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A Manipulator with a Depth Sensor and an Underactuated and Tactile Gripper for Identifying and Grasping Objects of Various Shapes and Sizes

Li-Yen Huang[1] Yu-Chen Lin[1] Yan-Chen Liu[2] Jui-Yiao Su[2] Pei-Chun Lin[1*]

[1]National Taiwan University, Taipei Taiwan [2]Industrial Technology Research Institute, Hsinchu, Taiwan

Abstract: We report on a methodology for identifying and grasping objects of various basic shapes in pick-and-place tasks with a manipulator containing a gripper. The gripper is designed to be underactuated and changeable in configuration (two-finger mode and three-finger mode) to increase its intrinsic adaptation to objects of various shapes. The tactile sensing system, composed of a pressure sensor array, a force-sensitive resistor, a potentiometer, and an accelerometer, is mounted on the gripper to provide in situ contact information for object shape identification and grasp. In addition, a depth sensor is utilized not only to identify the position and orientation of the objects to be picked up, but also to incorporate the tactile sensing system that identifies object shapes. The methodology is implemented and experimentally evaluated. The performance of the system is also compared to that of the system with only the depth sensor or with only the tactile sensing system. These tests confirm the merit of integrating sensory data from the pick-and-place tasks with the function of identifying object shape.

Keywords: Underactuated, Gripper, Tactile, RGB-D camera, Shape identification, Force control

I. Introduction

Grasping is one of the important tasks in factory manufacturing or assembly processes such as packaging, assembly, painting, etc. Planning a robotic gripper to grasp multiple objects involves diverse domains. For human grasping, we preshape our hands to grasp objects in order to engage the hand with the object. The evolution of hand preshaping may depend on visual feedback about arm and hand position as well as on target shape and location at specific times during movement [1]. For robots, integration and coordination of sensors and actuators are essential for determining adequate configuration of the robot to stably grasping objects. There are two main stages during grasping. The first stage is to find the object and decide the preshape of the gripper with a visual sensor, and the second stage is to grasp the object stably depending on the tactile feedback. The hand-eye coordination provides a solution for grasping many kinds of objects. In order to complete a task, integration of sensor output, a multi-configuration gripper, and control of force are necessary.

For performing the task, a self-adaptive gripper that can take on multiple postures is required. In manufacturing, a gripper that can adapt to any tools or grasp versatile materials is very useful. The direct advantage is the decrease of the manufacturing cycle time and of the space required for gripper inventory. In order to meet multiple demands, we designed a compliance gripper. The compliance of the gripper can be achieved by using an underactuated mechanism. Underactuation means that the number of actuators is smaller than the degrees of freedom (DOFs) of actuators is smaller than those of the mechanism. Graspers with underactuation are relatively low-cost, lightweight, and easy to control in comparison with ordinary fully-actuated grippers. An underactuated gripper can also grasp various objects because the fingers of the gripper can adapt themselves to the shape of the objects by their passive mechanical behaviors [2]. In recent years, many flexible and universal grippers have been designed by industrial manufacturers. Unlike the traditional gripper, the universal gripper can adapt itself to various kinds of tool shape. The famous adaptive grippers include a 2-Finger Adaptive Robot Gripper, produced by Robotiq [3], the Barrett Hand, manufactured by Barrett Technology Inc. [4], and the SDH Gripping Hand, made by Schunk [5]. The 2-Finger Adaptive Robot Gripper has different grasping modes and can create an astonishing grasping force due to its passive compliance. The Barrett Hand is underactuated and can adapt to multiple objects. Moreover, it has an ability to spread two of its three fingers to positions opposite the third finger, creating different grasping postures. The SDH Gripping Hand has tactile sensing, making it intelligent for various robot tasks. We designed our gripper with reference to Robotiq's Gripper and the Barrett Hand.

One of the difficulties of gripper preshaping before grasping is the wide variations of the object shapes and orientations. The solution is to simplify objects from our daily life. Everything can be considered as the composite of basic shapes [6]. For example, a cup can be seen as the composite of a cylinder and a rectangular solid. This decreases the complexity of selecting an suitable posture. For this reason, identifying and manipulating objects that have basic shapes is practical. In most research, models of objects are saved in a CAD database and the object is recognized by a tactile or visual sensor. In some work, FEM (Finite Element Method, FEM) is used to identify the relationship between deformation of the objects and the pressures sensed by the sensor array [7]. Machine learning is another approach widely adopted by the researchers [8].

