A Novel Optical Tracking based Tele-control System for Tabletop Object Manipulation Tasks

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***Abstract*— For a robot serving in a complex environment such as in a restaurant, it is difficult to perform a task like tabletop object manipulation completely by itself, in that some information may be missing. An approach to deal with this is to use a tele-control system and method to control the robot or demonstrate. In this paper, a LeapMotion sensor based non-contact tele-control method is developed for a robot to perform tabletop object manipulation tasks. A coordinate system for mapping from the operation space of the LeapMotion sensor to the workspace of the robot is established. A gesture recognition and action generating algorithm is proposed for control or to demonstrate the motion to the robot. To evaluate the performance of the LeapMotion sensor and proposed method for tele-control of a robot, a comprehensive assessment index based on entropy weighting is proposed. Three common tele-control modes, including demonstration mode, teleoperation mode and semi-teleoperation mode, are developed on a PR2 robot. The experimental results show that the proposed tele-control system is more appropriate for use in task demonstration.**

***Index Terms*— LeapMotion sensor, tele-control, gesture recognition, action generating, comprehensive assessment index**

I. INTRODUCTION

Object manipulation may be a difficult task for a robot serving in a complex environment. For example, some visual information or manipulative skills may be lacking. In these cases, some human-robot cooperative methods such as teleoperation or demonstration are efficient for dealing with the problems [1], [2]. Through the cooperation with humans, additional information can be provide for a robotic system to execute the task and even acquire some experience and even learn something].

The most traditional and common way to control a robot is based on programming methods which have already been widely used with industrial robots. A demonstration controller with buttons or a six-dimensional mouse is used as the interface [3]. However, the interface is not intuitive and efficient. And in most such systems, the robot only records positions and orientations without interpreting gestures, so these systems are not applicable to more complex pick-and-place tasks. A more natural method based on a kinesthetic interface is used for demonstration. A human can drag the robotic arm to follow his actions, for example in research by Hersch et al [4] on a humanoid robot and by Hwang et al [5]. But this method also focuses on the trajectory tracking rather than on gesture recognition. Furthermore, this is a typical contact control method in which a human works within the same space as the robot. As a result, it cannot be used in human-unfriendly environments.

Therefore, some non-contact tele-control approaches are more suitable for these cases, such as robotic systems based on a mechanical master-slave device [6], [7], [8], and some optically and visually based hand tracking systems [9], [10], [11]. These methods directly track the movement of the hand and record the trajectory; the robot performs the actions based on this recorded information.

For more complex pick-and-place tasks, hand gestures are another important input to action planning. An highly efficient method for tracking hand gestures is based on a data glove that can record the motion of each finger [12], [13]; some haptic systems can even measure the contact force of a grasping or pinching action [14]. However, a data glove has no ability to track the hand trajectory, so other sensors are added to track hand positions [15]. Some visually based methods are also used for gesture recognition [16]. For example, the Kinect, which is popular for body tracking, is used to detect the motion of fingers and the palm. However, the tracking accuracy is unsatisfactory [17]. The LeapMotion[1] sensor, developed by Leap Motion Inc., is a new non-contact finger/hand tracking sensor. It has a high tracking accuracy and provides an interface for pose and gesture recognition, shown in Fig. 1.

In this paper, a non-contact tele-control system based on a LeapMotion sensor is developed for a robot to perform tabletop object manipulation tasks. Considering the characteristics of the LeapMotion sensor, a gesture recognition and action generating algorithm is proposed. The coordinate system is established to combine the operation space of LeapMotion sensor and the work-visual space of the robot. To evaluate the performance of the LeapMotion sensor and the proposed method in tele-control for robots, an entropy weighting

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[1]http://www.leapmotion.com

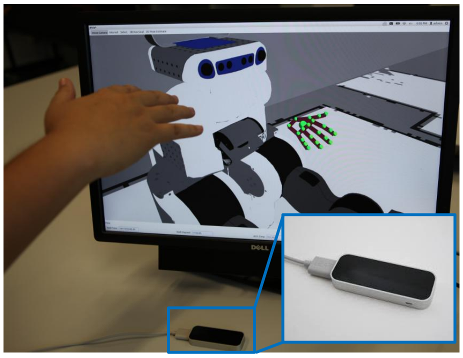


Fig. 1. Hand Tracking by Leap Motion sensor

based comprehensive assessment index is proposed, which combines several different criteria such as operation time and accuracy. Three groups of experiments are performed with different tele-control modes implemented on a PR2 with ROS[2] (Robot Operation System). The discussion and analysis of the experimental result are based on the proposed assessment index and the failure mode of the experiments.

