Task-Level Teleoperated Manipulation for the HRP-2Kai Humanoid Robot

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Abstract— **This paper presents the strategy used by our team, AIST-NEDO, at the DARPA Robotics Challenge (DRC) to deal with the designated manipulation tasks by means of a task-level teleoperation of the HRP-2Kai humanoid robot, considering a disaster-hit scenario that is inherently non-structured and a limited communication between the user and the robot. The strategy, based on the information provided by a laser rangefinder (LRF) and a set of cameras installed at the head and at both hands, consisted in the alignment of 3D models representing the desired manipulation targets with a measured point cloud, in order to provide a reference frame to describe the manipulation motion required for each task. Each motion was carefully planned in advance by assuming minimum information of the object representing the manipulation target. In order to exemplify the before mentioned approach, two representative tasks of the DARPA Robotics Challenge are described, as well as the corresponding results obtained during the competition.**

I. Introduction and Motivation

Disaster response is attracting attention from the robotics research community, and even more since the Fukushima Daiichi nuclear power plant accident that followed the 2011 Great East Japan earthquake and tsunami. As a concrete materialization of this increasing interest, a challenge was proposed by the American Defense Advanced Research Projects Agency (DARPA) to use robots in disaster-hit facilities that were made too hazardous for direct human operator intervention. It is worth noticing that the challenge did not impose any constraint on the design of the robot, but since the environment (industrial ladders, doors, valves, cars) as well as the tools (levers, drills, hammers) were meant to comply with the human morphology, it was a natural option to develop the necessary means to make the humanoid robots capable of performing inspection and disaster recovering actions inside a non-structured environment [1].

This environment can be considered to be "kind of" known in the sense that we know which actions are required in advance and that we have a rough idea of the spatial distribution of this environment, altered due to the disaster itself. Given these conditions, only very limited assumptions about the structure of the environment can be made beforehand, in contrast to structured scenarios where semantic knowledge of their structure can be leveraged for highly autonomous robots operating in them [2].

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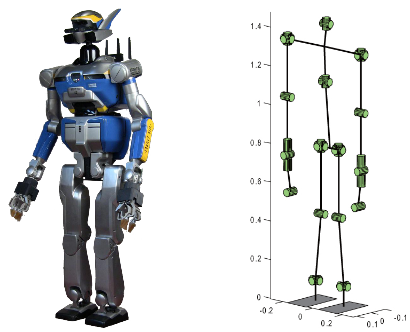
Furthermore, it is also mandatory to consider that within a disaster-hit facility it is not possible to rely on a stable, wide bandwidth wireless communication system with the robot. The signal may be degraded and blackouts may occur frequently. Then, it is not feasible to consider a purely teleoperated robot. First, because of the high dimensionality of its control system, and second because the capabilities of the robot and the operator should include near real-time feedback without disruptions in the communications as well as transmission of large amounts of data to the operator. On the other hand, a fully autonomous robot navigating and interacting in an non-structured environment should include extensive databases of information about possible objects of interest to be found, highly efficient grasping algorithms and the ability to react to unforeseen situations, which are still unsolved problems [3]. Furthermore, failures are critical and up to now no fully autonomous robotic system has shown to be highly reliable, especially under unexpected conditions [4]. A feasible alternative is the development of supervised semi-autonomous high Degrees-Of-Freedom (DOF) robotic systems; that is, task-level teleoperated systems in which the operator cognitive burden is minimized by lowering the control space dimensionality [5], such that these operators function as supervisors setting high level goals, assisting the robot with complex perception tasks, directly changing robot parameters to improve its performance and making decisions when facing unexpected situations [2].

II. Related Work

From some years ago, there has been plenty of research on fully autonomous robots capable of performing tasks in structured environments (kitchens, offices, etc.), as the one presented by Blodow et al [6] or Beetz et al [7]. For that purpose many different control architectures have been proposed, some of them are described by Medeiros [8]. For non-structured environments there is one basic paradigm called *supervised autonomy*, proposed first by Cheng and Zelinsky [9], which has become the current state of art for the DARPA Robotics Challenge since the Trials and also for the Finals. During these competitions, each team relied on an Graphic User Interface (GUI) showing the a 3D model of the robot and the environment, in such a way that the operator(s) could control the robot beyond the joint-level, by specifying task-level commands that were robot-centric and/or object centric, as described by the teams Tartan Rescue [10], MIT [11], RoboSimian [12] and ViGIR [3]. In this paper, we describe our implementation of this approach.



