved in a file, we can get a new pose of the object from vision and generate the final matrix that has the new position and orientation of the robot's wrist in matrix form using (4):

$$ {}^{B}T_{G} = {}^{B}T_{O} \times {}^{O}T_{G} \tag{4}$$

We then calculate rotational angles of the grasp pose using the calculated matrix from (4) with (5)

$$\begin{cases} \gamma = tan^{-1}(c_{32}/c_{33}) \\ \beta = tan^{-1}(-c_{31}/\sqrt{{c_{32}}^2 + {c_{33}}^2}) \\ \alpha = tan^{-1}(c_{21}/c_{11}) \end{cases} \tag{5}$$

VI. Results and Discussion

We tested our system on a comprehensive set of estimated poses that included different types of orientations of the object. We conducted 75 experiments in total. We used two types of grasps-top grasp and side grasp. We conducted two types of experiments: general validation experiments and human validation experiments. For the general validations experiments, the objects were attached to a tripod and for human validations experiments, a human held the objects in hand and then the robot grasped it. We placed the objects in various locations in front of the robot and in various orientations in the 3D space. For the experiments using the color-based pose detection and estimation system, we used a screwdriver and a wrench. Figure 7 shows the objects used in the experiments.

Figure 7. Objects for Experiments.

For running experiments using the homography based planar pose estimation system, we used a sticker-book and a cartoon book. The pose estimation systems showed robust performance. Figure 8 shows the pose estimation in ROS Visualizer (RViz) for color-based pose estimation system. In the figure, the green axis is parallel to the object and touches its base which indicate that the pose estimation is accurate.

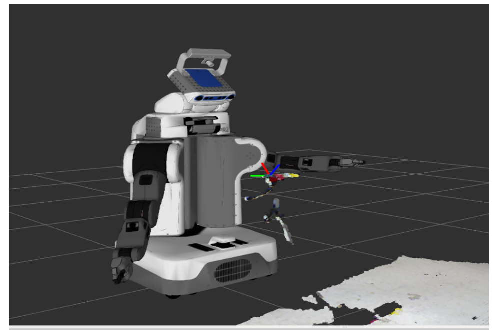

Figure 8. Checking Pose Estimation in Rviz.

We ran 45 experiments in general scenario. We conducted 30 and 15 experiments respectively using the right and left arm. Table I shows the general validation results.

TABLE I. GENERAL VALIDATION RESULTS

Objects	Top Grasp	Side Grasp	Successful Grasp (Top | Side)	Accuracy (Top | Side)
Wrench	12	24	12 | 22	100% | 91.67%
Screwdriver	6	N/A	6 | N/A	100% | N/A
Books	N/A	5	N/A | 5	N/A | 100%

The results from the human validation experiments indicate that the training and pose estimation have been precise enough for the robot to accurately grasp objects from human hands. We ran 24 and 6 experiments using the right and left arm, respectively. Table II shows the experimental results for human validation experiments.

TABLE II. HUMAN VALIDATION RESULTS

Objects	Top Grasp	Side Grasp	Successful Grasp (Top | Side)	Accuracy (Top | Side)
Wrench	9	7	9 | 6	100% | 85.72%
Screwdriver	9	N/A	9 | N/A	100% | N/A
Books	N/A	5	N/A | 5	N/A | 100%

The robot could successfully grasp the objects in 72 out of 75 experiments in different grasp poses which are suitable for the usage of the objects. In 3 experiments, pose estimation during testing was not accurate enough for a successful grasp. Poses of the objects could be detected instantly after they were placed in the scene. The grasps could be initiated in about a second after the poses were estimated and be completed in about 5 seconds. This makes the pose estimation and grasping a real-time operation. In successful experiments, the robot grasped the objects perfectly with respect to the training. It demonstrates that both the grasping system and the pose estimation systems are robust and they can handle rotations of objects in multiple axes and in different angles. It also shows that this system is ideal for training robots to grasp linear shaped tools, such as screwdrivers, wrenches, saws, hammers, etc. as well as objects with more complex shapes, such as box, book, magazine, etc. The pose estimation and the grasping had been robust and accurate enough for the robot to grasp objects from human hand. Grasping from human hand is sensitive as if the robot tries to grasp in incorrect locations, it will place

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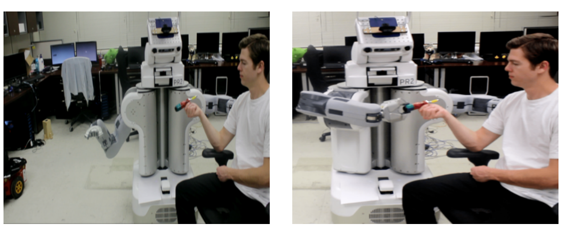
its grippers on human hand but in our experiments, that issue did not occur. There are some poses which are not reachable by a 7-DOF robot. For instance, when the object is pointing inward or back in x-axis in the robot reference frame, it is not possible for the end-effector to make a top grasp. There are also poses for which right arm is reachable but left arm is not reachable and vice versa. Thus, in our experiments, we used both arms so that we could cover all segments in a 3D coordinate system. Figure 9 shows the side grasp of a wrench tied to a tripod which displays that the gripper lined up with the wrench and the grasp pose is similar to the way human grasps a wrench.