The rest of this paper is organized as follows: the main methodology for gesture recognition and action generating based on LeapMoion sensor is introduced in section II; a comprehensive assessment index for performance evaluation is shown in section III; the experiments are described and discussed in section IV; and some conclusions are given in the last section.

II. Methodology for Gesture Recognition and Action Generating

To perform a non-contact tele-control for a robotic system, the gestures of the operator should first be recognized. With different gestures and trajectory tracked by LeapMotion sensor, an array of actions are defined and generated, which actually can be considered as mapping the actions from the operator's hand to the robot's gripper.

A. Cooperative Action Coordinate Transforming

In the control method developed in this paper, the action planning process is shared between the human and the robot. The key operational positions and gestures are given by the human through LeapMotion sensor. This information provides an array of actions to carry out the tasks. While for planning the trajectories of the actions and avoiding collisions in detail, the packages of Object Recognition Kitchen (ORK) and Open Motion Planning Library (OMPL) are implemented on the PR2 to share the planning process. To combine these two components into one operational space, a coordinate system is built, as Fig. 2 shows. The ${}^E\boldsymbol{O}$ and ${}^L\boldsymbol{O}$ are the visual and manipulative coordinates of the human operation; ${}^V\boldsymbol{O}$ and ${}^R\boldsymbol{O}$ are the visual and manipulative coordinates of the PR2; the coordinate ${}^T\boldsymbol{O}$, which represents the observing space and shown on screen, is the connection between the human and PR2 coordinates. Visual information provided by the Kinect, mounted on the head of the PR2, is shown in rviz (a visualization tool in ROS) on the screen and allows the human to share the PR2's view. And with the transformation Equation 1, the manipulation coordinates of PR2 and human are matched so that the position and gesture of the palm in the human operational space is mapped into the PR2 workspace. A LeapMotion sensor is used to collect hand motion and the gesture of the human palm. The sensing range (with maximum range $200 \times 325 \times 200\ mm^3$) [17] of the LeapMotion sensor is much smaller than the workspace of the PR2, so a scale coefficient k is used to scale the operational space of the human to an appropriate range.

$$ {}^L T_R = k \cdot {}^T T_L^{-1} \cdot {}^T T_R \tag{1} $$

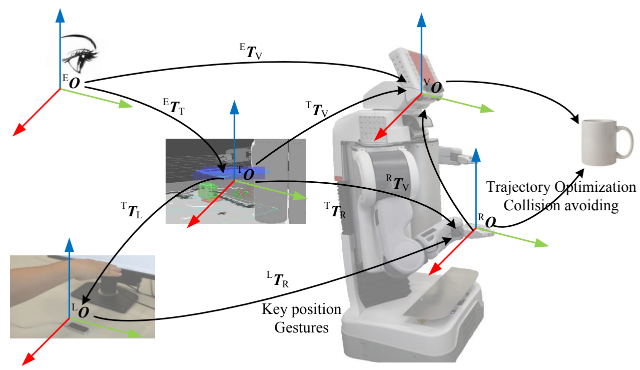


Fig. 2. Coordinate system of the cooperative grasp planning.

B. Gesture Recognition

The tabletop object manipulation action consists of a sequence of positions and gestures of the palm. The gestures can also be seen as the combination of basic data, such as the orientation, direction and pose of palm and fingers. The LeapMotion sensor is used to obtain these basic data from the human hand. It provides the position and orientation of the palm and the position and direction of each finger. Moreover, it also provides APIs through which the status of each finger (extended or not) and the strength of the grasp and pinch, which depend on the closure degree of fingers, can be obtained easily.

