2013 IEEE/RSJ International Conference on
Intelligent Robots and Systems (IROS)
November 3-7, 2013. Tokyo, Japan

Practical Object-Grasp Estimation without Visual or Tactile Information for Heavy-Duty Work Machines

Mitsuhiro Kamezaki, *Member, IEEE*, Hiroyasu Iwata, *Member, IEEE*, and Shigeki Sugano, *Fellow, IEEE*

Abstract – **This paper proposes a practical framework to estimate whether or not a grapple installed in demolition machines is in a grasp state. Object grasp is a highly difficult task that requires safe and precise operations, so identifying a grasp or non-grasp state is important for assisting an operator. These types of outdoor machines lack visual and tactile sensors, so the proposed framework adopts practically available lever operation and cylinder pressure sensors. The grasp is formed by a grasp motion, which is operations to make the grapple pinch an object, and the grasp state, where the grapple holds the object in any manipulator movements. Thus, the framework determinately confirms the grasp motion through the requisite conditions defined by using sequential changes of binarized operation and pressure data for the grapple and the manipulator, and stochastically confirms the grasp state through the enhancement conditions defined by using force and movement vectors including vertical downward force, movement in the longer direction, and horizontal reciprocating movement. The results of experiments conducted to transport objects using an instrumented hydraulic arm indicated that the proposed framework is effective for identifying grasp/non-grasp with high accuracy, independently of various operators and environments.**

I. Introduction

RESCUE and recovery work at disaster sites [1], sorted dismantling for recycling resources, and tree thinning for forestry improvement [2], are socially expected to be carried out using construction machinery, which is able to produce the massive force. The above advanced tasks require grasping objects including transporting debris, removing fallen trees, and crushing waste products, which differs from conventional simple excavation. These tasks are thus conducted by using machines equipped with a grapple, which has a grasping mechanism, as shown in Fig. 1. An object grasp is an initial state for various elemental tasks such as transport, removal, and bending, so it is essential to execute the advanced tasks. On the other hand, 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 the position and orientation of the end-point of the grapple in accordance with a distant object while paying attention to a contact with the environment. Moreover, the ground and debris conditions are often unstable, and the operator may have insufficient visibility, particularly 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 machinery, and falling and breakage of transported objects. Consequently, advanced construction machinery must be able to grasp objects safely and precisely. This requires highly sophisticated skills involving cognitive and control abilities in machine operators. An effective way to address these problems is to provide operational support by using an intelligent system that identifies grasp/non-grasp, i.e., whether or not the grapple has grasped an object. The authors previously proposed an intelligent system that provides operator support [3], [4] and work-analysis support [5] on the basis of identifying work states. This study thus proposes a method to estimate a grasp or non-grasp for construction machinery. The proposed framework is also useful in underwater maintenance work [6], tele-operated object handling at disaster sites [1], and demolition work in high places using a long-reach arm, where visual and tactile information is unsatisfactory.

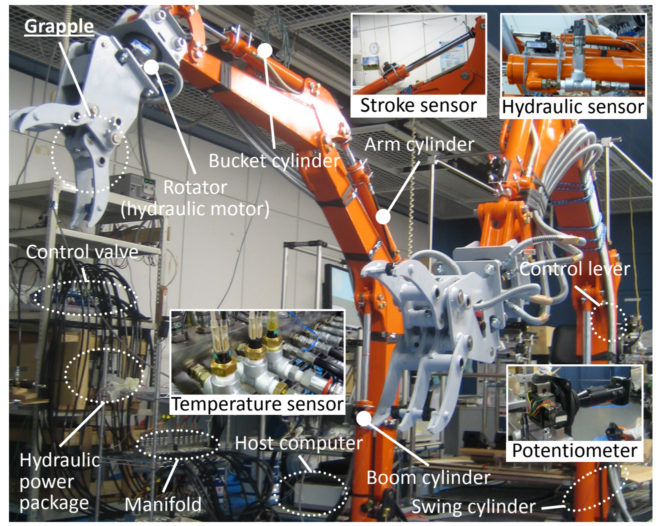

Fig. 1 Instrumented hydraulic arm system with four types of sensors

II. Analysis of Grasp in Construction Machinery

Problems in grasp estimation were first analyzed and requirements for a practical grasp estimation method for construction machinery were clarified.