Tactile sensory feedback is important for avoiding slippage or crashing objects with unknown weights or fragileness when grasping them. Success at grasping strongly depends on the interaction between the forces of the gripper and the object. In [9], Chebotar et. al. offers an explanation of how a robot learns a manipulation action via tactile sensing using spectral clustering and principal component analysis. In [10], the authors present a real-time sensor fusion algorithm that can be used to accurately estimate object position, translation, and rotation during grasping. In [11], the authors provide a

*corresponding email: peichunlin@ntu.edu.tw

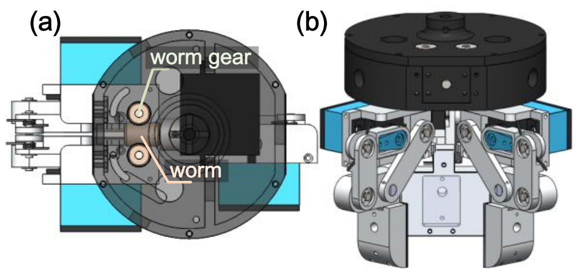


Fig. 1. Two grasping modes of the gripper: (a) two-finger mode and (b) three-finger mode.

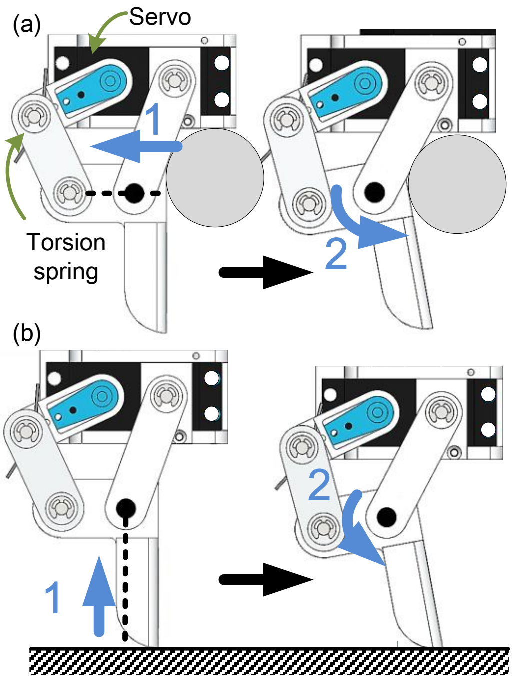


Fig. 2. Change of finger configuration during contact: (a) the distal phalanx first touches the object, and (b) the fingertip touches the ground.

methodology for measuring object characteristics, including stiffness, weight, and friction.

Previously, we developed a tactile sensing system [12, 13], and in that work, we used it to identify and manipulate objects of various shapes and sizes by using tactile sensory information and a depth sensor. The gripper could also adjust its grasping force through contact with the objects. The depth sensor was also included to enhance the ability of the overall system to robustly perform pick-and-place tasks and to identify object shape.

Initially, the depth sensor searches for objects and obtains their positions. Then, the trajectory of the robot manipulator is planned so as to move the end effector to the location where the object is. The shape of the object is pre-identified, so that the gripper can adjust its configuration for stable grasping. During grasping, the system again identifies the shape and size of the object by fusing the original object information from the depth sensor with the new tactile information.

We constructed a decision tree classifier based on geometrical characteristics, and a database and learning process was not required. In addition, we constructed a force control procedure. The gripper self-adjusts the grasping force, which needs to be large enough to lift up the object but not excessive. Finally, the gripper and the object are moved to the destination and release the gripper to complete the task.

Section II describes the mechanical design. Section III introduces the control strategy for task execution in the workspace using visual and tactile feedback. Section IV reports the experimental results, and Section V concludes the work.

II. Hardware of the Manipulator

The manipulator is composed of four components that will be described below: the underactuated gripper, the tactile sensing system, the SCARA robot arm, and the depth sensor.

A. The Underactuated Gripper

Fig. 1 shows the CAD drawing of the gripper. It has two characteristics that increase its adaptation to objects that have considerable shape and size variations. One is the design of the changeable finger configuration. As shown in Fig. 1, the gripper can be operated in either two-finger mode or three-finger mode. The transformation of the finger number of the gripper is achieved by the rotation of two fingers that are driven by a worm and a worm gear pair installed at the finger base. The multi-mode design of the gripper increases its adaptation, so that it can grab objects of different shapes and sizes, such as a ball or a pen.