In this paper, the combination of palm orientation, finger extension status and grasp/pinch strength together define the gestures, as shown in Fig. 3. Some gestures that apply to common pick-and-place tasks are defined and listed in Table I. The orientation of the palm is described using the Euler angle (α, β, γ along x, y, z axes). To describe the extension status of the thumb and fingers, a five-bit binary number is used (0 for non-extended, 1 for extended); grasp and pinch strengths are between 0 and 1, with 1 indicating a stronger grasp or pinch. The Algorithm 1 is used to guarantee stable recognition of gestures. When an instantaneous gesture is recognized, the corresponding gesture counter is incremented. Every two seconds, the gesture counters are ordered according to their values. With a LeapMotion sensor

[2]http://www.ros.org

sampling frequency of 10 Hz, a gesture counter value above 15 indicates that the corresponding gesture is stable in this two-second period.

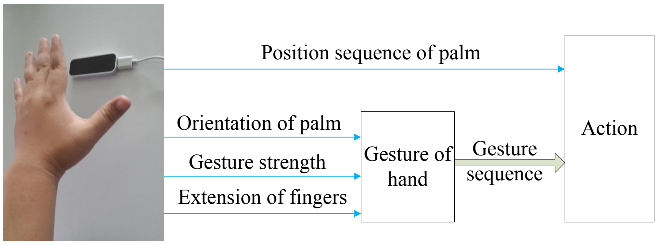


Fig. 3. Framework for action and gesture recognition

Algorithm 1 STABLE RECOGNITION OF GESTURE

while ($sampling\_count < 20$) **do**
  Comment: Sampling basic data via Leap Motion sensor
  $basic\_data \leftarrow$ SamplingBasicData( )
  $sampling\_count{+}{+}$
  $gesture\_state \leftarrow$ RecognizeInstantaneousGesture(basic_data)
  Comment: Count the number of PH, PL, PR, PF, PB, HG, LG, RG, HP and HpP
  if $gesture\_state == PH$ **then**
    $PH\_count{+}{+}$
  end if
  ...
  if $gesture\_state == HpP$ **then**
    $HpP\_count{+}{+}$
  end if
end while
Comment: Order the gesture_counts (PH_count, PL_count, ..., HpP_count), and put the maximal count gesture on the top
$stable\_count \leftarrow$ MaxOfCounts($PH\_count, \ldots, HpP\_count$)
if $stable\_count > 15$ **then**
  Comment: The top gesture is the stably recognized gesture
  $stable\_gesture \leftarrow$ GetTopGesture( )
end if
return

C. Action Generating

With these gestures and palm positions, several actions are defined to connect the movement of the human hand and the PR2 gripper. Each action is defined as a sequence consisting of two gestures and positions, and corresponds to a movement of the human hand and the PR2 gripper. However, because of the different structure of the human hand and the two-finger PR2 gripper, there is no one-to-one correspondence between the actions of the human hand and those of the PR2 gripper. For example, to grasp a cup from the right side, a human action (gesture sequence) would locate the palm on the right side (PL) of the cup and grasp (LG). To safely perform the next action, a pick up movement is also added to the PR2 grasping action. Therefore, the PR2 action (gesture sequence) should be to locate the gripper on the right side of the cup, open the gripper, move towards the cup, close the gripper and lift it a short distance. Table II lists in detail all actions defined for the scenarios in this paper.

In the table, $\boldsymbol{P}_p(P_{px}, P_{py}, P_{pz})$ and $\boldsymbol{P}_c(P_{cx}, P_{cy}, P_{cz})$ are the previous and current positions of the gesture, respectively. Note that the gesture-switch actions, e.g. the grasp/pinch/release actions, are executed at the previous position in that the position of the palm drifts when the gesture changes; the push and drag actions are only performed in the horizontal plane so that the gripper can avoid pressing down on the table or rising over the edge of the dish.

III. PERFORMANCE EVALUATION BASED ON COMPREHENSIVE ASSESSMENT INDEX

Based on the LeapMotion sensor and the proposed method introduced in section II, several tele-control methods for robotic systems can be implemented, including the demonstration mode, teleoperation mode and semi-teleoperation mode. A comprehensive assessment index to compare these control methods and evaluate the performance of the LeapMotion sensor in non-contact robot controlling is introduced in this section.

