

Object Shape Reconstruction Based On The Object Manipulation

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Abstract—This paper presents an approach for the object shape reconstruction based on the object manipulation using tactile information and force feedback. The tactile information collected during the manipulation process and the kinematic information of the hand are used to identify points on the surface of the object in contact with the hand and thus allowing the object shape reconstruction. Distance invariants are measured on the reconstructed object shape in order to perform the object identification. The proposed approach was implemented using the Shunk Dexterous Hand (SDH2). Different tests were performed in real executions and some examples are presented in the paper.

I. INTRODUCTION

Tactile feedback is used by humans for retrieving object information, such as texture, temperature and shape, and to assist grasping and manipulation with the detection of important events, like slippage, or object deformation. By monitoring these events, the human hand is able to update the grasping force according to the object weight, stiffness, or friction. In fact, it has been shown that people have difficulties to perform manipulation tasks when they are deprived of tactile feedback. For this reason, sensors that can retrieve tactile information have been developed in order to equip robotic hands with such sense. Besides, several characteristics of the grasped objects can also be recognized with touching. The shape of the object, the irregularity of the contact surface, the temperature of the object are some of them [1]. The tactile information is important for dexterous robotic hands in order to recognize the properties of the grasped object and to achieve dexterity and precise objects handling.

The object manipulation using robotic hands equipped with tactile sensors to detect contacts and increase their capabilities is a challenging subject. Humans are able to manipulate any unknown object without seeing it or having any a priori information about its properties. However robots normally need precise information about these properties in order to manipulate the object successfully. The information that humans need about the properties of the object is obtained during the manipulation using the tactile sensors they have in their hands [2]. The robotic researchers are often inspired by this human ability to create applications for robotic hands equipped with tactile sensors which try to imitate the human way of doing things.

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A tactile sensor in robotics, like human tactile receptors, is able to detect the contact and measure the applied forces. It can be used to obtain information about the shape of the object, its pose, the location of the contact points and the contact force applied to the object by the robotic fingers. Slippage detection and estimation of the friction coefficient between the fingers and the object are also some of the intended common applications of tactile sensors [3].

This paper presents an approach to identify objects using the tactile and kinematic information collected during a manipulation process with a robotic hand. The used hand is a Schunk Dexterous Hand (SDH2). This is a three finger hand with seven degrees of freedom (*dof*). Each finger has two tactile sensor arrays. The object manipulation is performed using two fingers of the hand. The orientation of the object is computed combining tactile and kinematic information, as well as the distance between contact points. These results allow a partial shape reconstruction of the manipulated object and the identification of the object based on distance invariants.

The paper is organized as follows. After this introduction, Section II presents a review of related work. Section III introduces the bases of the manipulation approach. In Section IV it is discussed the proposed approach for the object shape reconstruction. An approach for object recognition based on partial object shape is presented in Section V. Experimental results are described in Section VI. Finally, Section VII presents the conclusions and future work.

II. RELATED WORK

Robot grasping and manipulation require very accurate knowledge of the location of the object within the robotic hand. A vision system could not provide very precise and robust pose tracking due to occlusions or light limitations. For this reason, visual information has been combined with kinematic and tactile information in order to estimate the pose of a grasped object [4]. The tactile information can be treated as a sequence of images in order to extract information about the contact conditions between an object and the hand [5], and therefore image processing techniques are used in order to process the tactile sensor information. On the other hand, machine learning techniques has been also applied in order to improve the object manipulation using tactile information, specifically, in order to estimate the grasp stability [6][7].

Tactile sensors has been also used as tools to recognize objects in robotic in-hand manipulation tasks. The reconstruction of the shape of an unknown object can be performed using tactile sensors without requiring object immobilization,

instead, the robot manipulates the object without grasping it. The robot can infer the shape, motion and the center of mass of the object based on the motion of the contact points measured by tactile sensors [8]. A different way of using the tactile information is using it to generate a contact point cloud and then use statistical point cloud features to provide robust descriptions of the grasped object [9]. Besides, a compact 3-D representation of unknown objects can be obtained using a probabilistic spatial approach based on Kalman filters to build a probabilistic model of the contact point cloud [10].