The other characteristic is the design of the underactuated fingers. The fingers are composed of a five-bar linkage mechanism, as shown in Fig. 2, where one of the DOFs is actuated by a small servo and the other is passively controlled by a torsion spring and mechanical limits. When the fingers close to grasp, the distal phalanx of the fingers moves without changing their orientation before touching the object. If the inner distal phalanx of the fingers touches the object, the fingers grasp the object in a parallel configuration via mechanical limits, where the five-bar mechanism acts as a four-bar linkage. In contrast, if the lower distal phalanx of the fingers touches the surface or the upper distal phalanx of the fingers touches the object, the five-bar linkage deforms and encloses the object as shown in Fig. 2, which is referred to as the "envelope grasp."

In short, by utilizing a design that transforms the number of fingers and an underactuated finger design, the gripper is capable of grasping objects that have a wide range of shapes and sizes. The specifications of the gripper are listed in Table 1.

Table 1. The specifications of the gripper.

Kinematics	Number of fingers: 3 Number of movable fingers: 2 Number of motors: 4 Per finger: 1 Grasping mode change: 1
Motor type	RC Servo motor Futaba BLS172SV (Torque: 31 kg-cm)
Working range	Three-finger mode : 15–70 mm Two-finger mode : 0–70 mm
Payload	40 N
Weight	0.8 kg

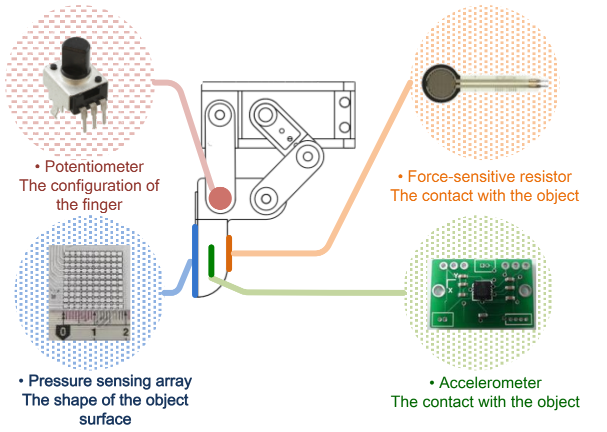


Fig. 3. The tactile sensing system, which has four kinds of sensors mounted on the gripper.

B. The Tactile Sensing System

Several sensors are mounted on the fingers, as shown in Fig. 3. A potentiometer is mounted on one joint of the finger to measure its rotational configuration. Together with the rotation state provided by the RC servo, the full kinematics of the five-bar linkage of each finger can be obtained, including important position information from the distal phalanx. In addition, the potentiometer can also act as a contact sensor if the finger touches any object under it and induces finger-bending behavior. A force-sensitive resistor is mounted on the outer surface of finger and an accelerometer is installed inside the finger. Both sensors are utilized to detect contact between the finger and the object. When the gripper approaches the object, the force-sensitive resistor can yield initial contact information. The accelerometer can detect the vibration generated by sudden contact or slippage between the finger and the object. A pressure-sensing array made by Industrial Technology and Research Institute (ITRI), Taiwan, is mounted on the inner surface of the distal phalanx and covered with a silicon pad to reduce the impact of contact. The shape of the object at the contact surface can be identified by the array. In short, by using these four sensors that have distinct characteristics, we can reliably identify object shape and grasp the object.

C. The SCARA Robot Arm

In order to test the performance of the gripper, a SCARA robot arm (shown in Fig. 4) was designed and built. Compared to other manipulator morphology, the robot in SCARA morphology has the advantages of rigidity, speed, low structure length index, and easy inverse kinematics.

D. The Depth Sensor

The ASUS Xtion pro has an RGB-D sensor, providing a color image and a depth image simultaneously. In this work, depth information was extracted at a speed of 30 fps and a resolution of 640 x 480 pixels was extracted in real time for object shape identification.

III. Object Shape Identification and Grasping

In this section, we will present the sequence of steps for controlling the SCARA manipulator and the gripper.

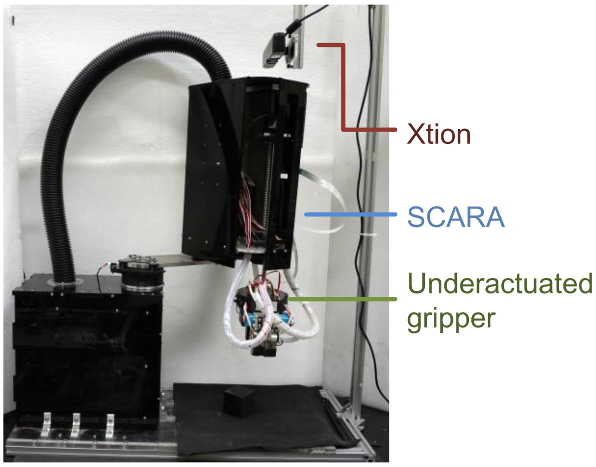


Fig. 4 Photo of the SCARA robot with the vision system and the gripper.