M. Kamezaki is with the Research Institute for Science and Engineering (RISE), Waseda University, 17 Kikui-cho, Shinjuku-ku, Tokyo 162-0044, Japan (corresponding author to provide phone and fax: +81-3-3203-4457; e-mail: kamezaki@ieee.org).

H. Iwata is with the Department of Modern Mechanical Engineering, School of Creative Science and Engineering, Waseda University, Green Computing System Research and Development Center, 27 Waseda-machi, Shinjuku-ku, Tokyo 162-0042, Japan (e-mail: jubi@waseda.jp).

S. Sugano is with the Department of Modern Mechanical Engineering, School of Creative Science and Engineering, Waseda University, 3-4-1 Okubo, Shinjuku-ku, Tokyo 169-8555, Japan (e-mail: sugano@waseda.jp).

URL: http://www.sugano.mech.waseda.ac.jp/

A. Problems in grasp/non-grasp estimation

1) Mechanism and sensors: A grapple is 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. 2. A grapple opens (closes) by extending (contracting) the cylinder and its forks synchronously move in the reverse directions. The sensors available in these structures are potentiometers for detecting the amount of lever input and hydraulic sensors for detecting joint load, owing to the limitation from the severe work environments. Lever sensors reveal when the forks are opening/closing (Fig. 2 (a)). Pressure sensors reveal when the forks come into inside/outside contact with objects by using the pressure balance of the piston-rod-side pressure P_1 and bottom-side pressure P_2 of the cylinder (inside contact: $P_1 < P_2$ and outside contact: $P_1 > P_2$) (Fig. 2 (b)). Angle sensors are not installed and the two forks are linked, so a null grasp (completely closed without grasp) and a contacted fork (upper/lower) cannot be identified.

2) Difficulty of grasp estimation: The inside contact provides the essential information for representing the possibility of a grasp. However, grasp is not determined by the inside contact alone, owing to a contact with the inside part of either fork or a null grasp. By contrast, humans can use visual and tactile information obtained from their eyes and hands to easily identify grasp/non-grasp. Related studies have investigated an object grasping strategy using visual or tactile information [7], [8] and adaptive grasping control [9]. They were applied to instrumented manipulators for indoor applications. On the other hand, for construction machinery, grasp estimation is inevitably difficult because of the insufficient sensor capabilities. Thus, no studies have systematically focused on developing a method to identify grasp/non-grasp in the construction machinery field.

B. Grasp motion and grasp state

To develop an object grasp estimation framework for construction machinery, we analyzed the sequence of a grasp. A grasp can be divided into a grasp motion and a grasp state. (i) A grasp motion is represented 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 essential to achieve the grasp. If the grasp motion is not observed, the grasp possibility vanishes. This deterministic sequence is called a requisite condition for grasp (RCG). (ii) A grasp state is defined as one where the object does not move from the grapple in any manipulator movements. Various objects (e.g., with different shapes and mass) are found in various positions (e.g., on the ground and on walls) in disaster response work in particular, so the grasp state is inherently difficult to definitively determine. Thus, the grasp state must be stochastically estimated. This probabilistic estimation is called the enhancement condition for grasp (ECG).

C. Requirements for grasp estimation

From the above analysis, this study proposes a grasp estimation framework to confirm requisite and enhancement

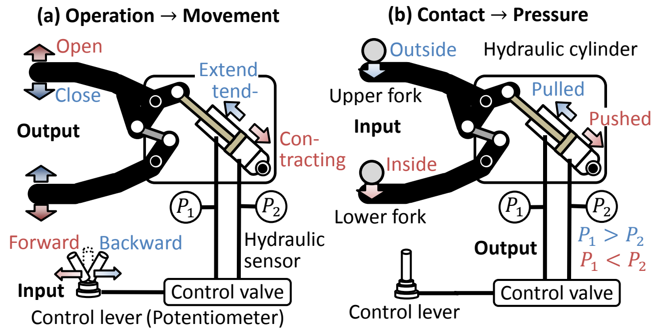

Fig. 2 Grapple configuration and acquirable information

conditions for grasp, taking into consideration practical sensors and a feasible algorithm for outdoor machines. The following analysis and developments were thus conducted.

