A Pragmatic Approach to Modeling Object Grasp Motion Using Operation and Pressure Signals for Demolition Machines

Mitsuhiro KAMEZAKI ∗, Hiroyasu IWATA **, and Shigeki SUGANO ***

Abstract : In this paper, an object grasp motion, which is a requisite condition to make a demolition machine grasp an object, is pragmatically modeled, considering accurate and robust identification. Grasping an object is a highly difficult task that requires safe and precise operations, particularly in disaster response work. Identifying a grasp or non-grasp state is essential for providing operational support. These types of outdoor machines lack visual and tactile sensors, so pragmatically available lever operation and cylinder pressure sensors are adopted as parameters for modeling. The grasp motion is simply defined by using sequential transitions of the on-off state of the operation signal and cylinder pressure data for the grapple and the manipulator. The results of experiments conducted to transport objects using an instrumented hydraulic arm indicated that the modeled grasp motion model effectively identifies a grasp or non-grasp state with high accuracy, independently of operators and work environments.

Key Words : disaster response work, construction machinery, state identification, grasp motion model.

1. Introduction

Complex disaster response tasks, such as rescue and initial recovery works using tele-operation technologies [1] and post-disaster restoration including sorted dismantling for recycling resources [2], [3], are socially expected to be achieved by using construction machinery. This is because it has the advantage of being able to produce the massive force. The above tasks require grasping objects including transporting debris, removing fallen trees, and crushing waste products, which differs from conventional simple excavation and ground leveling [4].

These tasks are therefore conducted by using demolition machines equipped with a grapple, which has a grasping mechanism, as shown in Figs. 1 and 4. An object grasp is an initial state for various elemental tasks such as transport, removal, and bending, so it is an essential state to execute the advanced tasks.

On the other hand, machine operations to grasp an object are difficult and must be done safely and with high precision. This is because an operator is required to carefully adjust both the position and orientation of the grapple in accordance with a distant object while paying attention to a dangerous contact with the environment. Moreover, the ground and debris conditions are often unstable, and the operator may have insufficient visibility of a target object in disaster response situations. These factors can cause false recognition such as mistaking a non-grasp for grasp (and vice versa) and a loose grasp for a firm one. This can result in operational errors and secondary disasters such as collapsing debris, the toppling over of the machine, and falling and breakage of transported objects. Consequently, demolition machines applied to disaster response work must be able to grasp objects safely and precisely. As stated above, this requires highly sophisticated skills involving cognitive and control abilities in machine operators.

An effective approach to solving this problem is to provide operational support using an intelligent system [5]. The authors have previously proposed an intelligent system that provides operator support [6], [7] and work-analysis support [8] on the basis of identifying work states [9], and experimental results indicated that the proposed system was effective to improve work performance. In accordance with the approach, this study proposes a method to estimate a grasp or non-grasp state, i.e., whether or not the grapple has grasped an object, for demolition machines. A function to estimate a grasp or non-grasp is also valuable in underwater maintenance work [10], tree thinning for forestry improvement [11], demolition work in high places using a long-reach arm, and object handling using tele-operated rescue robots [12], where a machine operator often lacks adequate visual and tactile information.

2. Analysis of Object Grasp

Problems in object grasp estimation were first analyzed and requirements for a pragmatic grasp estimation method for demolition machines were clarified.

2.1 Difficulty of Grasp/Non-Grasp Estimation

1) Available sensors: A grapple is a kind of end-effector attached to the end-point of a manipulator. A link mechanism connects two forks (upper and lower) with one hydraulic cylinder, as shown in Fig. 1. A grapple opens or closes by extending or contracting the cylinder and its forks synchronously move in the reverse directions. The sensors available in these structures are only two: potentiometers installed at the control lever for detecting the amount of input signal and hydraulic sensors installed at the hydraulic cylinder for detecting joint load, owing to the limitation from the severe work environments. This means that a joint angle sensor installed at the grapple is not
available owing to easily breakage although it would be useful for grasp estimation. Potentiometers reveal when the forks are opening or closing, as shown in Fig. 1 (a). Pressure sensors reveal when the forks come into inside or outside contact with objects by using the balance of the piston-rod-side pressure $P_1$ and bottom-side pressure $P_2$ of the cylinder, i.e., $P_1 > P_2$ denotes an inside contact and $P_1 > P_2$ denotes an outside contact, as shown in Fig. 1 (b).

