Object Shape Perception in Blind Robot Grasping Using a Wrist Force/Torque Sensor

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***Abstract*— This paper investigates the modeling of 3D models through haptic exploration in blind scenes. Experimental setup consists of Mitsubishi arm, force/torque sensor and Phantom Omni. A Force/Torque sensor at the wrist of the 6–DOF manipulator is used to acquire data through touching objects in the environment. Robot Operating system (ROS) is implemented to connect the different components on real time. A mathematical model is presented for spherical fingertip to find out the contact location. And, it is experimented in order to proof the concept. Finally, a successful exploration procedure is proposed and applied to model a water bottle.**

I. Introduction

In the past, robotics was considered to be an advanced research topic and robotics courses consisted mainly of theoretical foundations on electro mechanics, kinematics, dynamics, and control [1]. Robotics platforms are starting to be massively introduced in new type of environments [2]. They can, for example, be used in domestic tasks, healthcare services, entertainment, and education. Last decade, hands-on robotic courses [3] have been added to classrooms as an introduction to the field. The emphasis was put into construction and building of complete robotic systems. In recent years, manipulation is becoming crucial in many aspects of life. For example, it is being used in medical healthcare. In [4] a 10–DOF robotic metamorphic instrumental hand prototype as a physical carrier of multi-manipulation. It is expected to enhance manipulation in robot-assisted minimally invasive surgery, where the human hand is prevented from being employed because it can't get into patient's abdomen through small incision.

Robotic grasping of unknown objects is important because of wide range of applications. For instance, transporting work pieces from place to place in factories. Another application is home object arrangement in apartments [5]. Fast and automatic robotic grasping is largely influenced by the way of unknown objects is realized. The process of identifying an object before grasping is of vital importance. In [6] a method of creating representation and re-targeting manipulations for object adjustments is illustrated before final grasping. A basic step before even interacting with the object is to model the object [7] and then the robotic system manually explores the object. Most of the explored regions can be identified by a probabilistic map representation of the shape of the explored object. By adopting a probabilistic representation model of the object and contact points on the object surface generated during in-hand exploration, some characteristics of the object shape associated with the object can be learnt [8]. Hence, a key point for good manipulation is a good exploration, which means extracting information about an object by all means either vision or other tools.

A method of identifying object is to use vision tools. In [9], some work has been developed to implement approaches that are involved in haptic manipulation and exploration. Robotic system is able to select and segment the aimed object from the surrounding environment using vision attention. This information of the identity and state of the object are extracted to achieve grasp parameters. In [10], a novel paradigm called haptic vision is used to construct 3D shapes and analyze the posture of the object. However, many exploration scenarios consist of environments with low visibility conditions such as, underwater robotic manipulation, smoky and foggy disaster environments [11].

Under the stated circumstances above, blind exploration of objects is being studied extensively. Typical blind exploration task is defined as being able to extract specific object characteristics using haptic input and exploration patterns. Texture obtained from the lateral motion and hardness from press and release [12]. In [13], a robotic hand equipped with tactile sensors explores unknown environments. In [14], it presents an approach to perform haptic recognition of objects using statistical point cloud features.

With literature focus on tactile sensing, the contribution of this work is related to the development of blind exploration using force/torque sensor (F/T) to develop shape models for arbitrarily chosen objects. Section II demonstrates the experimental setup and the use of Robot Operating System (ROS) framework in the study. Mathematical model of the experiment is presented in section III. Section IV shows a verification of the method used and section V presents the blind exploration task by navigating through the object using an autonomous algorithm. Conclusions are made in section VI.