1) Modeling relationship between grapple and object: The analysis of the positional relation between a grapple and an object was used to model contact states in order to distinguish grasp from non-grasp, considering the available sensors. Six contact states R_x were defined (section III).

2) Requisite condition for grasp: On the basis of an analysis of grasp motion, the requisite condition for grasp (RCG) was modeled by using the sequential changes of operation and pressure data. Five grasp motion states S_x and their transition model were determinately defined (section IV).

3) Enhancement condition for grasp: The conditions that enhance the grasp possibility were analyzed to model the enhancement conditions for grasp (ECG) C_x by using force and movement vectors. Three C_x and a grasp evaluation value E for stochastic grasp judgment were defined (section V).

III. Relation Model Between Grapple and Object

On the basis of the analysis of the positional relationship between a grapple and an object, the contact states R_x was modeled to distinguish grasp from non-grasp. Hereafter, we refer to the grapple and manipulator as the hand and arm, respectively. Acquirable data in practical construction machinery are the operation and load for the hand and the operation, load, and angle for the arm. Thus, the parameters to define a contact are the arm load (L_A), inside hand load (L_H^+), and outside hand load (L_H^-), and the parameters to define the operational intention of an operator are the arm operation (O_A), hand close (O_H^+), and hand open (O_H^-). When a relevant parameter is zero, zero is substituted into the upper right superscript (e.g., L_A^0). The contact states R_x are defined using six parameters, which are schematically shown in Fig. 3.

1) Non-grasp/non-contact: States where the hand does not contact an object are inevitably regarded as non-grasp states. We call a state where the hand is not completely closed a no contact R_1 (L_H^0, L_A^0), whereas a state where it is completely closed is a null grasp R_2 (L_H^+, L_A^0). The no contact R_1 arises from arbitrary operations ($R_1/O_H, O_A$). The null grasp R_2 arises from a hand close operation (R_2/O_H^+), and the grapple cylinder is in the stroke-end in this state.

2) Non-grasp/contact: In this state, the hand is in physical

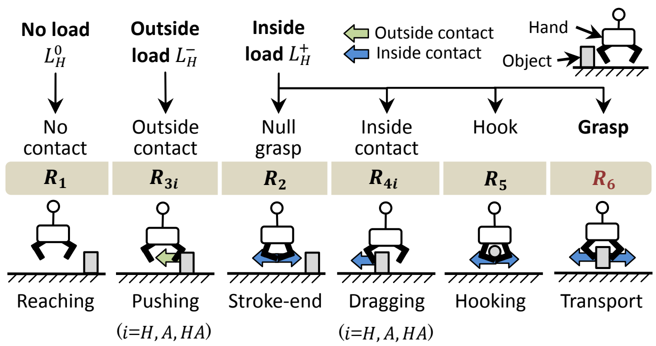

Fig. 3 Geometric relationship between hand and object

contact with an object but is not grasping it. We call a state where the hand is in contact with an object on the outside of the hand an outside contact R_3 (L_H^-, L_A) and the state where the hand is in contact with an object on the inside of the hand an inside contact R_4 (L_H^+, L_A). The inside contact R_4 is easy to change to a no contact R_1 by actuating the arm because the object is not secured by the two forks. The outside contact R_3 arises from three types of operations: a hand open operation (R_{3H}/O_H^-), an arm operation (R_{3A}/O_A), and both of these $(R_{3HA}/O_H, O_A)$. Similarly, the inside contact R_4 arises from a hand close operation (R_{4H}/O_H^+), an arm operation (R_{4A}/O_A), and both of these $(R_{4HA}/O_H, O_A)$. Moreover, 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_H^+, L_A). The hook R_5 arises from arbitrary operations $(R_5/O_H, O_A)$.