(a) Actual robot. (b) Structure.

Fig. 1. HRP-2 Kai humanoid robot.

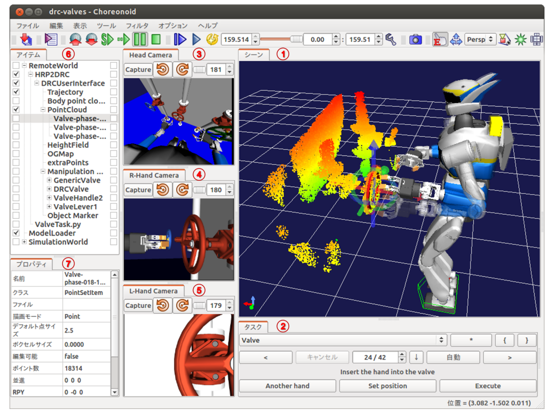


Fig. 3. Teleoperation interface implemented in Choreonoid [16].

III. HRP-2KAI HUMANOID ROBOT

HRP-2Kai stands for Humanoid Robotics Platform no. 2 Improved (Kai means improvement in Japanese). This humanoid was developed in phase two of the Japanese national project HRP (Humanoid Robotics Project) and was recently improved to be able to cope with disaster response tasks [13].

This robot, depicted in Fig. 1a, has the kinematic structure shown in Fig. 1b. As seen in this diagram, the robot has 32 degrees of freedom (dof): 6 at each leg, 2 at the waist, two at the head, 7 at each arm and 1 at each hand. This robot features a set of exteroceptive sensors that are actively used during the manipulation tasks: a 3D scanner system built in its head and four cameras, placed at the head, at the back and at each hand. The 3D scanner system was implemented with a Laser Range Finder (LRF) synchronized with the head pitch joint, as shown in Fig. 2a. The hand camera is mounted in each hand as shown in Fig. 2b, together with a LED light and a laser. It is worth to mention that this camera is not lined up with the longitudinal axis at the center of the hand.

IV. GRAPHICAL USER INTERFACE FOR TELEOPERATION

The Graphical User Interface (GUI) used for the teleoperation of HRP-2Kai was implemented in Choreonoid, an integrated robotics GUI environment [14] [15]. A snapshot of this GUI is shown in Fig. 3. As can be seen, the teleoperation interface features several windows, each one of them corresponding to (1) the scene view, (2) the task sequencer, (3) the head camera, (4) the right hand camera, (5) the left hand camera, (6) the item view, and (7) the property view.

(a) 3D scanner and head camera. (b) Left hand camera.

Fig. 2. Exteroceptive sensors of HRP-2 Kai [13].

The scene view is used to teleoperate the robot through the direct control of a 3D model showing the robot's current configuration, as well as the planned motion represented by one (or several) translucent version(s) of the robot, one per each key configuration. The *point cloud* of data corresponding to the measured points on the surface of the objects in the environment is captured by the 3D scanner and presented also in the scene view. From this information it is possible to extract the *height field* of the floor, used by the walking control system to achieve a stable gait over uneven terrain [17], as well as to detect obstacles and objects of interest in the environment in order to perform a proper whole-body collision-free posture planning, as required by the manipulation task [18].

The object that is the target of the manipulation task can be identified in the point cloud by overlapping a simplified 3D model of it, as shown in Fig. 3. This model, referred as *Manipulation Marker*, provide a reference frame with respect to which the manipulation task can be described once it is aligned with the corresponding points. This alignment can be done manually by using a set of arrows and rings provided by the interface to translate and rotate the marker, or automatically with the aid of a built-in function included in the Point Cloud Library (PCL), used by Choreonoid.

The manipulation motion is specified by providing the attitude (position and orientation) of the hands of the robot, and calculated by solving the whole-body inverse kinematics problem [18]. This motion can be either planned in advance or manually changed during the execution of the task by using *Hand Markers* (3D models of the hands that can also be translated and rotated).

The *task sequencer* is provided by the interface to execute a previously planned manipulation task step by step, such that the complex perception be entrusted to the operator, which can also supervise every step of the task. For some tasks the point cloud does not provide enough information for them to be performed effectively. Then, the operator can also rely on the image captured by every camera, and shown in the corresponding window. Finally, the item window enlists the components required by Choreonoid to implement the teleoperation interface, shown together with their properties.