In some object recognition approaches the tactile information is treated as low-resolution images. Then, different techniques are applied in order to perform the object identification, for instance, the bag-of-words approach which, by unsupervised clustering on training data, learns a vocabulary from tactile observations that is used to generate a histogram codebook. The histogram codebook models distributions over the vocabulary is the core identification mechanism [11]. Using a fusion sensor approach, a multi-sensory object representation is built by fusion of tactile and kinesthetic features. The recognition approach is based on extracting key features of tactile and kinesthetic data from multiple palpations using a clustering algorithm [12].

Leaving aside the tactile sensors, the representation of an object can be built using the joint force/torque information, closing a finger over the object and detecting the contact by the force/torque variation. The geometric and kinematic model of the finger is used in order to estimate the shape of the grasped object [13].

In contrast to these previous works, our approach uses the manipulation process, instead of repeatedly palpating the object, in order to collect the tactile information, which will allow the partial identification of the shape of the object in contact with the hand. This shape recognition is performed using the kinesthetic and the tactile information collected during the manipulation, and applying geometric invariants.

III. OBJECT MANIPULATION

The robotic hand used in this work is the Schunk Dexterous Hand (SDH2) shown in Figure 1. This is a three finger hand with seven active degrees of freedom (*dof*). The SDH2 has tactile sensors attached on the surfaces of the proximal links and the distal links (fingertips), thus the tactile sensor system contains six sensor pads. The pad over each proximal link has 84 tactile sensor cells while the pad over each fingertip has 70 cells. The configuration of the sensor pads and sensor cell arrangement is described in Table I. Two finger of the hand are coupled and can be rotated on the base to work opposite to the other in the same plane.

To manipulate a grasped object, the two coupled fingers of the SDH2 are used performing a prismatic precision grasp [14], this grasp is comparable with a human grasp with the thumb and index finger opposed. The fingers are moved over a circular path whose diameter is given by the distance between the contact points, as it is shown in Figure 2.



Fig. 1. The three finger Schunk Dexterous Hand (SDH2) with seven *dof* and six tactile sensors arrays.

TABLE I
CONFIGURATION OF SENSOR PADS ON THE SDH2 HAND.

Location	Num. of Cells	Res. (mm)	Grid
Proximal	84	3.4 x 3.4	6 x 14
Fingertip	70	3.4 x 3.4	6 x 9 + 4 x 4

The contact points are expressed in a reference system located at the base of the finger f_1 as P_1 and P_2 . The distance d between the contact points is given by,

$$d = \sqrt{(P_{1x} - P_{2x})^2 + (P_{1z} - P_{2z})^2} \quad (1)$$

the center of the circumference can be computed using the contact points as,

$$G_x = \frac{P_{2x} - P_{1x}}{2} + P_{1x} \quad (2)$$

$$G_z = \frac{P_{2z} - P_{1z}}{2} + P_{1z} \quad (3)$$

The object can be rotated clockwise or counterclockwise to follow the circular path. We use a discrete variation step of the inclination of the object $\Delta\alpha^d$. Using geometric reasoning (see Figure 2), the variation of contact P_1 on the z_0 -axis, Δz can be expressed as function of $\Delta\alpha^d$ as,

$$\Delta z = \sin(\Delta\alpha^d) \frac{d}{2} \quad (4)$$

thereby, the points over the circular path can be computed using the circumference expression,

$$(x - G_x)^2 + (z - G_z)^2 = \left(\frac{d}{2}\right)^2 \quad (5)$$

where z can vary in Δz at each manipulation step. The sign of Δz depends on the current rotation direction and must be considered in order to compute correctly the next contact points.

Algorithm 1 summarizes the procedure used to manipulate an object using tactile feedback. It requires as input the desired

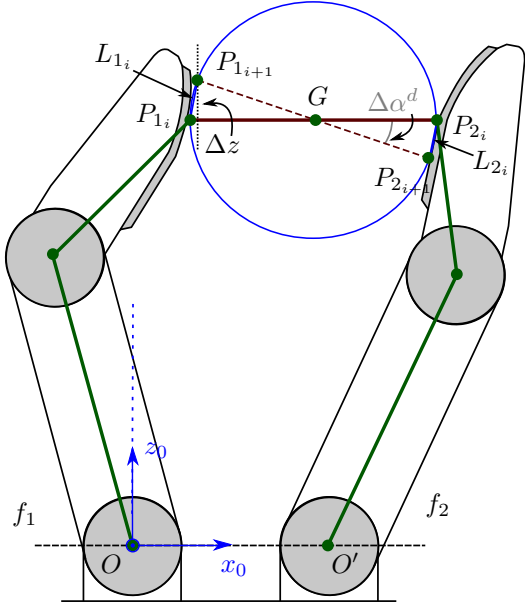


Fig. 2. Two fingers model of the SDH2 hand used to manipulate unknown objects following a circular path.