3) Grasp/contact: This state is where the two forks contact and grasp an object at their inside surfaces without the forks contacting each other. We call this state a grasp R_6 (L_H^+, L_A). The grasp R_6 arises from a hand close operation $(R_6/O_H^+, O_A)$.

Thus, six contact states were defined as follow: the no contact R_1, null grasp R_2, outside contact R_{3i}, inside contact R_{4i}, hook R_5, and grasp R_6. Contact states from R_1 to R_5 are defined as non-grasp states, as shown in Fig. 3.

IV. Requisite Condition for Grasp

On the basis of the contact states R_x defined in the previous section, the RCG was then defined by using grasp motion states S_x and their state transitions.

A. Modeling of requisite condition for grasp

The parameters change as follow when the grasp R_6 is established: the inside hand load L_H^+ is generated by the hand close operations O_H^+, and the arm load L_A is generated by the arm operations O_A. A state transition model was thus modeled by using five grasp motion states S_x, as shown in Fig. 4.

1) Initial state S_0: A state where there is no hand operation (O_H^0) and no hand load (L_H^0) is defined as an initial state S_0. S_0 changes to a hand-close operation state S_1 when a hand close operation $(O_H^0 \rightarrow O_H^+)$ is added.

2) Hand-close operation state S_1: Hand close operations are continuously input. The distance and velocity of the fork movement depends on the object shape and the hand size, and angle sensors are not installed on the grapple. We thus use

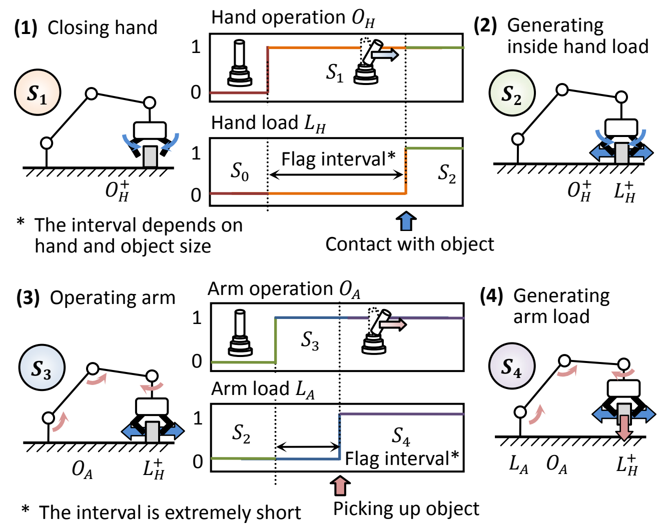

Fig. 4 Sequential state transition during grasping motion

only the on-off state of hand closing. Until the state changes to S_1, if the hand load is zero (L_H^0), the current state is regarded as a no contact R_1. If the outside hand load (L_H^-) arises from an arm operation (O_A), the current state is regarded as an outside contact R_{3A}. If the inside hand load (L_H^+) arises from an arm operation (O_A), the current state is regarded as an inside contact R_{4A}. If the outside hand load (L_H^-) arises from a hand open operation (O_H^-), the current state is regarded as an outside contact R_{3H}. S_1 changes to an inside hand load state S_2 when an inside hand load $(L_H^0 \rightarrow L_H^+)$ is added.

3) Inside hand load state S_2: The inside hand load must be continuously generated. After the inside hand load has been generated once, the hand close operations do not need to be continuously input. S_2 changes to an arm operation state S_3 when an arm operation O_A is added.

4) Arm operation state S_3: The inside hand load and arm operations must be continuously input. S_3 changes to an arm load state S_4 when an arm load L_A is added.

5) Arm load state S_4: The inside hand load and arm load must be continuously observed. S_4 is regarded as grasp R_6 because it satisfies the RCG. After the arm load has been generated once, the arm operations do not need to be continuously input. Until the state changes to S_4, if the arm load is zero (L_A^0), the current state is regarded as a null grasp R_2. The inside contact by a hand close operation R_{4H} and hook R_5 cannot be fully classified. This problem will be solved by using the ECG described in section V.