V. Pulling and Inserting a Plug

One of the surprise tasks at the DARPA Robotics Challenge consisted of pulling out a plug from one socket and putting it back into another socket, in a set-up like the one shown in Fig. 4.

A. Detection of the socket and plug

In order to perform this task it is first necessary to identify the plug and the socket where it is originally inserted, by placing the corresponding Manipulation Marker within the poing cloud. The reason to identify both objects instead of just the plug is because almost half of it is not visible as it is inside of the socket, making it too difficult just to match the plug, given the low density of points belonging to it due to its small size.

By using a PCL's built in function it is possible to detect all the planes in the scene, one of them being the wall where the sockets are installed. Then, given that the front face of the sockets is parallel to this wall, it is possible to use the corresponding plane equation to calculate the socket's orientation with respect to the robot, in such a way that the plug is directed towards it. Having done this, one point belonging to the plug can be manually selected in order to compute an approximate initial position for the Manipulation Marker representing the socket and the plug. This one is later refined, after the robot has arrived to the desired stance and the point cloud has been adjusted by using the robot's hands as a reference, as seen in Fig. 5 (and explained in Subsection **??**).

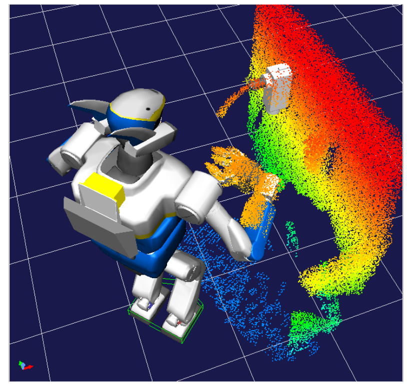


Fig. 5. Detection of the socket and the plug.

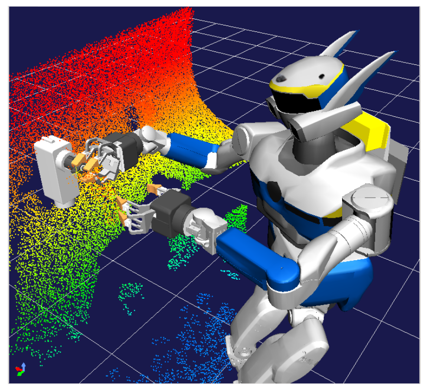


Fig. 6. Configuration of the robot before grasping the plug.

B. Grasping the plug

Having detected an approximate attitude for the socket, the robot first approaches the plug with one hand while aligning the camera installed at the other hand with the axis of the plug. This is to be able to make slight adjustments of the grasping hand by using visual feedback.

The size of the visible part of the plug is not that big compared to the hand of the robot, and because of that the tolerance for grasping the plug is minimum. Then, it is required to grasp the plug at the point in which the medial side of the hand touches the cylindrical shaped part of the socket. This can be done by reducing the angle of the gripper and then, by moving the hand along the axis of the plug until sensing 30 N of force (enough for considering that it arrived to the socket). This configuration of the robot just before moving the hand towards to the socket is depicted in Fig. 6.

This strategy is very effective (when adjusted properly) as the grasp can be done every time at the desired point even in the presence of uncertainties, as shown in the dynamical simulation depicted in Fig. 7.

C. Pulling and adjusting the plug

After grasping the plug, the robot pulls the plug. Due to the balancing process this motion may not be performed exactly along the axis of the plug, and it may hit the inner walls of

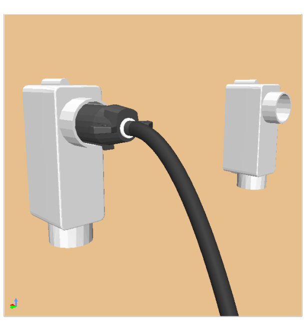


Fig. 4. Plug Task.