variation $\Delta\alpha^d$ on the object orientation at each manipulation step, and the desired force F^d to be applied to the grasped object. Before starting the manipulation process, the fingers of the SDH2 are closed over the object until the contact force F_i calculated as the average of the force values F_{1_i} and F_{2_i} measured by both sensors reach the desired F^d .

$$F_i = \frac{F_{1_i} + F_{2_i}}{2} \quad (6)$$

Then, the manipulation of the grasped object starts, this is an iterative process that is repeated while a stop signal is not activated. In each loop, the first step is the computation of the absolute positions of the contact points P_{1_i} and P_{2_i} using the finger direct kinematic, the sensor measurements and the knowledge of the sensor geometry (the shape of the fingertip is implicitly considered in this step). After this, the distance d_i between P_{1_i} and P_{2_i} , the distances L_{1_i} and L_{2_i} between two consecutive contact points on the same finger, and the actual variation of the object orientation $\Delta\alpha_i$ are computed. The change in the orientation of the object $\Delta\alpha_i$ after the manipulation can vary from the desired variation $\Delta\alpha^d$ due to the unknown object shape. The absolute orientation α of the object is given by the sum of the variations in the object orientation in each manipulation step as,

$$\alpha = \sum \Delta\alpha_i \quad (7)$$

where $\Delta\alpha_i$ is approximated by,

$$\Delta\alpha_i = \frac{L_{1_i} + L_{2_i}}{d_i} \quad (8)$$

The next step is the measurement of the applied force F_i over the object, and then the computation of the new contact points to be reached in order to perform the manipulation.

So, the expected distance d_{i+1} between contact points is computed as $d_{i+1} = d_i + \Delta d$ with Δd being a function of the force measured by the tactile sensors according to the follow relationship,

$$\Delta d = \begin{cases} 0 & \text{if } F_{\min} < F_i < F_{\max} \\ +\rho & \text{if } F_i \leq F_{\min} \\ -\rho & \text{if } F_i \geq F_{\max} \end{cases}$$

where the constant values F_{\min} , F_{\max} and ρ were empirically defined after experimenting with real objects. The next step is the computation of Δz for a desired variation $\Delta\alpha^d$ in the object orientation. Using the resulting Δz and the distance d_{i+1} , the next contact points $P_{1_{i+1}}$ and $P_{2_{i+1}}$ are computed, this points are over a circumference with diameter d_{i+1} and centered in G . If the friction constraints at $P_{1_{i+1}}$ and $P_{2_{i+1}}$ are satisfied (i.e. the angle φ between the normal direction at the contact point and the segment between the two contact points must always satisfy $\varphi < \tan^{-1} \mu$, with μ being a given friction coefficient), and the points $P_{1_{i+1}}$ and $P_{2_{i+1}}$ are inside of the fingers workspace, then the configuration of the fingers is updated (move f_1 and f_2 such that the contact points on the fingertips currently at P_{1_i} and P_{2_i} moves to $P_{1_{i+1}}$ and $P_{2_{i+1}}$ respectively), and a new iteration is started; else the direction of rotation is changed.

Algorithm 1 Manipulation with tactile feedback

Require: $\Delta\alpha^d, F^d$

- 1: $i = 0$
 - 2: **repeat**
 - 3: Close fingers (varying each joint in a predefined $\Delta\theta$)
 - 4: Compute F_i
 - 5: **until** ($F_i \geq F^d$)
 - 6: **repeat**
 - 7: Compute P_{1_i} and P_{2_i}
 - 8: Compute d_i
 - 9: Compute L_{1_i} and L_{2_i}
 - 10: Compute $\Delta\alpha_i$
 - 11: Compute F_i
 - 12: Compute d_{i+1}
 - 13: Compute Δz using $\Delta\alpha^d, P_{1_i}$ and P_{2_i}
 - 14: Compute $P_{1_{i+1}}$ and $P_{2_{i+1}}$
 - 15: **if** Friction constraints are satisfied **and** $P_{1_{i+1}}$ and $P_{2_{i+1}} \in$ workspace of the fingers **then**
 - 16: Move f_1 and f_2 to reach the expected contact at $P_{1_{i+1}}$ and $P_{2_{i+1}}$
 - 17: $i = i + 1$
 - 18: **else**
 - 19: Change the direction of rotation
 - 20: **end if**
 - 21: **until** Stop signal is activated
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IV. OBJECT SHAPE RECONSTRUCTION