2) Related works: Considering the available sensors, the inside contact provides the essential information for representing the possibility of a grasp. However, it is not determined by the inside contact alone. Angle sensors are not installed and the two forks are linked, and hence a null grasp where the grapple is completely closed without grasping anything ($R_2$ in Fig. 2) cannot be identified. Moreover, a contacted fork (upper or lower) that comes into contact with objects, and hence a contact with the inside part of either fork cannot be identified ($R_2$ in Fig. 2). By contrast, humans can use visual and tactile information obtained from their eyes and hands to easily identify a grasp or non-grasp. In related works, an object grasping strategy using visual or tactile information [13], [14] and adaptive grasping control [15] have been investigated. They were applied to instrumented manipulators for indoor applications. For demolicion machines, grasp estimation is inevitably difficult owing to the insufficient sensor capabilities. Thus, no studies have systematically focused on developing a method to identify a grasp or non-grasp in the construction machinery field.

2.2 Requisite Condition for Establishing Object Grasp

As stated in the section 2.1, an object grasp estimation system for demolition machines must be developed by using limited sensor information. Thus, the sequence of an object grasp, focusing on differences between a grasp and non-grasp, was analyzed. The analysis result indicates that an object grasp state is inevitably established only through an object grasp motion as the following sequence. An operator maneuvers a grapple to close the forks, pinch an object with both forks, and hold the object by the grasping force. The grasp motion is a deterministic process and requisite condition to establish the grasp. This means that the grasp possibility vanishes if the grasp motion is not observed. Consequently, identifying an object grasp motion is essential to estimate an object grasp state.

2.3 Modeling of Object Grasp Motion

1) Definition of elemental contact states: In order to distinguish grasp from non-grasp state, analysis of the positional relationship between a grapple and an object was conducted to model contact states. From the analysis, six elemental contact states $R$ were defined (section 3).

2) Modeling object grasp motion: An object grasp motion was then modeled by using the sequential changes of operation and cylinder pressure signals, considering pragmatic sensors available in demolition machines. Five grasp motion states $S$ and their transition model were defined (section 4).

3) Implementation and experiments: Considering identification accuracy and robustness, the proposed grasp motion model was implemented to an actual machine. Performance of object grasp estimation using the proposed model was evaluated through object transport experiments (section 5).

3. Definition of Elemental Contact States

To explicitly distinguish grasp and non-grasp states, relation model between a grapple and object, called the elemental contact states $R$, were first defined.

3.1 Parameters for Contact State Definition

The contact states $R$ were first modeled on the basis of the analysis of the positional relationship between a grapple and an object. Hereafter, the grapple and manipulator are referred to as the hand and arm, respectively. Acquirable data in pragmatic demolition machines are the quantity of operation input and joint load (both the hand and arm) and joint angle (only the arm), as stated in the section 2.1. The parameters to define a contact state are thus the arm load ($L_A$), inside hand load ($L_{H1}$), and outside hand load ($L_{H2}$), and the parameters to define the operational intention are the arm operation ($O_A$), hand close ($O_H$), and hand open ($O_{OH}$). Note that $L_A$ means either $L_{H1}$ or $L_{H2}$, and similarly, $O_H$ means either $O_H$ or $O_{OH}$. When a relevant parameter is zero, zero is substituted into the upper right superscript (e.g., $L_A^0$). Ten symbols in total are listed in the left side of Table 1.

3.2 Contact State Model between Grapple and Object

On the basis of state of the hand load ($L_{H1}^0$, $L_{H2}^0$, and $L_{H3}^0$), which is the most basic representation, the contact states $R$ are defined using ten parameters, as listed in the right side of Table 1. $R_i$, ($L_{H1}^0$, $L_{H2}^0$, $L_{H3}^0$) indicates states of the hand and arm load, and in this case, the contact state $R_i$ is with inside hand load ($L_{H1}^0$) and without arm load ($L_{H3}^0$). Other parameters are not used to define the contact state. ($R_i/ O_H, O_A)$ indicates flags to change a state to $R_i$, and in this case, the contact state $R_i$ is established by arbitrary hand ($O_H$) and arm operations ($O_A$). The contact state between a grapple and an object can be largely divided into no contact, outside contact, inside contact, and both outside and inside contact. Situations where both the outside and inside parts of the fork come together into contact with the environment are extremely rare and instantaneous state, which means that these situations easily change to other three contact states by movement of the manipulator. Considering avoiding the redundancy and satisfying the practicality, we defined the contact
state model on the basis of no contact, outside contact, and inside contact as follows.