During the procedure, the manipulator can automatically find objects, identify geometries of objects, choose a suitable grasping mode, grasp an object stably, and carry it to the destination. To carry out the above series of actions, the system needs sensor fusion. Tactile sensors and a camera cooperate to sense objects and identify the shape and weight of these objects. Our procedure achieves recognition of several basic shapes of objects, including cubes, cylinders, spheres, and rectangular solids of different sizes. We present a control system that uses applications that provide tactile and visual feedback. Our control strategy has four main parts. First, it shows the workflow of the whole system. Second, it preprocesses images to improve the manipulation of objects and third, it identifies basic shapes using tactile and visual sensors. Last, we provide our force control method, which yields a suitable grasping force.

A. Workflow

The whole process of grasping an object is given in Fig. 5. In the vision state, we take photos of the desktop with the camera. The depth image received from Xtion is easier to use for separating the object from the background than is the color image. During image preprocessing, the system extracts the bounding box of the object and finds the centroid of the image. The position of the object is determined by transformation of the centroid of the bounding box from the image coordinate to the world coordinate. Then the SCARA brings the gripper to the object position.

To position the gripper over the object, the position and the orientation of the object are necessary information. Among basic shapes of objects, spheres and standup cylinders that are isotropic can be grasped from any angle. The angle of the object needs to be known for grasping cubes, rectangle solids, and laydown cylinders. Image moment is useful for deducing the orientation of the object after image segmentation. The direction of the major axis is determined as the minimum sum of squares of the distances between all points and the centroid. The principal axes of rectangular solids and laydown cylinders can be obtained successfully by computing image moments. For cubes, image moments are equal along their central axis and the diagonal axis. The other method of deducing cube

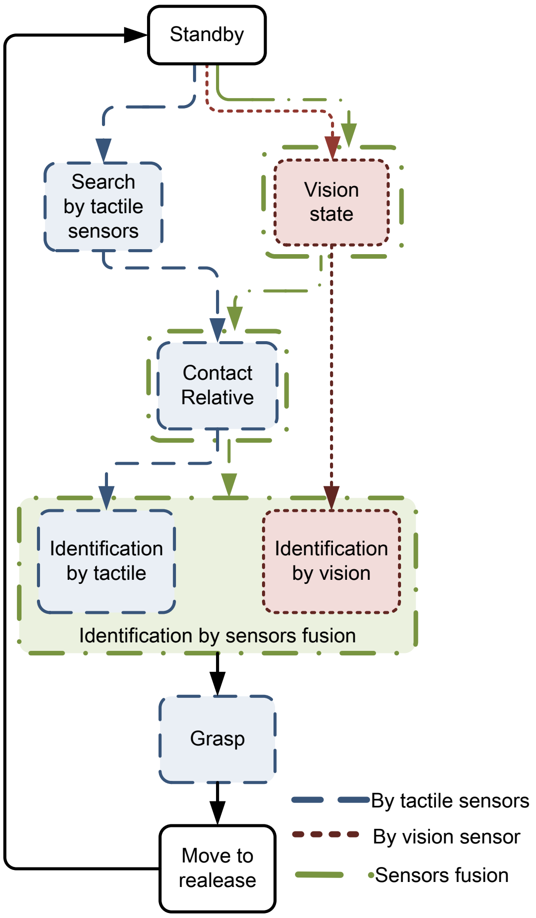


Fig. 5. The flow chart of the control strategy.

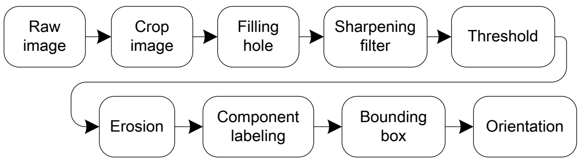


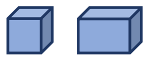
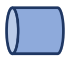
Fig. 6. The image preprocessing procedure for identifying shape and position of the object.

angle is to connect the corner of the object on the edge of the bounding box forming the estimated rectangular and the angle relative to the world frame of its edge. We decide which method to use by estimating object shape via depth features; more details on this are provided later in this paper.