A. Description of Control Modes

The concrete adjustments of the teleoperation, semi-teleoperation and demonstration modes for adapting the characteristics of the LeapMotion sensor and the proposed action recognition method are described as follows:

- **Demonstration mode** In this mode, the operator will perform the demonstration actions, and the desired positions and gestures are recorded by manually sent command. (wildfire-fuel) The action array is generated by these recorded information and shown in rviz. After demonstration, if the action array is appropriate for performing the task, the execution command will be sent and the robot performs the desired action array.
- **Teleoperation mode** In this mode, the method described in section II is used, and the robot performs the actions at the time of gesture recognition. The operator can see the markers of his/her hand and the action of the robot in the rviz, and adjusts the his/her operations. To increase the stability of the gesture recognition, the above-mentioned Algorithm 1 is used. Therefore, the control process is not an actual "real-time" process, with a recognition frequency 20Hz, the teleoperation action frequency of the control process is 1Hz.
- **Semi-teleoperation mode** In this mode, the robot moves following the current action performed by the operator. But different from the teleoperation mode, the action execution command is sent manually instead of being automatically triggered by the recognized gestures.

B. Comprehensive Assessment Index

To evaluate the performance of the LeapMotion sensor and the proposed tele-control method, the assessment indexes we selected include the average value $\bar{t}_i$ and variance $\bar{t}_{vi}$ of execution time, the average value $\bar{e}_i$ and variance $\bar{e}_{vi}$ of grasping accuracy, and the success rate r_{si}. A comprehensive

TABLE I

GESTURE LIST FOR HUMAN HAND AND PR2 GRIPPER

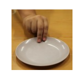
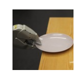
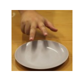
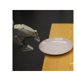
Gesture	Pose of Palm	Finger Extension	Finger Grasp	Strength Pinch	Human's Hand	PR2's Gripper
Palm Horizontal (PH)	$-40^\circ \leq \alpha \leq 40^\circ, -40^\circ \leq \beta \leq 40^\circ$	B11111	[0, 0.5)	[0, 0.5)		
Palm to Left (PL)	$40^\circ < \alpha < 130^\circ,\ -40^\circ \leq \beta \leq 40^\circ$	B11111	[0, 0.5)	[0, 0.5)		
Palm to Right (PR)	$-130^\circ < \alpha < -40^\circ, -40^\circ \leq \beta \leq 40^\circ$	B11111	[0, 0.5)	[0, 0.5)		
Palm Forward (PF)	$-40^\circ \leq \alpha \leq 40^\circ, -130^\circ < \beta < -30^\circ$	B11111	[0, 0.5)	[0, 0.5)		
Palm Backward (PB)	$-40^\circ \leq \alpha \leq 40^\circ, 30^\circ < \beta < 130^\circ$	B11111	[0, 0.5)	[0, 0.5)		
Horizontal Grasp (HG)	$-40^\circ \leq \alpha \leq 40^\circ, -40^\circ \leq \beta \leq 40^\circ$	N/A	(0.5, 1]	[0, 0.5)		
Left Grasp (LG)	$40^\circ < \alpha < 130^\circ, -40^\circ \leq \beta \leq 40^\circ$	N/A	(0.5, 1]	[0, 0.5)		
Right Grasp (RG)	$-130^\circ < \alpha < -40^\circ, -40^\circ \leq \beta \leq 40^\circ$	N/A	(0.5, 1]	[0, 0.5)		
Horizontal Pinch (HP)	$-40^\circ \leq \alpha \leq 40^\circ, -40^\circ \leq \beta \leq 40^\circ$	N/A	[0, 0.5)	(0.5, 1]		
Horizontal Pre-pinch (HpP)	$-40^\circ \leq \alpha \leq 40^\circ, -40^\circ \leq \beta \leq 40^\circ$	B11100 or B11000	[0, 0.5)	[0, 0.5)		