The transition diagram of grasp motion states S_x and identified contact states R_x are shown in Fig. 5. A grasp motion state S_x changes from S_0 to S_4 in order depending on the obtained data, and S_4 satisfies the RCG. When the hand load is zero, S_x is back to an initial state S_0. Moreover, S_1 changes to S_0 when O_H^0 occurs, and S_3 changes to S_2 when O_A^0 occurs.

B. Implementation

The operational data $(O_A, O_H^+$, and $O_H^-)$ can be precisely obtained from the potentiometers. The arm operation is output as the logical addition of three cylinders such as the boom,

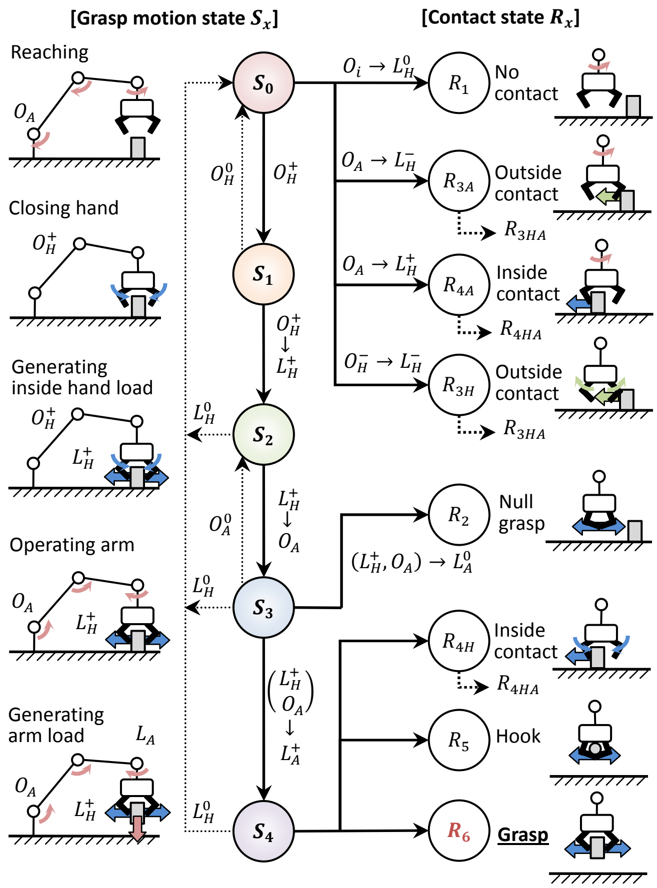

Fig. 5 Estimation model for requisite condition

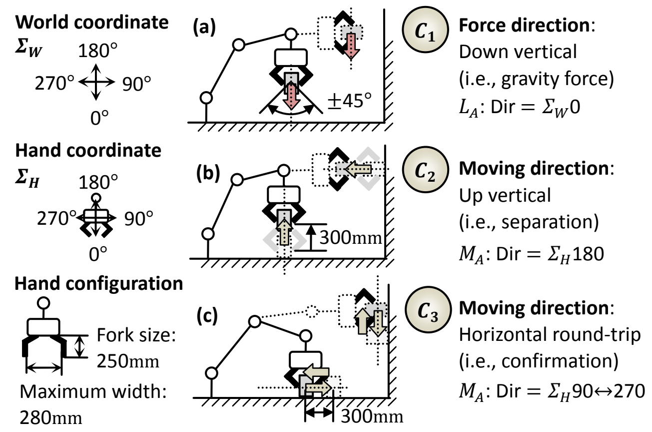

Fig. 6 Conditions for enhancing a grasp state

arm, and bucket cylinders, as shown in Fig. 1. Inside/outside contacts (L_H^+ and L_H^-) can be identified by using the piston-side and bottom-side pressures of the grapple cylinder, as stated in section II A. The arm load (L_A) is determined by using an external force measurement system, which was developed in our previous studies [10]. For identifying the on-off state of the hand and arm loads, the threshold is set to 5% above and 10% above of the full range (16 MPa).