1) No contact \( R^0 \): In this state, the hand does not contact an object, as shown in Fig. 2 (a). Thus, this state is definitely regarded as non-grasp states. A state where the hand is not completely closed is called a no contact \( R_1 \) (\( L^0_4 \), \( L^0_3 \)). The no contact \( R_1 \) arises from arbitrary operations (\( R_1 \mid O_H, O_A \)).

2) Outside contact \( L^0_5 \): In this state, the hand is in physical contact with an object on the outside of the hand and is not grasping it, as shown in Fig. 2 (b). This state is called an outside contact \( R_2 \) (\( L^0_5, L^0_4 \)). The outside contact \( R_2 \) is change to a no contact \( R_1 \) by actuating the arm because the object is not grasped by the two forks. The outside contact \( R_2 \) arises from three types of operations: a hand open operation (\( R_{3H} \mid O_H \)), an arm operation (\( R_{3A} \mid O_A \)), and both of these (\( R_{3HA} \mid O_H, O_A \)).

3) Inside contact \( L^0_6 \): In this state, the hand is in physical contact with an object on the inside of the hand, as shown in Fig. 2 (c). A state where the hand is completely closed but is not grasping an object is called a null grasp \( R_2 \) (\( L^0_6, L^0_5 \)). The null grasp \( R_2 \) arises from a hand close operation (\( R_{4H} \mid O_H \)), and the grapple cylinder is in the stroke-end in this state. Moreover, the state where the hand is in contact with an object on the inside of the hand and is not completely closed but is not grasping it is called an inside contact \( R_4 \) (\( L^0_6, L^4 \)). The inside contact \( R_4 \) is easy to change to a no contact \( R_1 \) by actuating the arm because the object is not supported by the two forks. Similarly, to the outside contact, the inside contact \( R_4 \) arises from a hand close operation (\( R_{4H} \mid O_H \)), an arm operation (\( R_{4A} \mid O_A \)), and both of these (\( R_{4HA} \mid O_H, O_A \)). The state where the hand holds an object on its inside and the two forks are in contact with each other is called a hook \( R_5 \) (\( L^0_6, L^5 \)). The hook \( R_5 \) arises from arbitrary operations (\( R_5 \mid O_H, O_A \)).

From the above analysis, six contact states were defined as follow: the no contact \( R_1 \), null grasp \( R_2 \), outside contact \( R_3 \), and inside contact \( R_4 \), hook \( R_5 \), and grasp \( R_6 \), as listed in the right side of Table 1. Contact states from \( R_1 \) to \( R_6 \) are defined as non-grasp states, as shown in Fig. 2. This figure also illustrates example tasks in each contact state.

4. Modeling of Object Grasp Motion

On the basis of the contact states \( R \), the object grasp motion was then modeled by using grasp motion states \( S \) and their state transitions.

4.1 Requirements

On the basis of the description about an object grasp motion stated in the section 2.2, the grasp \( R_6 \) is established through the following parameter change process: the inside hand load \( L^0_H \) is generated by the hand close operations \( O_H \), and the arm load \( L_A \) is generated by the arm operations \( O_A \). Consequently, object grasp motion can be described as a directed sequence of definite flags. To enhance the usefulness, an object grasp motion model must be developed not only to distinguish the grasp \( R_6 \) from non-grasp \( R_1-5 \) but also to identify all contact states. To realize this function, state transition model is adopted to quantity object grasp motion, and each state is called grasp motion states \( S_x \).

4.2 Transition Model Using Grasp Motion States

A state transition model was modeled by using five grasp motion states \( S_x \) to enable each contact to be identified, as shown in Fig. 3. The solid arrowed lines indicate the transition of the grasp motion state \( S_x \) and the dotted arrowed lines indicate contact states \( R_x \) identified by the grasp motion state \( S_x \) and simple parameter changes. This figure shows that the grasp motion state \( S_x \) directly correspond to the grasp state \( R_x \), and also shows that other non-grasp states can be estimated by using the grasp motion states from \( S_0 \) to \( S_5 \) and simple parameter changes. The relationship among the contact states, grasp mo-
The outside hand load (L_{OA}) is added during the arm operations. The system thus does not output any contact states in S_2.