(a) (b

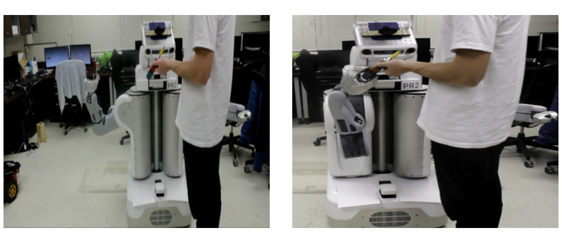
Figure 9. (a) Initial Pose of the Right Gripper and a Wrench. (b) Side Grasp of the Wrench Using the Right Gripper.

This grasp then can be used to work with the tool. The training ensures that the gripper lines up with the objects in rotations in all axes in the 3D coordinate. Thus, the system shows capability of handling complex rotations and the resultant grasp pose is always suitable for usage of the objects. The robot grasped objects in a very accurate manner from human hand. The color-based pose estimations system worked robustly while the human held the objects in hand and we were able to receive very accurate pose estimations from the vision systems for complex rotations of the tools. Figure 10 and Figure 11 show grasps of a screwdriver from human hand in which the robot was able to grasp the screwdriver from the top of its base.



(a) (b

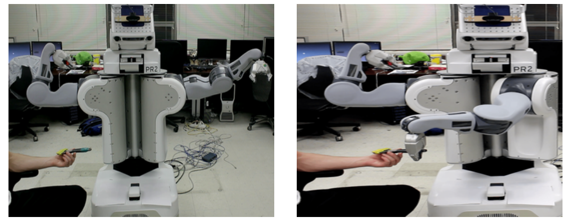
Figure 10. (a) Initial Pose of the Right Gripper and a Screwdriver. (b) Top Grasp of the Screwdriver Pointing Towards the Robot.



(a) (b

Figure 11. (a) Initial Pose of the Right Gripper and a Screwdriver. (b) Top Grasp of the Screwdriver Pointing Towards the Human.

The system had also been successful in using both of the robot's arms. The use of the left arm allows the robot to grasp objects in poses that are not feasible to grasp with the right arm. Figure 12 shows the side grasp of a wrench using the left arm. The robot also successfully grasped books from human hand. Figure 13 and Figure 14 show the results.



(a) (b

Figure 12. (a) Initial Pose of the Left Gripper and a Wrench. (b) Side Grasp of the Wrench Using the Left Gripper.

(a) (b

Figure 13. (a) Initial Pose of the Right Gripper and a Sticker-book. (b) Side Grasp of the Sticker-book.

(a) (b

Figure 14. (a) Initial Pose of the Right Gripper and a Cartoon-book. (b) Side Grasp of the Cartoon-book.

VII. CONCLUSION AND FUTURE WORK

This paper discussed an approach that enables humanoid robots to grasp objects for usage using two different vision systems for object pose detection and estimation. Application of mathematical theories and development of software systems were integrated in our work. The system had been robust enough for grasping objects such as a screwdriver and a wrench from human hand and a comprehensive set of poses had been tested for grasping with human validation. The predefined training generated accurate grasps which are suitable for usage of the objects. The accuracy of the results indicate that the system is robust.

We plan to extend the project to add more features to it. An important addition to the project would be an introduction of the movement of both arms of the robot simultaneously. If we receive two different poses coming from the vision system simultaneously then the robot could grasp both the objects at the same time. We would like to introduce a dialogue feature in the work for collision avoidance [22]. If a robot attempts to grasp an object, it would initiate a dialogue with humans in its surrounding environment. If it gets positive response from the humans, it will execute the grasp. Otherwise, it will not move its arm. The dialogue will enhance the safety in the movement of the robots' arms and will ensure that the robot avoids obstacles in its surrounding environment while grasping an object. We would also like to add an automated planning system for robots so that if the robot planner fails to plan for a grasp pose using one arm, it would automatically try with the other. This would increase the robustness of the grasping system.

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