When the distance between the fingers of the gripper is close to the length of the longest side of an object, the gripper cannot position above the object with inaccuracy estimated position and orientation. Due to the inaccuracy of camera calibration and low resolution, the above method of positioning the object is imprecise. The angle is also not accurate enough. We use the tactile sensor to adjust position. Every finger of the gripper has a potentiometer that can detect the object under the finger. The body of the gripper is moved toward the finger that has touched the object until the gripper can position over the object. If both sides of the finger have touched the object, the gripper cannot position over the object by adjusting position. The error of estimated angle is not acceptable in this case. The gripper will rotate the fourth axis to adjust the angle until the gripper position over the object.

The next step is identification, which means initially rechecking that the gripper is just above the object and that both sides of the fingers touch the object. The purpose of identifying the object shape is to choose a suitable finger configuration and grasping mode for the gripper. The system will also know the size of the object, which is more straightforward than knowing the image area. Objects of the same size but of different shape occupy different areas in an image, causing classification errors. The distance between the fingers is more reliable information. While the gripper holding the object, we obtain the surface features by using the pressure array sensor. To determine the shape of the object, we have developed a method to integrate the data from the visual and tactile sensors. The gripper provides four different kinds of the grasping mode; these are displayed in Table 2. Each of the basic shape objects is associated with a unique mode of stable grasp. The Envelope Grasp holds the object by constraining its geometry. Alternatively, the Parallel Grasp utilizes friction force. Without knowledge of the weight of the object, the gripper grasps objects iteratively to deduce the required force. Finally, the SCARA brings the gripper holding the object to the destination.

Table 2. The grasping strategy.

	Two finger mode	Three finger mode
Parallel Grasp		
Envelop Grasp		

B. *Image Preprocessing*

Image preprocessing is needed initially to enhance the data from the image. It cuts the image to a suitable size and deals with noise. The process of image preprocessing is shown in Fig. 6. Initially, the image is cropped to a suitable size by removing its unwanted parts. Then, the depth image is needed to fill holes. The depth image from Xtion has a problem of missing data induced by reflections, transparent objects, and light scattering. There are multiple reasons causing noise or holes in the depth data. When the depth image has pixels that cannot be estimated, holes arise in the resulting image. To fill the hole, the missing data is estimated by extrapolating the non-zero neighboring values around it. The mean filter is used to fill holes. Next, the image is sharpened by the Sobel filter. Then, we set a depth threshold to isolate the object from the background and erode the image to cut off low noise. Component labeling is used to find the contour and the bounding box of the object, thus to distinguish the object against the background of the whole image. It tracks pixels along the contour under 8-connected neighbors. Afterwards, the depth image is processed to distinguish the object by using its bounding boxes.

C. *Shape Identification*

We investigate how the tactile sensors and the camera work in object recognition and propose a feasible strategy that uses tactile sensor, camera, and integrated information.

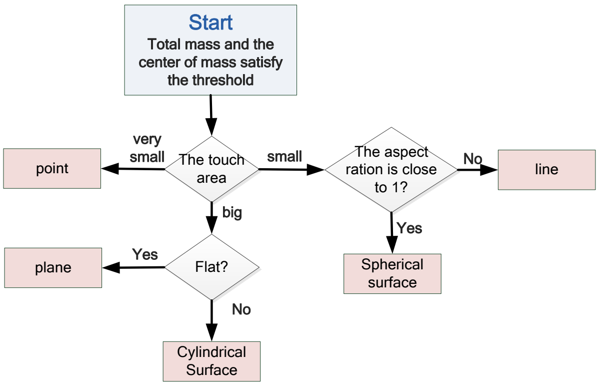


Fig. 7. The procedure for identifying object shape with the tactile sensing system.

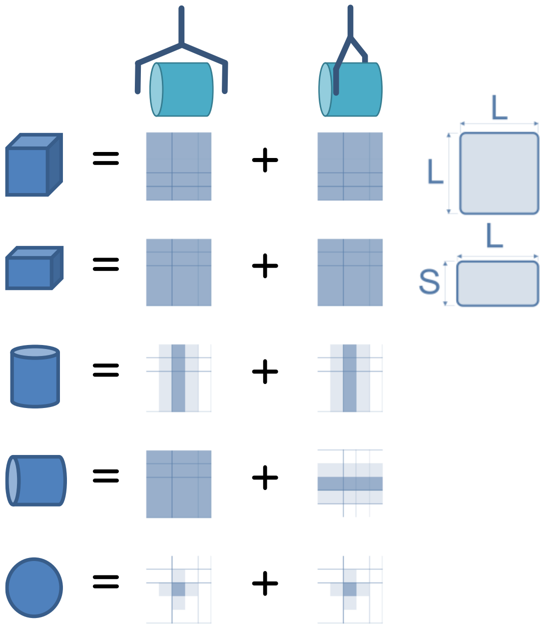


Fig. 8. Classifying object shape using the tactile sensing system after grasping twice.