The object shape reconstruction using tactile information is useful in applications where it is not possible to apply

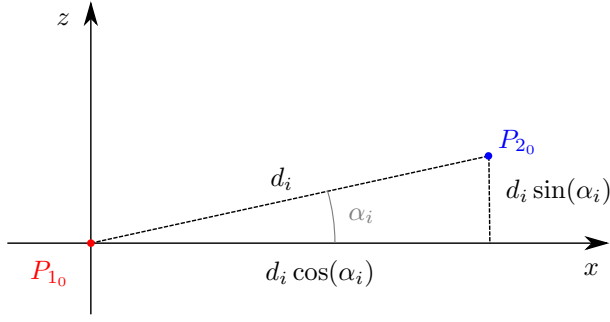


Fig. 3. Coordinate system defined on the object to perform the object shape reconstruction. Points P_{1_0} and P_{2_0} are the initial contact points, i.e. $i = 0$.

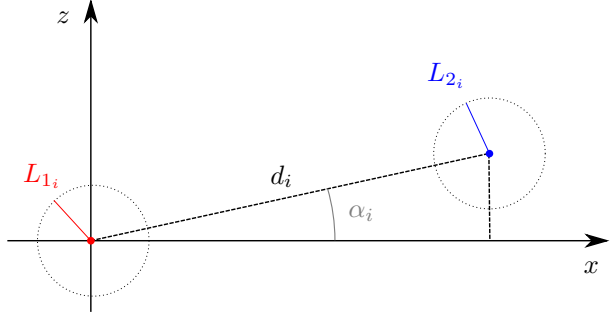


Fig. 4. Circular regions with radius L_{1_i} and L_{2_i} , where the points belonging to the object surface are located.

artificial vision. Even providing artificial vision, the tactile information is a good complement to reduce uncertainty in the object model [15].

The proposed approach uses the data collected during the object manipulation: the distance d_i between contact points, the object orientation α_i , and the distances L_{1_i} and L_{2_i} between two consecutive contact points on the same finger. Each couple of contact points has associated a distance between them and an object orientation. Consider a coordinate system on the object, whose origin coincides with the first contact point P_{1_i} detected on the finger f_1 . The point defined by $(d_i \cos \alpha_i, d_i \sin \alpha_i)$ for $i = 0$ is coincident with the first contact point P_{2_i} on the finger f_2 (see Figure 3). Note that $P_{2_i} = (d_i, 0)$ for $\alpha_i = 0$.

Given L_{1_i} and L_{2_i} , the new contact points on the object surface are located within two regions defined by circumferences with radius L_{1_i} and L_{2_i} centered on P_{1_i} and P_{2_i} respectively, as shown in Figure 4. The regions are given by,

$$x_{1_i}^2 + z_{1_i}^2 = L_{1_i}^2 \quad (9)$$

$$(x_{2_i} - d_i \cos \alpha_i)^2 + (z_{2_i} - d_i \sin \alpha_i)^2 = L_{2_i}^2 \quad (10)$$

To determine the coordinates of the points of the object boundary (x_{1_i}, z_{1_i}) and (x_{2_i}, z_{2_i}) , the constraints on the distance between the contact points d_i and the orientation α_i are added, given by,