TABLE II

ACTION LIST OF HUMAN HAND AND PR2 GRIPPER

Action of Human	Actions of Human Previous	Actions of Human Current	Change in Position	Action of PR2
To locate on the top/right/left/front/back side	PH/PR/PL/PF/PB	PH/PR/PL/PF/PB	N/A	move to P_c with PH/PR/PL/PF/PB
To grasp on the top	PH	HG	$\lvert P_p - P_c \rvert < 20mm$	PF→move down→HG→move up
To release from top	HG	PH	$\lvert P_p - P_c \rvert < 20mm$	PF→move up
To grasp toward right side	PR	RG	$\lvert P_p - P_c \rvert < 20mm$	PR→move right→RG→move up
To release from right side	RG	PR	$\lvert P_p - P_c \rvert < 20mm$	PR→move left
To grasp toward left side	PL	LG	$\lvert P_p - P_c \rvert < 20mm$	PL→move left→LG→ move up
To release from left side	LG	PL	$\lvert P_p - P_c \rvert < 20mm$	PL→move right
To locate with pinch pose	HpP	HpP	$\lvert P_p - P_c \rvert < 20mm$	Moving with HpP
To pinch	HpP	HP	$\lvert P_p - P_c \rvert < 20mm$	HpP→move forward→HP→move up
To release pinch	PH	HpP	$\lvert P_p - P_c \rvert < 20mm$	HpP→move backward
To push forward	PF	PF	$\lvert P_{p\_z} - P_{c\_z} \rvert < 20mm$	move to $P(p_{cx}, p_{cy}, p_{pz})$ with PF
To drag backward	PB	PB	$\lvert P_{p\_z} - P_{c\_z} \rvert < 20mm$	move to $P(p_{cx}, p_{cy}, p_{pz})$ with PB

assessment index is calculated using these five criteria and based on a linear weighting method. It is represented as

$$[y_i]_{3\times4} = [x_{ij}]_{3\times5} \cdot [\omega_j]_{5\times1} \tag{2}$$

where y_i is the assessment index of the three control mode groups and x_{ij} is the normalized assessment criteria shown in (3).

$$[x_{ij}]_{3\times 5} = \left[N\left(\frac{1}{\bar{t}_i}\right) N\left(\frac{1}{\bar{t}_{vi}}\right) N\left(\frac{1}{\bar{e}_i}\right) N\left(\frac{1}{\bar{e}_{vi}}\right) r_{si} \right] \quad (3)$$

where the subscripts $i = 1,2,3$ represent the experiments in the demonstration mode, the teleoperation mode and the semi-teleoperation mode, respectively; and $N(\bullet)$ represents the normalization function of the criteria. The weight parameter ω_j is calculated by the entropy weight method shown in (4).

$$\omega_j = \frac{(1 - S_j)}{\sum_{j=1}^{5}(1 - S_j)} \quad (4)$$

where S_j is the entropy value of the j^{th} criterion, which measures the disorder of the information provided by the criterion and calculated by (5).

$$S_j = -\sum_{i=1}^{3} p_{ij} \ln(p_{ij}), \quad p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{3} x_{ij}} \quad (5)$$

IV. Experiments and Discussion

The experimental scenario is shown in Fig. 4. The robot should grasp a pepper shaker from the tabletop and put it on a tray. The operation duration starts from the first action and finishes with the release action of the robot's gripper. The initial positions have been marked in the table. Each time the robot's gripper grasps the pepper shaker, the position of the pepper shaker will shift to the grasping center. This position shifting is measured to be the grasping error, as shown in Fig. 5. When the pepper shaker is put on the tray, the task is marked as successfully performed.

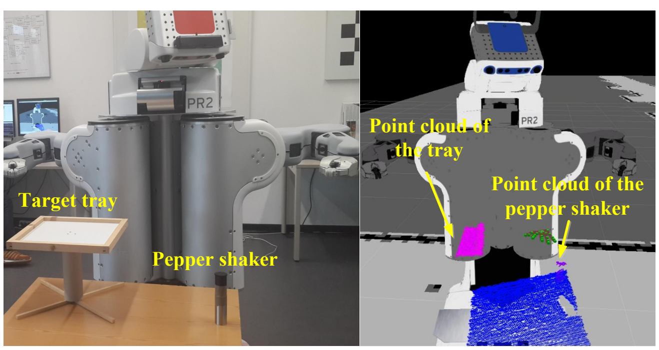


Fig. 4. Experimental scenario

For each control mode, the experiments will be repeated 20 times. The original data of each criterion are shown in Table III. In the process of the experiments, two main factors influence the result. One is the stability of gesture recognition, the other is the occlusion of the view in the observing space shown in rviz.