II. EXPERIMENTAL SETUP

The experimental setup consists of two aspects which are the hardware and software. In the study, three main hardware components were used to achieve the results. They are Mitsubishi controller, Phantom Omni device and F/T sensor as shown in Fig.2. In the beginning phase of the research study, all the system components ranging from the Mitsubishi controller, F/T sensor and the phantom Omni are integrated together to ease the process of obtaining data instantly and to allow them to communicate in real time. Codes using Python language are developed under the Robot Operating system Framework (ROS). ROS is open source software that is used for robot application. Three separate packages are created for each of the hardware modules mentioned above. Fig. 1 shows process of communication between the different packages. Phantom Omni publishes a topic of the current position of the end-effector and send it via message. Mitsubishi controller subscribes to the topic sent from the Phantom Omni. Meanwhile, F/T sensor sends the values of the forces and torques back to the Phantom Omni where it subscribes and saves them to a file. Timestamp is also being saved in order to account for the delay between the phantom Omni and the Mitsubishi controller. As a result, there are nine variables for each timestamp which are the coordinates x, y and z of the end-effector, the force components (Fx,Fy,Fz) and the torque components (Tx, Ty,Tz).

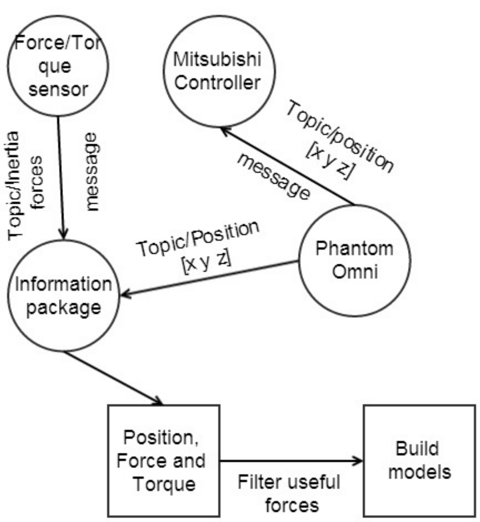


Figure 1: ROS package diagram

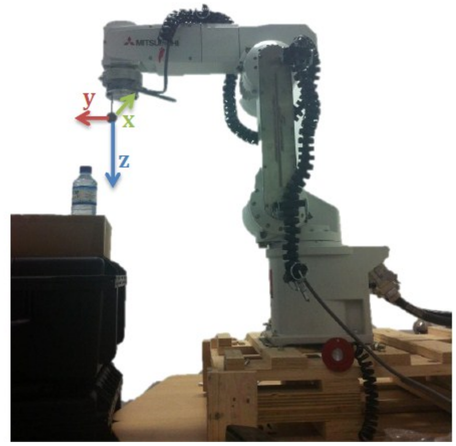


Figure 2: Experimental setup (Mitsubishi Arm + F/T sensor + sphere + object)

A tip is placed at the end-effector of the Mitsubishi arm. The tip is chosen to be spherical. The reason behind choosing spherical fingertip is because of the simplification it achieves. For instance, it is omni directional referring to the existence of every direction. As an explanation, any exploratory plan can be done as the sphere can touch the object from all directions. Another reason is that if a sphere is touching an object, there will be only one contact point. This contact point is determined using mathematical model shown in the subsequent section.

III. MATHEMATICAL MODEL

When a sphere touches an object, the force will always be normal to the tangent to the circle and directs toward the center. This force is illustrated in Fig. 3. The force components (Fx, Fy, Fz) are provided by the F/T sensor. The position of the contact point (x, y, z) where the force is acting at has the following proportional relation with for force components:

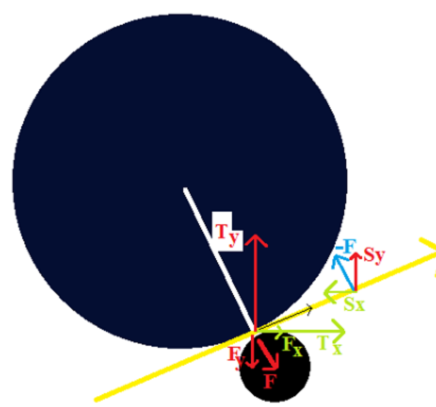


Figure 3: Force Representation

$$\frac{F_x}{x} = \frac{F_y}{y} = \frac{F_z}{z} \tag{1}$$

Then the acting point P on the sphere surface expressed in the sphere coordinate system is obtained:

$$P = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = R * \begin{bmatrix} \frac{Fx}{norm(F)} \\ \frac{Fy}{norm(F)} \\ \frac{Fz}{norm(F)} \end{bmatrix} \quad (2)$$