4) Arm operation state S_4: In this state, the inside hand load (L_{OA}) and arm operations (O_A) must be continuously input. State S_3 changes to an arm load state S_4 when an arm load (L_A) is added during the arm operations. S_4 also changes to S_2 when the arm operations are not input (O_A^0). When the hand load is zero, S_2 is back to an initial state S_0.

5) Arm load state S_5: In this state, the inside hand load (L_{OA}) and arm load (L_A) must be continuously observed. State S_4 is back to an initial state S_0 when the hand load is zero.

The transition diagram of grasp motion states S_i and identified contact states R_i are shown in Fig. 3. A grasp motion state S_i changes from S_0 to S_4 in order depending on the obtained operation and load signals, and the current state is regarded as a grasp in S_4.

<table>
<thead>
<tr>
<th>Contact state</th>
<th>Grasping motion state</th>
<th>Parameter change</th>
</tr>
</thead>
<tbody>
<tr>
<td>R_1</td>
<td>No contact</td>
<td>S_0</td>
</tr>
<tr>
<td>R_2</td>
<td>Null grasp</td>
<td>S_2</td>
</tr>
<tr>
<td>R_{strap}</td>
<td>Outside contact (by O_H)</td>
<td>S_3</td>
</tr>
<tr>
<td>R_{arm}</td>
<td>Outside contact (by O_A)</td>
<td>S_4</td>
</tr>
<tr>
<td>R_{hook}</td>
<td>Inside contact (by O_A)</td>
<td>S_5</td>
</tr>
<tr>
<td>R_{hand}</td>
<td>Inside contact (by O_A)</td>
<td>S_6</td>
</tr>
<tr>
<td>R_6</td>
<td>Grasp</td>
<td></td>
</tr>
</tbody>
</table>

* Non-grasp: R_1-R_5, and grasp: R_6
5. Experiment

Experiments to evaluate the object grasp motion model were conducted by using an instrumented hydraulic arm, which has four types of sensors, as shown in Fig. 4 [16].

5.1 Implementation

The operation signals such as $O_A$, $O_{0A}$, $O^H$, and $O^H_0$ can be precisely obtained from the potentiometers installed at control levers. The on-off state of the arm operation ($O_A$ and $O_{0A}$) is output as the logical addition of three cylinders such as the boom, arm, and bucket cylinders, as shown in Fig. 4. The on-off state of the arm load ($L_A$ and $L_{0A}$) and the hand load ($L_H$ and $L_{0H}$) are defined by using an external force measurement system, which was developed in the authors' previous study [17].

A load detecting system for practical use requires minimizing the complexity of a detection algorithm while maximizing the detection accuracy. The detection system first estimated the analog external force applied to the cylinder by identifying the dominant error force component, including self-weight and driving force, by using hydraulic pressure sensors and cylinder stroke sensors. Inclination sensors, e.g., gyro sensors, to measure the posture of the base of the machine must be also installed on the machine's body for compensating the self-weight force correctly when the ground is uneven and non-horizontal such as one at disaster sites. It then defined the binary on-off decisions by using the detection threshold force. It second redefined ternary outputs such as on, off, or not determinate (ND) on the basis of evaluating the detection condition to address indeterminate conditions. It finally output the ternary front load decision by combining the cylinder decisions to improve the robustness on the basis of priority analysis. In our target system, a threshold to identify the on-off state of the hand and arm loads is set to 5% above and 10% above of the full range (16 MPa), respectively. Inside or outside contacts such as $L^+_H$ and $L^-_H$ can be identified by using the piston-side and bottom-side pressures of the grapple cylinder, as stated in the section 2.1. Considering the large variance of hydraulic pressure, the inside contact is denoted by $P_2 > 2 \times P_1$ and the outside contact is conversely denoted by $P_1 > 2 \times P_2$ to ensure identification robustness.