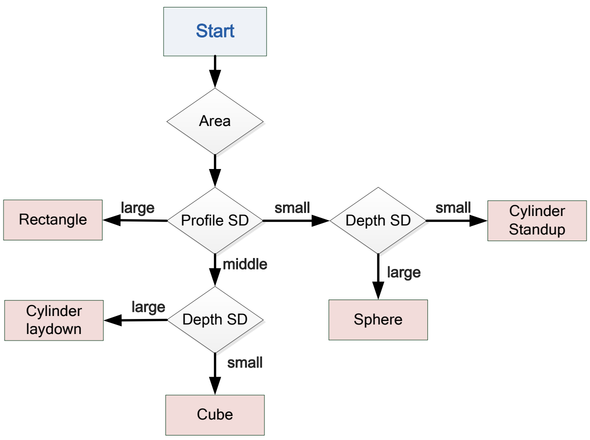


Fig. 9. The procedure for identifying object shape with the visual sensors.

C1. Shape identification by tactile sensors

First, we explore object appearance using tactile sensors alone. When the object touches both sides of the fingers, the distance between fingers is equal to the diameter or the length of the object. From the potentiometer, we know the configuration of the fingers by inverse kinematics. After calculating the size of the object, we use the pressure sensing array to identify the exterior surface of the object. There are three kinds of surface: spherical, cylindrical, and plane surfaces. These are discriminated by certain properties of the values from the pressure sensing array, including the mean, standard deviation, and the aspect ratio of the touch area. Fig. 7 shows the sequence of the discrimination. We also need to grasp twice to distinguish a cube from a rectangular solid or a cube from a cylinder. After the gripper grasps the first time, it rotates 90 degrees and carries out the second grasp. Because both cubic and rectangular solid have planar surfaces, the distinction depends on the relative lengths. On the other hand, a cylinder has one planar surface. Grasping twice can ensure touch with the cylindrical surface. The combination of tactile data from grasping twice is shown in Fig. 8.

C2. Shape identification by visual sensors

The depth image also contains various object features. We empirically chose some parameters in order to construct the object classifier: area, standard deviation of the depth, and standard deviation of the profile distance. Area was used to distinguish the size of the object. The standard deviation of the depth can identify flat surfaces, spherical surfaces, and cylindrical surfaces. For example, the standard deviation of the depth of a flat surface is smaller than the standard deviation of the depth of a cylinder surface. ,

The standard deviation of the profile distance means the standard deviation of distances from every point on the contour to the centroid, which can separate squares from circles on the image. We built a decision tree based on the above image characteristics. It is displayed in Fig. 9. Once we set appropriate thresholds for every node of the decision tree, it classified efficiently and effortlessly. Also, the meaning at every node is straightforward.

C3. Shape identification by visual and tactile sensors

We also wanted to know the classification by both tactile and visual feedback. Different sensors are sensitive in different areas, and complement each other's strengths. Integration of sensor information produces better classification. Via experiment, we noticed that the pressure array was sensitive to small objects that had obvious variations in curvature and low image resolution (i.e., fewer pixels). On the other hand, large objects could be identified clearly by the visual sensor, and the variation in curvature is not clearly perceived by the pressure sensing array. Consequently, we deduced that the classifier would perform better with integrated information from both sensor types. We developed an identification strategy that uses visual and tactile feedback, as shown in Fig. 10. First, the size of the object is discriminated by the potentiometer; this indicates the distance between the fingers. Then, the shape of the object can be classified for size, which means that the features of shape and size are not joint. Classification by vision only recognizes object shapes. Lastly, we preferred to use the pressure

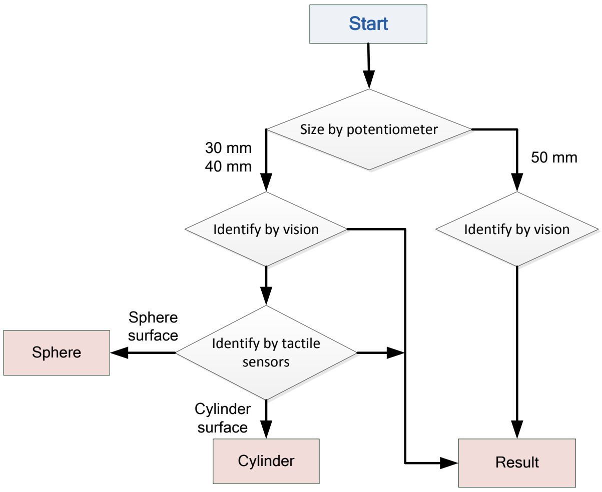


Fig. 10. The procedure by vision and tactile sensor.