V. Enhancement Conditions

On the basis of the requisite conditions, the ECG (C_x) was defined to improve the estimation accuracy and robustness, and the grasp evaluation value E was defined.

A. Modeling of enhancement condition for grasp

The RCG cannot fully distinguish grasp R_6 from R_{4H} and R_5, as shown in Fig. 5. To solve this problem, it is necessary to confirm the grasp state, where the hand continues to hold a grasped object in any manipulator movements during S_4. A large circular motion of the end-point is preferable to confirm a grasp state, but it occurs in few situations in actual work. The possible movements and phenomena to increase the grasp possibility were thus analyzed, focusing on movement and force vectors (magnitude and direction) because a grasp state must be stochastically defined, as stated in section II B. To define the direction, world (Σ_W) and hand coordinates (Σ_H) were prepared. From the analysis, three enhancement conditions C_x were defined, as shown in Fig. 6.

1) Down vertical force C_1: When the arm grasps an object and detaches it from the surroundings, the arm is subject to the gravity force from the grasped object. The force direction is thus down vertical (L_A: dir = $\Sigma_W 0$), and is independent of object location and manipulator posture, as shown in Fig. 6 (a). The direction is measured by using a force vector measuring system [10], and the judgment tolerance is set to $\pm 45°$ considering the robustness. Moreover, an unstable large variation of force direction caused by oscillating a manipulator occurs for less than 0.5 s, so the confirmation duration time is set to 3 s to surely distinguish down vertical from others.

2) Up vertical movement C_2: After the hand has grasped an object, the operator maneuvers the hand in a direction opposite to the approach, i.e., vertically up in the longer direction of the hand (M_A: dir = $\Sigma_H 180$), as shown in Fig. 6 (b). The fork size of the hand is adopted as the minimum distance to release an object from the hand, and the judgment threshold is set at 300 mm in our target hand.

3) Horizontal round-trip movement C_3: To dissolve an inside contact, the hand must make a round-trip movement in a direction perpendicular to the approach direction (M_A: dir = $\Sigma_H 90 \leftrightarrow 270$), as shown in Fig. 6 (c). The maximum width when the hand is completely opened is adopted as the minimum distance to release an object from the hand, and the judgment threshold is set at 300 mm in our target hand.

B. Grasp evaluation value

To evaluate the grasp possibility, a grasp evaluation value E is defined. The evaluation value E is set to zero from S_0 to S_3 because they do not satisfy the RCG, and changes to 1 at S_4. E increases 1 point according to which ECGs are established during S_4, and comes to 4 points when all the ECGs are established. In summary, E= 0 represents a non-grasp, E= 1 represents the possibility of a grasp, and E= 4 represents a grasp with highest relative possibility, as shown in Fig. 7.

VI. Experiments

We conducted experiments to evaluate the proposed grasp estimation framework consisting of RCG and ECG by using an experimental setup, as shown in Fig. 1 [11].

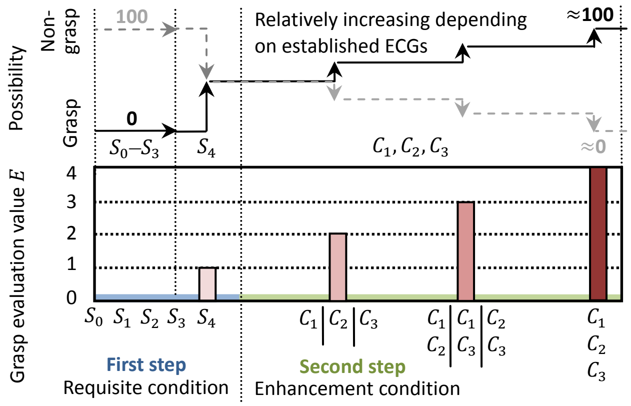

Fig. 7 Grasp evaluation value and grasp/non-grasp possibility

A. Experimental conditions

1) Experimental task: The work 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. 8 (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. 8 (b). To reproduce operational error during the grasping motion owing to the lack of a sense of depth, we placed the objects in front of and behind other objects, and the objects were overlapping each other, as shown in Fig. 8 (a). 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. 8 (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 grasp estimation, we defined success rate S_R and failure rate F_R. 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 system D $(= D_T + D_F)$, and it is given by $F_R = D_F/D$.