To collect and combine all the contact points to form the object shape, point P should be transformed into the global coordinate system as:

$$P_G = {}^{G}_{H}T \times {}^{\mathrm{H}}_{1}T \times P \quad (3)$$

where:

${}^{\mathrm{H}}_{1}T$ is the transformation matrix from the sphere coordinate system to the robot end-effector coordinate system.

${}^{G}_{H}T = {}^{G}_{1}T\,{}^{1}_{2}T\,{}^{2}_{3}T\,{}^{3}_{4}T\,{}^{4}_{5}T\,{}^{5}_{6}T\,{}^{6}_{H}T$ is the transformation matrix from the end-effector coordinate to the global coordinate system via the six joint coordinate system transformations of the 6DOF Mitsubishi robot.

R is the radius of the sphere.

IV. SCENARIO VERIFICATION

In this section, the theoretical model described above is tested using manual exploration by applying a force to the spherical fingertip attached to the Mitsubishi using another sphere. Another sphere is used in order to ensure the contact is one point. This force application is discrete, for which five seconds is recorded between each touch. The force is applied along an arc trajectory represented in Fig 4.

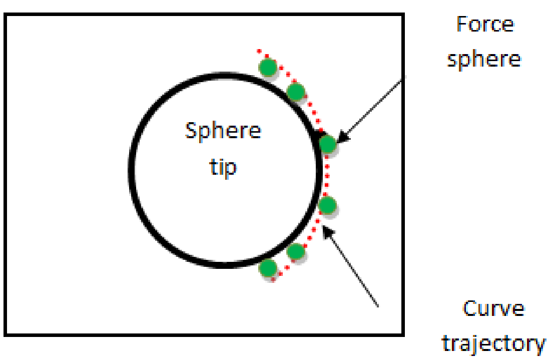
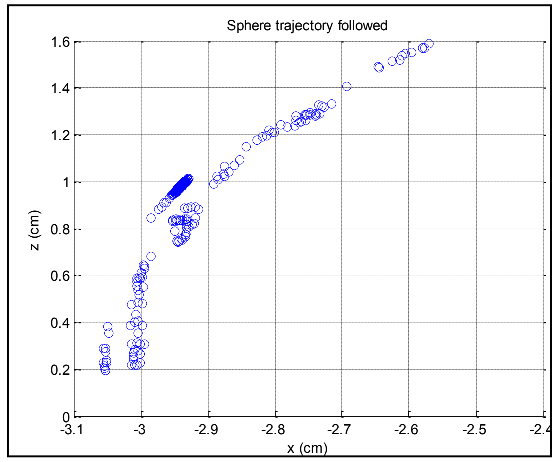
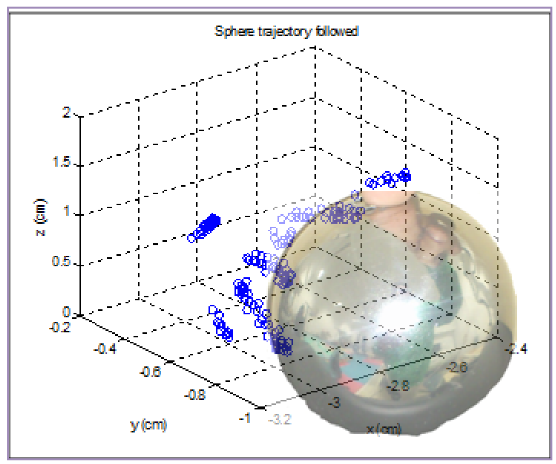


Figure 4: Schematic view of the verification scenario

The Data file of the nine variables representing the position and the inertia forces is reprocessed and filtered to include the useful data only using M-file. Useful data is where the body is hitting the spherical fingertip. When the ball is not hitting the spherical fingertip, all data are neglected. Finally, the coordinates of the points are computed using the mathematical transformation in equations above as shown in Fig. 5(a). As expected from Fig. 5(b), the data points of the trajectory followed during the experiment fit the original fingertip sphere.