$$d_i = \sqrt{(x_{2_i} - x_{1_i})^2 + (z_{2_i} - z_{1_i})^2} \quad (11)$$

$$(z_{2_i} - z_{1_i}) = m_i(x_{2_i} - x_{1_i}) \quad (12)$$

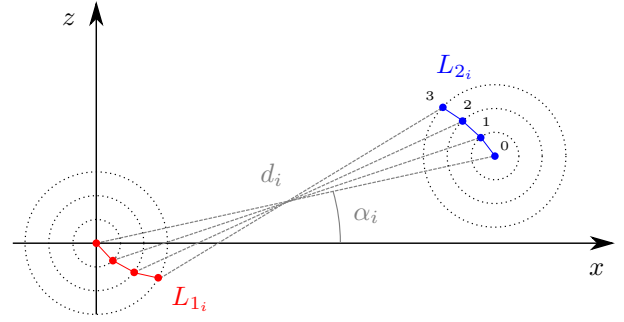


Fig. 5. Conceptual representation of a reconstructed object shape (numbered points) applying iteratively the identification of boundary points with constraints of distance and orientation.

where m_i is the slope of the segment defined by the points (x_{1_i}, z_{1_i}) and (x_{2_i}, z_{2_i}) , and it is defined as $m_i = \tan \alpha_i$.

The expressions (9), (10), (11) and (12) form a 4×4 equation system whose solution provides the points (x_{1_i}, z_{1_i}) and (x_{2_i}, z_{2_i}) for the object shape reconstruction. The solution of the equation system is given by,

$$x_{1_i} = x_{2_i} - \gamma \quad (13)$$

$$z_{1_i} = z_{2_i} - \beta \quad (14)$$

$$x_{2_i} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \quad (15)$$

$$z_{2_i} = \sqrt{L_{2_i}^2 - (x_{2_i} - d_i \cos \alpha_i)^2} + d_i \sin \alpha_i \quad (16)$$

where

$$\gamma = \sqrt{\frac{d_i^2}{1 + m_i^2}} \quad \beta = m_i \sqrt{\frac{d_i^2}{1 + m_i^2}}$$

$$\begin{aligned} a &= (-2d_i \sin \alpha_i + 2\beta)^2 + (-2d_i \cos \alpha_i + 2\gamma)^2 \\ b &= -2d_i \cos \alpha_i (-2d_i \sin \alpha_i + 2\beta)^2 \\ &\quad - 2\psi (-2d_i \cos \alpha_i + 2\gamma) \\ &\quad + 2d_i \sin \alpha_i (-2d_i \sin \alpha_i + 2\beta) (-2d_i \cos \alpha_i + 2\gamma) \\ c &= (d_i \cos \alpha_i)^2 (-2d_i \sin \alpha_i + 2\beta)^2 \\ &\quad + \psi^2 - 2\psi d_i \sin \alpha_i (-2d_i \sin \alpha_i + 2\beta) \\ &\quad + (d_i \sin \alpha_i)^2 (-2d_i \sin \alpha_i + 2\beta)^2 \\ &\quad - L_{2_i}^2 (-2d_i \sin \alpha_i + 2\beta)^2 \end{aligned}$$

$$\psi = L_{2_i}^2 - L_{1_i}^2 - (d_i \cos \alpha_i)^2 - (d_i \sin \alpha_i)^2 + \gamma^2 + \beta^2$$

Computing iteratively the points (x_{1_i}, z_{1_i}) and (x_{2_i}, z_{2_i}) the object shape is reconstructed as it is shown in Figure 5.

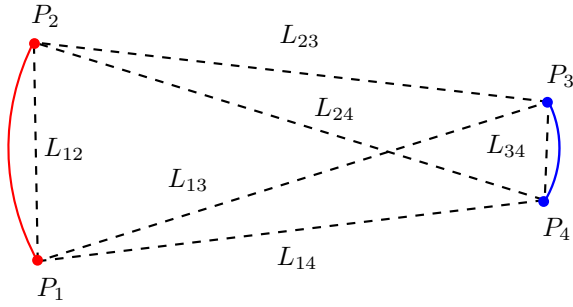


Fig. 6. Reconstructed shape using finger f_1 (red) and finger f_2 (blue), and their distance invariants. Points P_1, P_2, P_3 and P_4 are the extreme points.

V. OBJECT RECOGNITION

The object recognition is based on a modification of the approach described in [16]. In the proposed approach it is considered the partially reconstructed object shape and not only the distance between some points of the object boundary. The shape information is processed in order to compute distance invariants on the reconstructed object shape, as shown in Figure 6. In this case, the distance invariants are defined as the distances between each pair of extreme points of the reconstructed portions of the object boundary.