5.2 Experimental Condition

1) Experimental task: The machine had three pitch joints, a yaw joint, and a roll joint with a grapple. The evaluation task we set was a sequential transport task. The objects to be transported were set in a material yard that had three layers (upper, middle, and lower stands), as shown in Fig. 5 (a). They were eight objects to be transported, which differed in the shape, center of gravity, stiffness, and mass (larger than 10 kg), as shown in Fig. 5 (b). To reproduce operational error during the grasping motion owing to the lack of a sense of depth, the objects were placed in front of and behind other objects and overlapping each other. The operators were expected to grasp an object placed on the left stand and transport it to the right stand by using a swing joint (yaw-axis). Wooden objects were to be set on the middle stand and other objects on the lower stand, as shown in Fig. 5 (c). The operators are eight novice operators who were familiar with the operational method, as well as one skilled operator, and they all conducted the task three times.

2) Success and failure rate: To evaluate the performance of

Fig. 4 Instrumented hydraulic dual arm system.

Fig. 5 Experimental environment for object transport.
grasp estimation using the grasp motion model, the success rate $S_R$ and failure rate $F_R$ were defined. The success rate $S_R$ represents the ratio of the number of successful estimations determined by the estimation system ($D_T$) divided by the total number of actual grasps observed by the observer ($N$), and it is given by $S_R = D_T/N$. The failure rate $F_R$ represents the ratio of the number of failed estimation determined by the estimation system ($D_F$) divided by the number of grasp detected by the estimation system ($D$), and it is given by $F_R = D_F/D$.

5.3 Experimental Results

Figures 6 and 7 show an observed grasp $G_{OB}$, the estimation results using the hand load $G_{HL}$ and the grasp motion model (GMM) $G_{GMM}$, and grasp motion states $S_x$ for a novice and skilled operator, respectively. $G_{OB}$ was determined by an observer and represents actual grasps or non-grasps. It is changed to 1 (grasp) when an object is lifted and 0 (non-grasp) when the object is released. $G_{HL}$ is changed to 1 when $L + H$ or $L - H$ is observed. $G_{GMM}$ is changed to 1 when $S_4$ is observed.

1) Results in time-series representation: As Figs. 6 (c) and (d) show, the GMM was adequately identified depending on the grasp motion states $S$. $G_{HL}$ often included failed estimations, as shown in Figs. 6 (a) and (b). By contrast, $G_{GMM}$ was effective for less failed estimations, as shown in Figs. 6 and 7. These figures also indicate that the number of failed estimations in $G_{HL}$ for the skilled operator is less than a novice operator and time taken to complete a task for the skilled operator is shorter than the novice operator.

2) Results in statistical representation: Figure 8 shows the success rate $S_R$ and failure rate $F_R$ for estimations using $G_{HL}$, $S_x$, and $G_{GMM}$ for 234 grasps in 27 operations for all 9 operators. The success rate $S_R$ for $G_{HL}$ is 100% but the failure rate $F_R$ is 48%, meaning that half of the estimated grasps were misidentified. By using the grasp motion state ($S_1 - S_3$), $F_R$ gradually decreases while sustaining a 100% $S_R$. Grasp motion model $G_{GMM}$ ($S_4$) identifies all grasps, and it reduced $F_R$ to under 6%, meaning that $F_R$ decrease by 87% compared with $G_{HL}$. The failed estimations were caused by only an inside contact by a hand close operation $R_4H$ (the number of $R_4H$ and hook $R_5H$, which $G_{GMM}$ cannot identify, was 15 and 0 times, respectively). Student’s $t$-test indicated a significant difference between $G_{GMM}$ and $G_{HL}$ ($t = 3.36, p < 0.01$). The results confirmed that estimation using the object grasp model $G_{GMM}$, defined by using the simple transition model based on the on-off state of operation and pressure signals, greatly contributes to reducing the failure rate while not missing any actual grasps, independently of operational skills and object locations.

5.4 Analysis of Operational Skill and Work Result

1) Relationship between the number of error contacts and completion time: Figure 9 shows the relationship between the number of the hand loads ($L_{HL}$), which means the number of error operations, and completion time. The completion time (the number of $L_{HL}$) was 568 s (50) on average for all the operators. That for novice operators (average) and the skilled operator was 595 s (52) and 349 s (33), respectively. The result shows that
that the number of $L_{HF}$ must be reduced for decreasing the completion time. Moreover, the comparison among Group A, B, and C illustrated in Fig. 9 reveals that a novice operator (B and C) satisfies either less contacts or short completion time, by contrast, a skilled operator (A) satisfies both of them. This analysis indicates that a grasp motion model is available to estimate types of operational skills of operators.