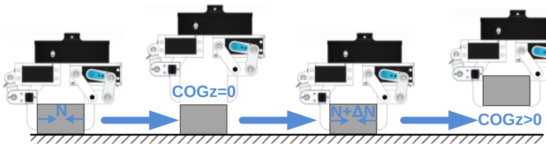


Fig. 11. The operation of force control.

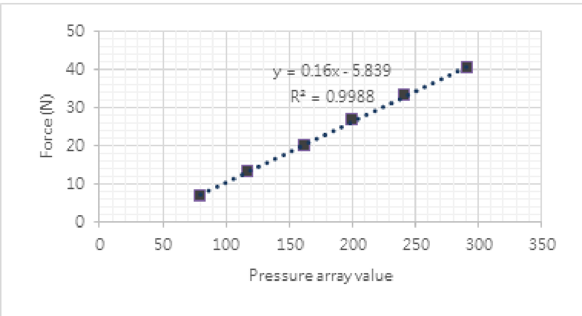


Fig. 12. The force measured by the load cell to the pressure array value.

sensing array, which is good at detecting small objects, as a patch for the tactile classifier.

D. Force Control

We designed a simple operation to grasp objects stably with minimal force without knowing their weight. With Parallel Grasp, objects are grasped depending on the friction force. The fingers provide enough normal force to hold an object without slippage, while an object will crack under excessive force. Our approach is to increase force iteratively until the object is lifted up successfully. Figure 11 shows the procedure for grasping an object. The pressure array sensor detects slippage via the centroid of y moving down. That is to say that normal force is not enough to support the weight of the object. The gripper will increase force on the next iteration. The force sensed by the pressure array sensor is linear, as shown in Fig. 12. The gripping force will increase 1.5 N each time and repeat until the object is lifted. The process ensures that the grasping force is suitable.

IV. Experiment and Result

In this section, we show three cases of identification: by tactile sensor, by visual sensor, and by both of them. We also present the performance of grasping force adjustment.

A. Identification

We evaluated our strategy for automatically identifying different sizes and shapes of objects by conducting several experiments. We placed the test objects randomly in the 200 x 200 mm^2 workspace. The test objects were several objects of different sizes with basic shapes, being 30 mm, 40 mm, and 50 mm in diameter. Table 3 shows their dimensions and shapes. After settling down the experiment environment, the gripper was moved out of the workspace to clear the view of the camera. The Xtion took images, and the system preprocessed the images to give the position and angle of the objects. Then, the SCARA brought the gripper to an estimated position by the visual sensor. In order for the gripper to position among the object, it rechecked the relative position using the signals from the potentiometers. The gripper then adjusted position until it positioned the object. Then, the system began identification.

The first experiment was identifying the object by the tactile sensors only. The gripper grasped twice. The gripper rotated 90 degrees the second time. During the two grasps, the size was obtained by the potentiometer and the shape of contacted object was detected by the pressure sensing array. Table 4 shows the results. The experiment is repeated 10 times with each objects. We notice that the rate of identification was lower when the test objects were larger. The gripper tended to confuse flat surfaces with cylindrical surfaces. Because the pressure sensing array senses local variations, the curvature of a large cylinder is perceived as being similar to a flat surface. Moreover, any unevenness influences the data from the pressure sensing array, which is not really robust.

The second experiment was recognition of the object by Xtion only. The result is shown in Table 5. In contrast with tactile sensing, small objects yielded poor results because of the low resolution of the depth image. The small size of the projected squares and circles was hard to discriminate with Xtion's resolving power. The exception was the 30 mm diameter sphere. Because of the smallest image area on the depth image, small spheres were separated and identified easily.

The third experiment combined feedback from the tactile and visual sensors. The system obtained the visual features in the visual state and the tactile features while grasping the object. The strategy of compounding both data achieves the classification results given in Table 6. The method takes into account objects of different sizes and raises the success ratio. However, with tactile compensation there is a chance of classification error. For example, a cube is confused with a laydown cylinder and the tactile feedback was in error.