The set of shape and distance invariants forms a signature of the manipulated object which is used for the recognition. Using previously stored models from a database of objects, a match of the points of the models with the object signature is searched. An example of the matching is shown in Figure 7. First, it is intended that the extreme points of the reconstructed shape contacting the finger f_1 fit with the points of the object model. If a match is reached, then it is verified that the extreme points of the reconstructed shape contacting the finger f_2 also fit with the model. In the first two examples in Figure 7, the computed signature does not match with the model of a circumference (Figure 7a), nor with that of an ellipse (Figure 7b). Figures 7c and 7d show a positive matching of the signature in a false case and with the correct object respectively. In order to avoid false positives like that in Figure 7c, once the signature has a coincidence with the model, a local comparison of all the points in the reconstructed boundary are performed against the points in the corresponding segment of the model. A polynomial regression is used to find a curve that best matches the points of the model within the extreme points, and then, the coefficient of determination between this curve and the points of the reconstructed object shape is used to decide whether both sets of points are equivalent or not. When both the signature and the local comparison are a positive match the model is assumed to be a real candidate for the manipulated object.

VI. EXPERIMENTAL RESULTS

The proposed approach has been fully implemented using C++ for the manipulation process with the SDH2 hand, and Matlab was used for the data analysis. Table II shows a list

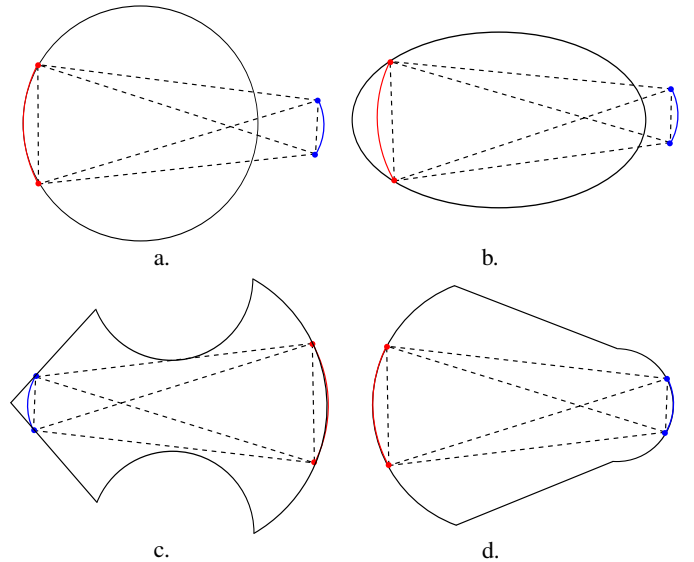


Fig. 7. Example of the matching using the reconstructed object shape and the object model. a) Comparison between signature and a circular model. b) Comparison between signature and elliptical model. c) Comparison between signature and the object-2 model produces a false positive. d) Positive matching between signature and object-1 model.

TABLE II
LIST OF MANIPULATED OBJECTS

Object	Shape	Dimensions (mm)
A	Cylinder	$r = 40$
B	Ellipse	$a = 37, b = 20$
C	Object-1	$r_1 = 45, r_2 = 20$

with three different manipulated objects and their characteristics, these objects were manipulated using the two coupled fingers of the SDH2 hand.

Each object is hold between the two fingers, then the fingers are closed until the detected contact force reach a desired value (note that the initial contact points are not known). After this, the object is manipulated by the two fingers that change the inclination of the object. First, the object is rotated counterclockwise and then clockwise. The object is inclined until the contact forces tend to exceed the friction cone limits or the finger reach the limit of their workspace. Then the fingers start to rotate the object on the opposite direction. This iteration is repeated three times. Table III shows the setup parameters used in the experimentation.

Figure 8 shows snapshots of a real execution of the manipulation process where the hand holds a cylinder. Figure 9 shows the real object contour and the matches between the object models and the reconstructed object shape. The noise in the reconstructed shape due to the sensor noise and the computational approximations was not significant in the matching procedure.