B. Experimental results

Figures 9 shows an observed grasp G_{OB}, the estimation results using the hand load G_{LH}, the RCG G_{RC}, and the ECG G_{EC}, grasp motion states S_x, enhancement conditions C_x, and grasp evaluation value E. G_{OB} was determined by an observer and represents actual grasps/non-grasps. It is changed to 1 (grasp) when an object is lifted and 0 (non-grasp) when the object is released. G_{LH} is changed to 1 when L_H^+ or L_H^- is observed. G_{RC} is changed to 1 when S_4 is observed. G_{EC} is defined according to E. Figure 10 shows the success rate S_R and failure rate F_R for each estimation system, i.e., G_{LH}, G_{RC}, and

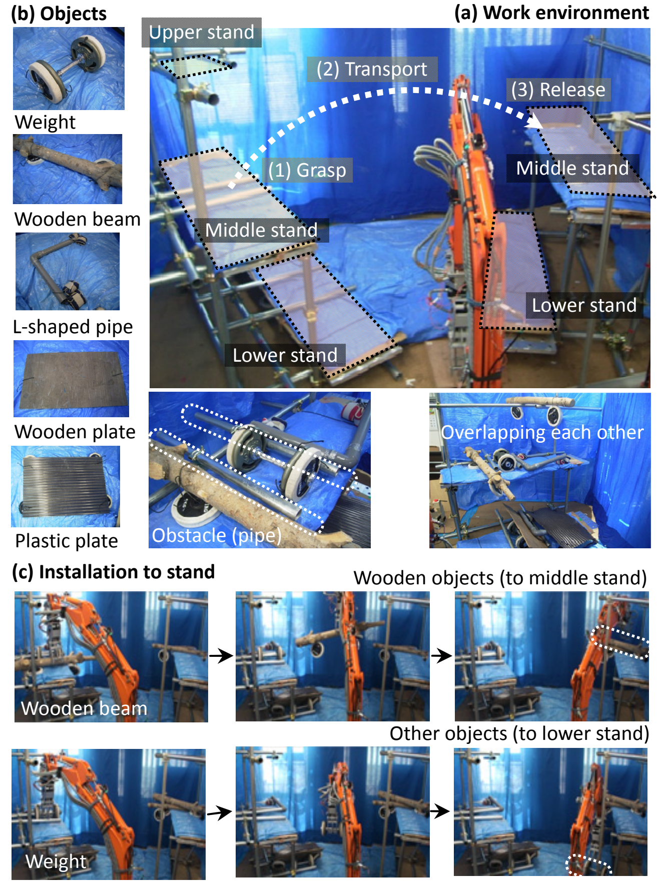

Fig. 8 Experimental work environment

G_{EC} for 234 grasps (D) in 27 operations for all 9 operators.

1) Requisite condition G_{RC}: Figures 9 (c) and (d) show that the RCG was adequately identified depending on the grasp motion states S_x. Failed estimations often occurred with G_{LH} in comparison with G_{OB}. By contrast, G_{RC} was effective for precisely estimating grasp, as shown in Figs. 9 (a)–(d). The success rate S_R for G_{LH} is 100% but the failure rate F_R is 48%, meaning that half of the estimated grasps were misidentified, as shown in Fig. 10. By using the grasp motion state (S_1–S_3), F_R gradually decreases while sustaining a 100% S_R. G_{RC} (S_4) identifies all grasps, and it reduced F_R to under 6%, meaning that F_R decrease by 87% compared with G_{LH}. T-test indicated a significant difference between G_{RC} and G_{LH} (t =3.36, p<0.01). From the results, we confirmed that G_{RC}, defined by using the simple transition model based on the on-off state of operation and pressure data, greatly contributes to reducing the failure rate while not missing any actual grasps, independently of operational skills and object locations.