From the result in Table III, one can see that in the teleoperation mode, the average execution time is the shortest. Nonetheless, the variance of execution time is larger than in the other modes. Moreover, the success rate of the teleoperation mode is also lower. This is caused by the low stability of the gesture recognition, especially during the transform

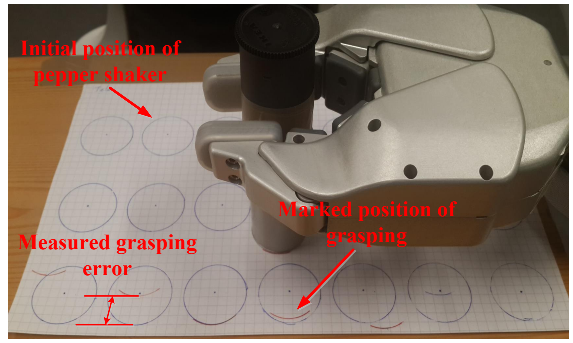


Fig. 5. Measurement of grasping accuracy

TABLE III
ORIGINAL DATA OF EXPERIMENTS

	Demonstration mode			Teleoperation mode			Semi-teleoperation mode		
	$t(s)$	$e(mm)$	s	$t(s)$	$e(mm)$	s	$t(s)$	$e(mm)$	s
1	168	-2.4	1	105	-6.9	0**	106	-9.6	1
2	129	4.0	1	119	-5.7	0*	98	-3.8	1
3	121	-1.9	1	147	8.9	1	134	-6.5	1
4	131	-3.5	1	80	-15.9	1	89	3.5	1
5	126	-3.1	1	68	-8.7	1	94	-7.8	1
6	108	3.7	1	73	9.5	1	117	-6.7	1
7	110	3.0	1	97	0.0	1	83	6.4	1
8	126	-6.9	1	84	-4.6	1	126	3.9	1
9	136	-3.3	0*	60	2.0	1	99	1.7	1
10	129	5.0	0*	73	-3.5	0**	130	-5.6	1
11	105	-1.0	1	89	15.0	0**	151	3.4	0*
12	126	-4.8	1	79	-3.6	1	109	-1.9	1
13	123	-0.5	1	86	-20.7	0**	89	-3.0	1
14	106	-4.5	1	97	-11.6	1	119	-6.7	1
15	115	3.0	1	71	-27.7	1	94	6.4	1
16	110	-5.7	1	69	-16.1	1	139	4.2	1
17	131	-2.4	1	80	0.5	0**	120	-1.2	1
18	120	2.5	1	91	-2.4	1	101	4.5	1
19	117	1.9	1	83	3.7	1	93	14.5	1
20	126	-8.8	1	73	-15	1	97	-13.5	1
Average	123	-1.3	0.9	86	-5.2	0.7	109	-1.9	0.95
Variance	196	15.7		400	113.6		196	41.1	

Note: t – execution time; e – grasping error; s – success mark, "0" for fail and "1" for success.
* caused by incorrect trajectory.
** caused by misrecognition of gesture.

between two different gestures. The mis-recognition happens and generates some undesired actions, which significantly prolong the execution time and may cause a failure in performing the task. Table IV shows the experimental result of gesture recognition, which compares the recognition rate between "Palm Horizontal (PH)", "Horizontal Pinch (HP)", "Palm to Right (PR)" and "Right Grasp (RG)". The most stable recognized gesture is PH; and when the gesture is PR or RG, some fingers are occluded and the recognition rate is decreased in that the feature of the hand is less in these situations.

Comparing the grasping accuracy, the most accurate and stable grasping occurs in the demonstration mode, which is just a little higher than in semi-teleoperation mode but significantly better than in teleoperation mode. This phenomenon is caused by the view occlusion, as shown in Fig. 6. Although the experimental scene can be observed by the operator

TABLE IV

GESTURE RECOGNITION RATE

	PH	HP	PR	RG
PH	98.5%	8.2%	6.3%	0
HP	1.3%	84.4%	0	4.8%
PR	0	0	82.5%	6.2%
RG	0	0	0	73.3%
others	0.2%	7.4%	11.2%	15.7%

through the depth camera of the robot, the view shown on screen is in 2D. Therefore, the operator needs to switch the view in the rviz. In demonstration mode, the actions are marked in visualized space with small markers, which will not affect the observation of the scene; by contrast, in the teleoperation and semi-teleoperation modes, the gripper of the robot will move close to the target object, so that the view of the operator is partly occluded and accurate positioning becomes more difficult.