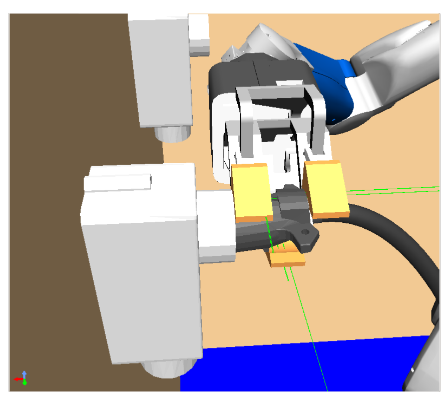


Fig. 7. The plug being effectively grasped at the desired point.

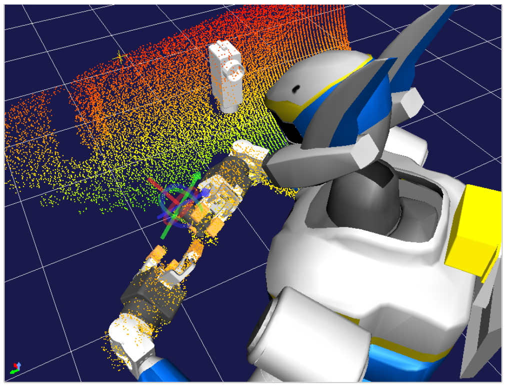


Fig. 8. After pulling the plug its attitude is adjusted.

the socket, modifying the planned relative attitude between the plug and the hand.

For this reason, before inserting the plug into the other socket, the robot first brings the plug in front of its chest, takes an updated point cloud, and uses the camera placed at the head and at the other hand to look at the plug from two perpendicular directions, as seen in Fig. 8. By using this information it is possible to fix the actual attitude of the plug with respect to the hand.

D. *Inserting the plug*

Once the Manipulation Marker representing the plug is fixed at the hand, it can further be properly aligned with the destination socket. This one can be represented with another marker (Object Marker), which can be adjusted within the point cloud before taking the plug to the pre-insertion position. However, because of inaccuracies of the point cloud, the camera at the other hand is used once again together with the camera at the head to look at the plug, and use this visual feedback to adjust its position to properly insert the plug within few movements. This is represented in Fig. 9.

Then, once the task is completed, the hand opens and an updated point cloud is taken, in order to correctly plan the returning motion without hitting the cable of the plug.

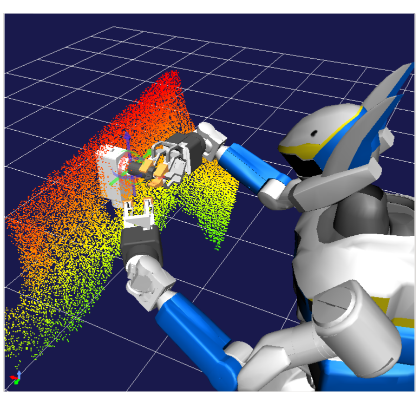
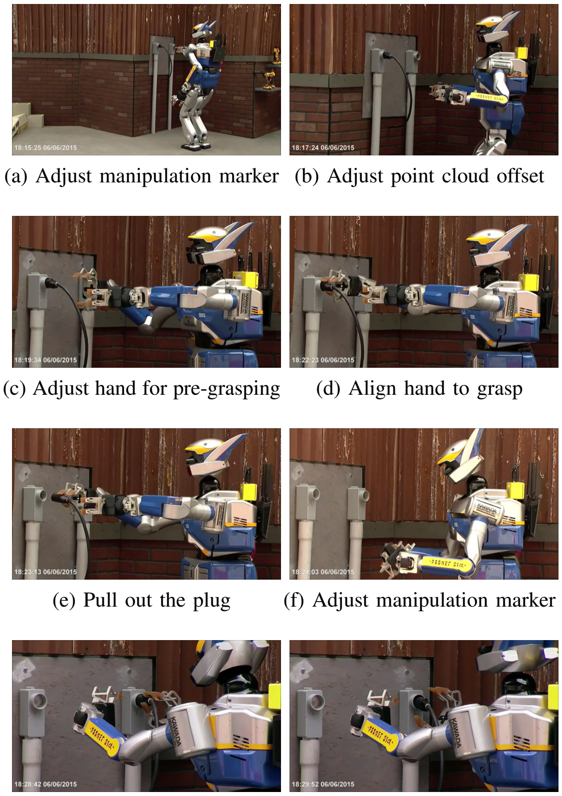


Fig. 9. The plug is inserted by using visual feedback.