(a) Points scattered of the sphere



(b) Points are fitted into the actual sphere

Figure 5: Verification result

V. EXPERIMENT

After it is assured that the scheme followed from the spherical fingertip generated good results, a further step toward modeling random shapes is investigated. The scenario described in this section is to model random objects using the same scheme, however autonomously. While many robots can navigate using maps, few can build their own maps. Usually, human map the object for the robot. Above results, Phantom Omni device was used for this purpose, where the Mitsubishi arm was controller by human using this device. Exploration has the potential to free the robots from this limitation. Exploration is defined to be the act of moving the robot through unknown environment while building the models from the subsequent movements. The mission for this task is to model a small water bottle using the autonomous approach. First the object is placed in front of the Mitsubishi arm. Then, it starts search for the object. Fig. 6 describes the searching algorithm of the object.

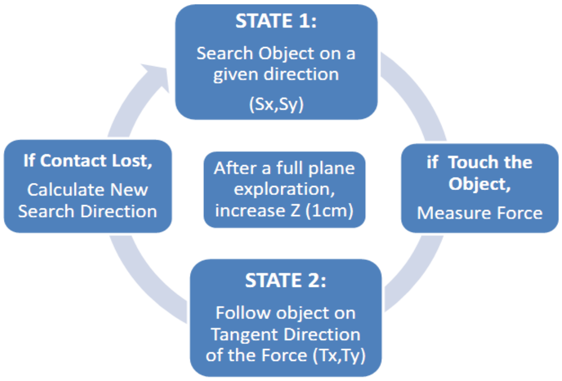
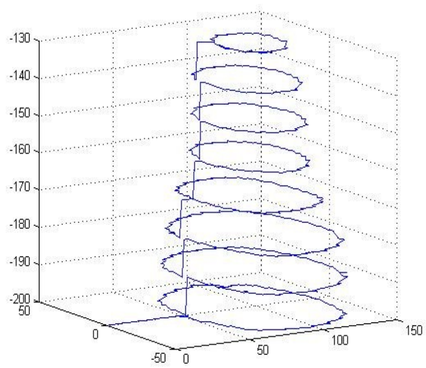
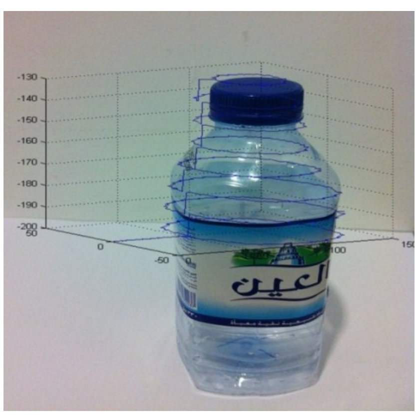


Figure 6: Object scanning algorithm

First, the robot spherical fingertip is located near the object. It measures the force continuously. If the force is touching an object above certain threshold, it follows the object in tangential direction. If the contact is lost and the force indicates a zero value, the robot tries new search direction. After the full exploration is achieved through one plane, the robot increases z value to repeat the algorithm for another plane. Experiment results are illustrated in Fig. 7 which clearly shows the final shape perception.



(a) Shape modeled from recorded data



(b) Shape model fitted into the actual object
Figure 7: Experiment results

VI. CONCLUSION

The paper has demonstrated the scheme followed for attempting to model 3D random object without using vision system. This modeling was through the data obtained from a force/torque sensor. The mathematical model used for translating the position from the spherical fingertip into world coordinate was illustrated as well. Finally, a successful experiment attempted to model a small water bottle is shown.

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