B. Force Control

The experimental results show the process of adjusting the gripping force. We prepared objects with similar shapes but different weights. The light one was printed by a 3D printer. The heavy one was in stainless steel. In Fig. 13 (a) and (b), we show the 30 mm cube. The light one weighed 12.5 g. It was grasped for one trial. The heavy one weighed 213 g. The gripper iteratively increased force until it lifted the object. First, it grasped the object with an initial force

Table 3. The test objects.

	30 mm	40 mm	50 mm
Sphere	D30	D40	D50
Cylinder	D30H30	D40H40	D50H50
Cube	L30	L40	L50
Rectangular solid	W50L40H30		

Table 4. The success rate of tactile identification.

Identification only by tactile sensors			
	30 mm	40 mm	50 mm
Sphere	80 %	90 %	80 %
Cylinder standup	90 %	50 %	40 %
Cylinder laydown	50 %	70 %	50 %
Cube	80 %	70 %	50 %
Rectangular solid	60 %		

Table 5. The success rate of visual identification.

Identification only by visual sensor			
	30 mm	40 mm	50 mm
Sphere	90 %	60 %	70 %
Cylinder standup	50 %	90 %	100 %
Cylinder laydown	30 %	60 %	90 %
Cube	70 %	80 %	90 %
Rectangular solid	90 %		

Table 6. The success rate of integrated sensor identification.

Identification by tactile and visual sensors			
	30 mm	40 mm	50 mm
Sphere	90 %	80 %	100 %
Cylinder standup	80 %	90 %	80 %
Cylinder laydown	70 %	60 %	90 %
Cube	60 %	50 %	70 %
Rectangular solid	80 %		

and attempted to lift it. The grasping force was not enough. The pressure array sensor detected sliding. The centroid of y on the pressure sensor moved down. The gripper grasped it again with additional force. The process was repeated three times until the gripping force was enough to lift the object. Fig. 13 (c) and (d) show another trial for the 40 mm cube. The force control experiment was done only in the two finger mode. Grasping in the three finger mode is more likely to perform a planar or three-dimensional form closure that is more stable and independent of friction force.

V. Conclusions

In this paper, we report on the development of a system which can pick-and-place and identify the shapes of objects of various shapes and sizes. The system automatically searches the workspace, finds an object, identifies basic shapes, chooses a stable grasping mode, adjusts force appropriately, and moves the object to the destination. We have integrated multiple sensors to complete the task. The depth sensor provides the position of the object and the visual features. The tactile sensors perceive local shape variation and slippage when grasping the object. They cooperate to identify various basic shapes of objects of different sizes. The gripper also can adapt its grasping force

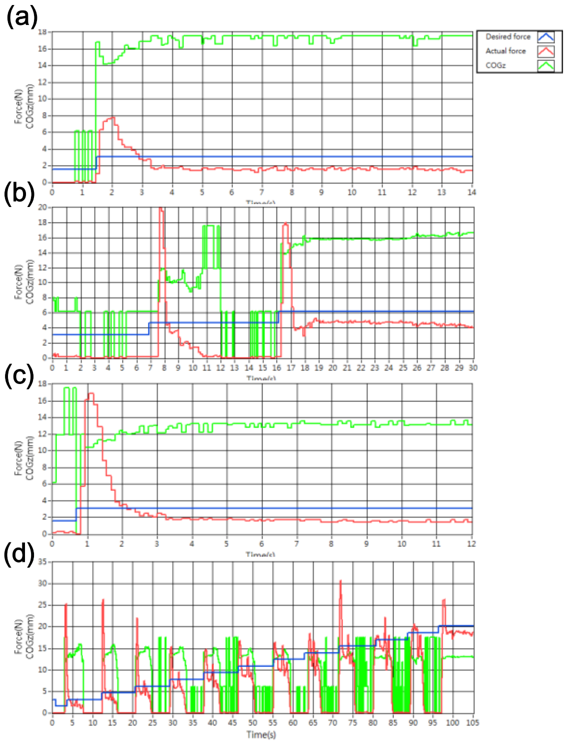


Fig. 13. Adjusting force to grasp (a) a 30 mm 12.5 g cube (b) a 30 mm 213 g cube (c) a 40 mm 20.5 g cube (d) a 40 mm 504 g cube.

suitably for objects of unknown weight. The proposed shape classifier and force control strategy were experimentally evaluated and were proven to be effective and feasible.

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