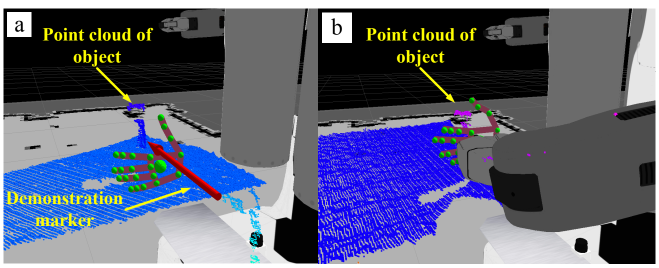


Fig. 6. Observing view in rviz during grasping; a) In demonstration mode; b) In teleoperation and semi-teleoperation modes

Considering both the execution time and operation accuracy, Figure 7 shows the result based on the comprehensive assessment index. The lines in the chart represent different criteria. One can see that performance in demonstration mode is better than in the others. Moreover, from the experimental process, the failure modes in the different control modes are also different. In demonstration mode and semi-teleoperation mode, the failures are all caused by incorrect trajectories; while in teleoperation mode, most of the failures are caused by undesired action, which is caused by mis-recognition of the gestures. Therefore, with the current LeapMotion sensor and action recognition method, the demonstration mode is better to perform robot control for a tabletop object manipulation task.

V. CONCLUSIONS AND FUTURE WORK

In this paper, a non-contact tele-control method is developed for a robotic system to perform tabletop object manipulation tasks. With a LeapMotion sensor, an algorithm for recognizing gestures and generating actions is proposed. Typical gestures were defined with reference to the orientation of the palm, the extension status of each finger and the strength of the grasp and pinch. The combinations of palm positions and gestures generate the actions for tabletop object manipulation. And with these typical actions, the robot could cooperatively execute the tasks with tele-control by a human.

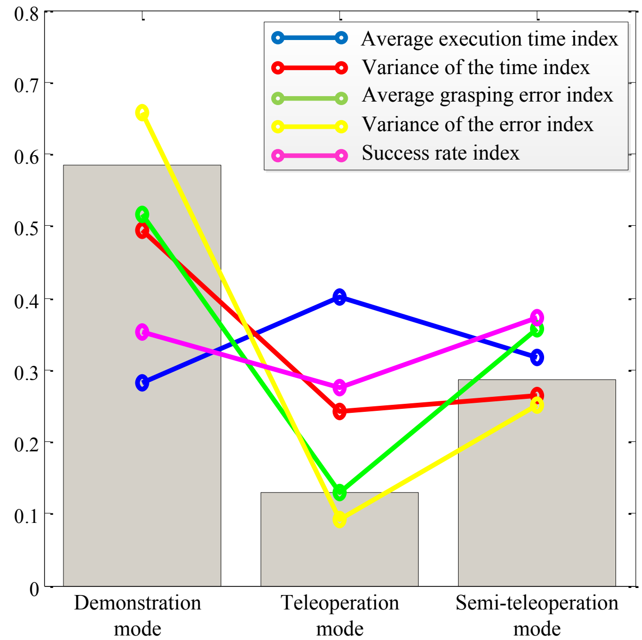


Fig. 7. Assessment index of the three control modes

To compare and evaluate the performance of the LeapMotion sensor and the proposed tele-control method, three typical tele-control modes–demonstration mode, teleoperation mode and semi-teleoperation mode–are developed and implemented on a PR2 with ROS. The execution time, grasping accuracy and success rate are used as the criteria for evaluation. To combine these different criteria, an entropy weighting based comprehensive assessment index is proposed(wildfire-fuel(wildfire-fuel)).

With the result of the comprehensive assessment index and the analysis of the failure mode, we found the most significant factors influencing the task execution performance are the gesture misrecognition and the view occlusion in observing space. Because the stability of the gesture recognition is relatively low, there is more gesture misrecognition in the teleoperation mode, which causes more execution failures in that undesired actions occur. Moreover, due to the view occlusion, one can hardly carry out a more accurate grasping positioning in semi-teleoperation mode than in demonstration mode. Therefore, the current Leapmotion sensor and the proposed tele-control method are more appropriate for performing a non-contact demonstration for robotic systems.

Besides improving the stability of gesture recognition, there ist still lots of further research to be done. For example, in this paper, the cooperative action plan between the robot and the human is at a lower level. The demonstration through the LeapMotion sensor could be combined with robot learning and abstracted into higher level experiences for task execution.

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