(a) Adjust manipulation marker (b) Adjust point cloud offset

(c) Adjust hand for pre-grasping (d) Align hand to grasp

(e) Pull out the plug (f) Adjust manipulation marker

(g) Adjust hand for pre-insertion (h) Plug is inserted

Fig. 10. Plug Task at the second day of the DARPA Robotics Challenge [19]

E. *Results*

With respect to the plug task, during the DRC Finals we were able to complete the task and get the point within 16 minutes and 34 seconds, mainly because we were supervising every motion of the robot in order to prevent any collision with the environment, and also due to blackouts. Some snapshots taken during the task at the DRC Finals are shown in Fig. 10, together with the description of the current process in accordance with the explanation given before.

VI. Door Task

A. *Outline*

The door task consists of the following four sequential steps.

Step1 Locate a door in the environment
Step2 Walk to the front of the door and grasp the door knob
Step3 Turn the knob and open the door
Step4 Walk through the door

To realize a reliable door passing, we pre-determined a robot pose grasping the door knob. Let us call it as *door approaching pose* which specifies the wrist point and the standing point with respect to the door lever as illustrated in Fig. 11.

From Step1 to Step2, we control our robot to realize the door approaching pose. The door knob operation (Step3)

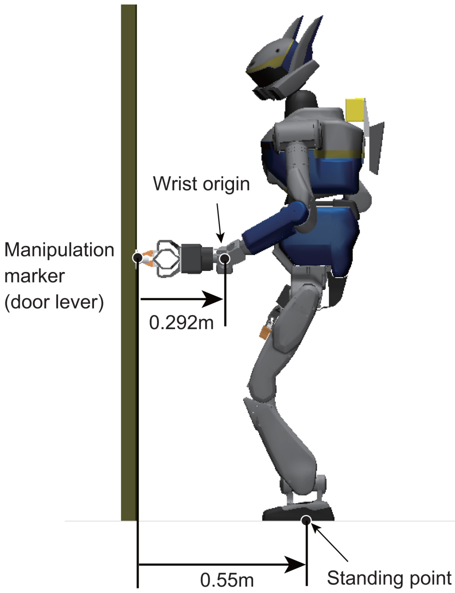


Fig. 11. Door approaching pose

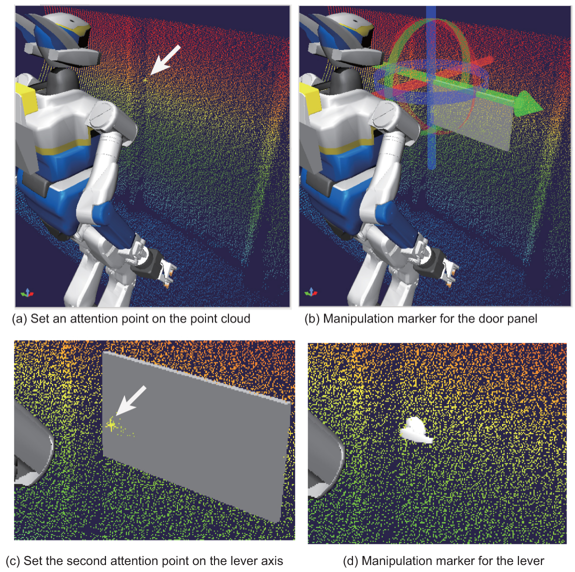


Fig. 12. Detection of the door lever in the control window

and the door passing through (Step4) always start from this fixed configuration. This means we can use a programmed sequence or its minimum modification at the door task.

B. Detection of the door lever

For a door task, a robot must detect the door orientaion and the position of the door lever. We took two step manual operations to extract the required information from the point cloud.

First, an operator specifies an "attention point" on the point cloud which might correspond the left edge of the door panel (Fig. 12(a)). We can expect a flat plane on the right of the attention point, and we can calculate the orientation of the door plane by the least square method. In Fig. 12(b) shows the automatically alligned "door manipulation marker." The marker covers a part of the door panel and we can interactively manipulate it on the pointcloud GUI. By manually translating the marker, we can mask the flat portion of the point cloud and extract the door lever as shown in Fig. 12(c). Since the door lever is relatively small with respect to the point cloud resolution, it contains only 10 to 20 points which makes conventional model fitting very difficult. Thanks to the robustness of the human perception, we can confidently assume the rotation center of the lever and the model allignment on the point cloud as Fig. 12(d).