TABLE III
PARAMETERS USED IN THE MANIPULATION

Parameter	Description	Value
$\Delta\theta$	Variation on joint values	0.25°
$\Delta\alpha^d$	Variation on object inclination	1°
F^d	Desired Force to grasp the object	$20\mu N$
ρ	Variation on distance d_i	1 mm

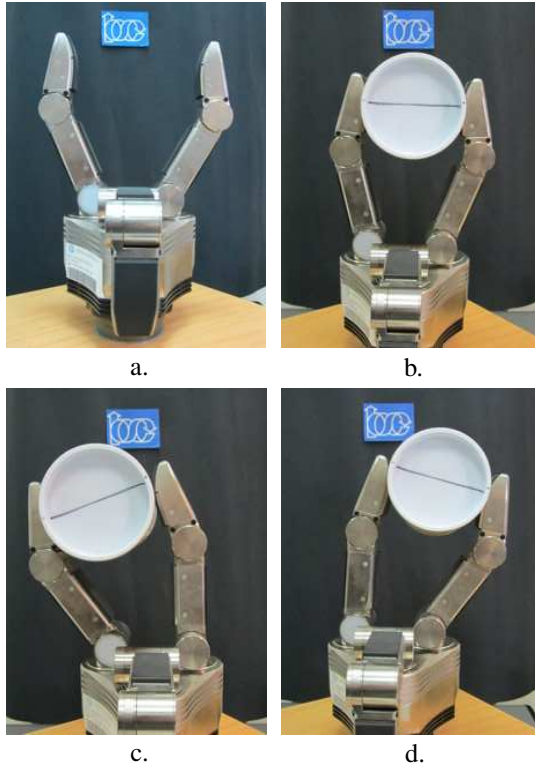


Fig. 8. Snapshots of a real execution of the manipulation of a cylinder. a) The SDH2 hand in the initial position. b) Cylinder grasped before that the manipulation process starts. c) Configuration where the fingers reach their workspace limit in counterclockwise motion. d) Idem in clockwise motion.

VII. CONCLUSIONS AND FUTURE WORKS

In this work we propose an object shape reconstruction approach based tactile feedback obtained during the object manipulation. The manipulation gives information about the distance between the contact points, the object orientation and the displacements of the object on the surface of the sensors. This information is used for the object shape reconstruction. The tactile sensors are used to detect at any time the contact points and consequently the position and orientation of the object. Using this information, the fingers are able to rotate the object until the contact forces reach the friction cone limits or the fingers reach the mechanical limit of movement. Furthermore, the detection of the contact force is used to adjust the distance between the fingers during the manipulation to adapt them to the objects shape. The experimentation showed that the collected information during the manipulation allows

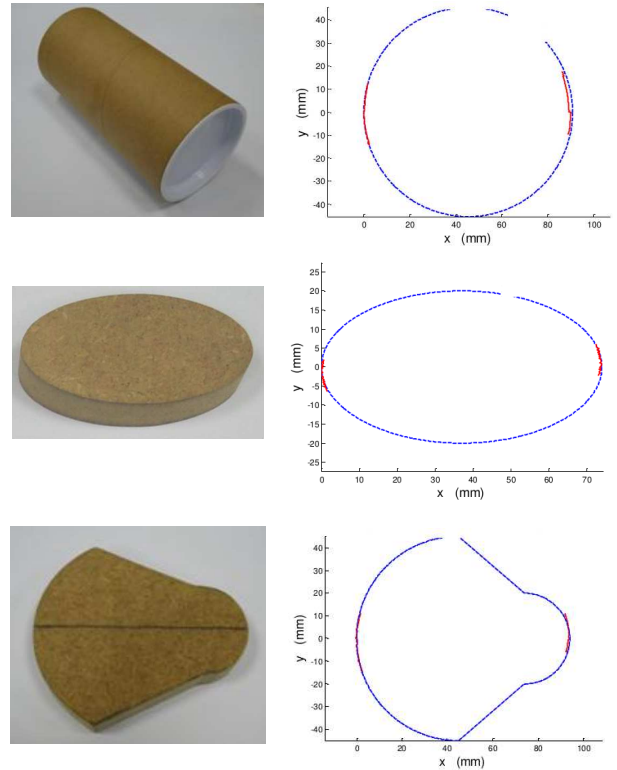


Fig. 9. Results of the object shape reconstruction for three objects and object identification. The right images show the object model (in blue) and the reconstructed shape (in red).

the object recognition.

An extension of the implemented work is to consider the use of three or more fingers in the manipulation process. The information collected would allow to reconstruct the shape of 3-D objects.

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