2) Work analysis using contact state loops: The number of contact state loops was calculated for analyzing causes of miss contact and grasping. State $S_1$ loop ($S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_4 \rightarrow S_0$) means a valid motion for grasping an object while $S_1$, $S_2$, and $S_3$ loop means a wasted motion. Specifically, $S_1$ loop ($S_0 \rightarrow S_1 \rightarrow S_0$) means a wasted hand close operation, $S_2$ loop ($S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_0$) means an error-contact with an object or the environment, and $S_3$ loop ($S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_0$) means an error-releasing owing to insufficient grasping force, an error-contact involving arm operations, or a null grasp. The ratio of $S_1$, $S_2$, $S_3$, and $S_4$ loops for the skilled operator was 9, 3, 3, and 85%, respectively, while that for the average of the novice operators was 20, 8, 3, and 69%, respectively. These results indicate that the skilled operator has less wasted motions, in particular, hand close operations ($S_1$ loop) and error-contact ($S_2$ loop), compared with the novice operators. Figure 10 shows the relationship between the number of contact state loops ($S_1$, $S_2$, and $S_3$) and the completion time. The figure also indicates that $S_1$ and $S_2$ loops increase more with the increase in the completion. From the above analyses, we found that the number of contact state loops can reveal unskilled operations in each phase of grasp motions. On the basis of the revealed characteristics, advice information to reduce wasted hand close operations or operational support to automatically grasp an object can be provided.

6. Conclusion

In this paper, an object grasp motion, which is a requisite condition for achieving grasp, was modeled as a fundamental study for practical object grasp estimation framework for demolition machines, which lack visual or tactile information, in order to enhance the perceptual capacity. Contact states were first modeled on the basis of states of the joint load for the demolition machines, which lack visual or tactile information, in order to enhance the perceptual capacity. Contact states were first modeled on the basis of states of the joint load for the demolition machines, which lack visual or tactile information, in order to enhance the perceptual capacity. Figure 10 shows the relationship between the number of contact state loops and completion time for each subject (novice and skilled). The number of loop ($S_1$ loop) means a wasted motion. Specifically, $S_1$ loop ($S_0 \rightarrow S_1 \rightarrow S_0$) means a wasted hand close operation, $S_2$ loop ($S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_0$) means an error-contact with an object or the environment, and $S_3$ loop ($S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_0$) means an error-releasing owing to insufficient grasping force, an error-contact involving arm operations, or a null grasp. The ratio of $S_1$, $S_2$, $S_3$, and $S_4$ loops for the skilled operator was 9, 3, 3, and 85%, respectively, while that for the average of the novice operators was 20, 8, 3, and 69%, respectively. These results indicate that the skilled operator has less wasted motions, in particular, hand close operations ($S_1$ loop) and error-contact ($S_2$ loop), compared with the novice operators. Figure 10 shows the relationship between the number of contact state loops ($S_1$, $S_2$, and $S_3$) and the completion time. The figure also indicates that $S_1$ and $S_2$ loops increase more with the increase in the completion. From the above analyses, we found that the number of contact state loops can reveal unskilled operations in each phase of grasp motions. On the basis of the revealed characteristics, advice information to reduce wasted hand close operations or operational support to automatically grasp an object can be provided.

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In this paper, an object grasp motion, which is a requisite condition for achieving grasp, was modeled as a fundamental study for practical object grasp estimation framework for demolition machines, which lack visual or tactile information, in order to enhance the perceptual capacity. Contact states were first modeled on the basis of states of the joint load for the grapple. An object grasp motion was then modeled by using a state transition of control signals (operation data) and cylinder pressure (load data) for the grapple and manipulator. Transport experiments were conducted using an instrumented setup, and the results indicated that the estimation using the grasp motion model can be effective to detect actual grasps with less failed estimations. On the other hand, estimation using the object grasp motion model remains a few failed estimations, as shown in Figs. 6 (d) and 8, and they were caused by an inside contact by a hand close operation ($R_{HF}$). To improve estimation accuracy, an advanced method to confirm a grasp state which is defined as one where the object does not move from the grapple in any manipulator movements is addressed.

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References


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