C. Door lever grasp and manipulation

By the method of previous subsection, we can expect our robot is standing in front of the door aligned to its surface normal with desired distance. Nevertheless, due to the LRF measurement noise and its callibration error, the hand position may not be acculate enough to grasp the lever. Such state in the dynamic simulation of Choreonoid is shown in Fig. 13(a). The right window shows the simulated robot and the left window shows the view of the left hand camera. An operator can fix this manually by the GUI buttons of 'Left','Right','Down', and 'Up' as seen in the left window bottom. In this case, an operator can adjust the hand position by clicking 'Right' button several times. Figure 13(b) shows the adjusted hand position to grasp the lever. By hitting the button 'OK', the robot move the left hand forward until it contacts the door surface (we specified a sleshold of 5N to detect the contact). The hand is in contact with appropriate position to grasp the door lever in Fig. 13(c).

D. Results at DRC Finals

In the DRC Finals, the task stage floor has a slope of 2.6 degrees by our measurement, and the door was set perpendicular to the slope. By this setup, once the door was enough opend it quickly open by gravity and remained opening state. This helped a lot our robot to pass the door.

On the other hand, we found that the door of each course has a different latch property as shown in Table.I.

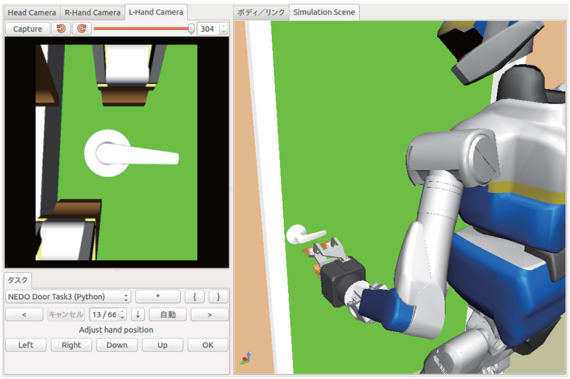
TABLE I
DOOR LATCH PROPERTIES AT DRC FINALS

Course	Lever angle to open	Date	Result
Green	30 deg	June 4 (rehasal)	Success
Yellow	70 deg	June 5 (day1)	Fail
Blue	50 deg	June 6 (day2)	Success

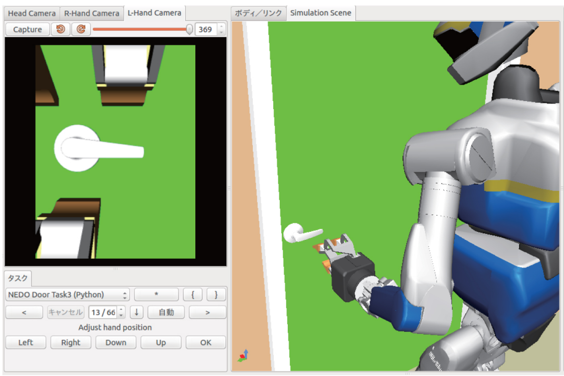
our robot had a trouble on turning the lever and releasing the latch.

VII. CONCLUSIONS

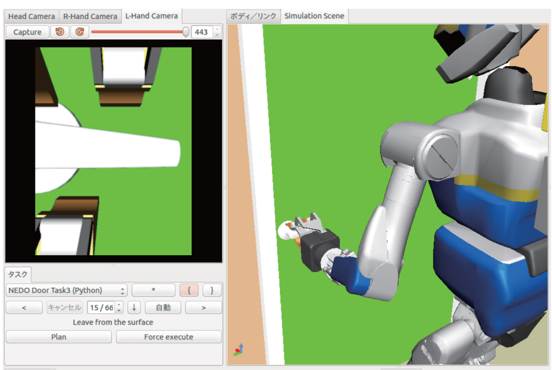
With respect to the plug task it is worth to notice that even though its execution lasted about 16 and a half minutes due to recognition, verification and blackouts, the number of slight adjustments required to insert the plug was only 3. This was the result of assuring a stable grasp by following the strategy explained before, as well as the use of a reference representing the target socket. Other teams that chose to



(a) Initial state for door lever approaching



(b) Hand position was adjusted



(c) Touch the door panel

Fig. 13. Approach for door lever grasping

grasp the cable instead of the plug itself required between 8 and 14 adjustments in order to complete the insertion.

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