2) Enhancement condition: Figures 9 (e) and (f) show that the grasp evaluation value E was identified according to the established C_x. To evaluate estimation ability, we defined three types of G_{EC}, which differ in the decision threshold of E, as shown in Fig. 9 (g). Figure 9 (g) shows that G_{EC} using a larger threshold completely eliminated failed estimations but often overlooked the actual grasps. Figure 10 statistically indicates that the failure rate F_R for $E \geq 2$ decreases to 2%, and F_R for $E \geq 3$ decreases to 0%. We confirmed that G_{EC} greatly

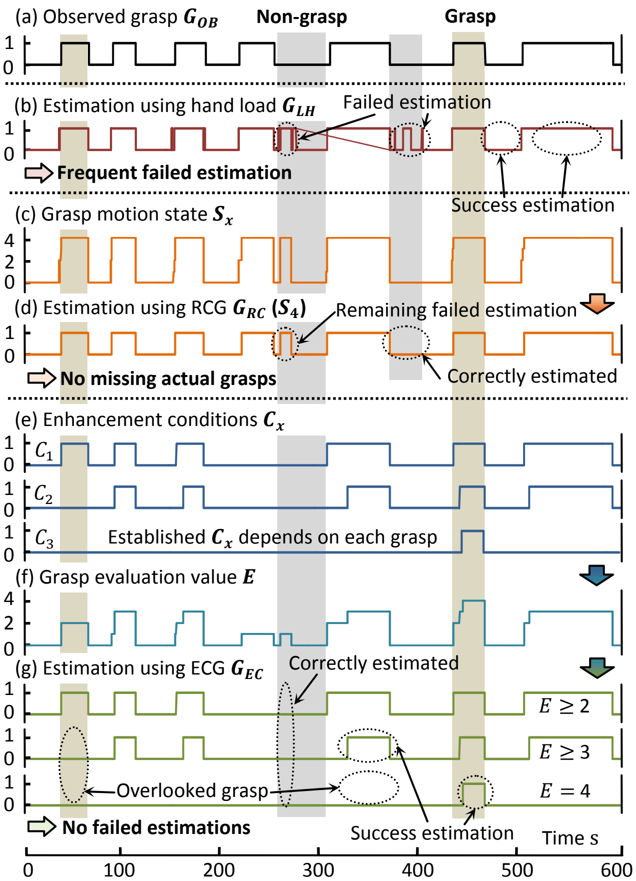

Fig. 9 Identification result using each estimation system

reduced the failure rate, by contrast, the missing grasps greatly increased as the decision threshold of E increased. This is because the ECGs were established only in 79% (C_1), 59% (C_2), and 10% (C_3). C_1 was expected to occur in all grasps, but it was not detected in 20% of the grasp because the object was securely grasped but not transported (just grasped and released). C_2 and C_3 were determined by using the displacement of the end-point, so they are strongly affected by the environmental conditions and tasks. However, the ECGs are useful to eliminate failed estimations. Considering a trade-off relationship between S_R and F_R, it is thus reasonable to use G_{RC} when actual grasps must be detected (e.g., to comprehend work tendencies) and G_{EC} when failed estimation must be avoided (e.g., an active grasp control).

VII. Conclusion and Future Work

A practical object grasp framework for a construction manipulator was proposed that does not use visual or tactile information in order to enhance the perceptual capacity. The proposed framework estimates grasp/non-grasp states on the basis of requisite (RCG) and enhancement conditions (ECG) for grasp. The RCG is the essential condition for achieving grasp, which was defined by using a state transition of lever operational and cylinder pressure data for the grapple and manipulator. The ECG is the condition necessary to enhance the grasp possibility, which was defined by using force direction applied to the end-point of a manipulator and movement vector of the grapple. The possibility of a grasp was stochastically evaluated by using a grasp evaluation value. Transport experiments were conducted using an instrumented setup, and the results indicated that the RCG and ECG can respectively be used to detect actual grasps with less errors and to eliminate errors in return for decreasing success rate. In the future, we analyze ECG from the degree of contribution to estimating grasp in a target environment, and adaptively adjust an additional point for the grasp evaluation value.

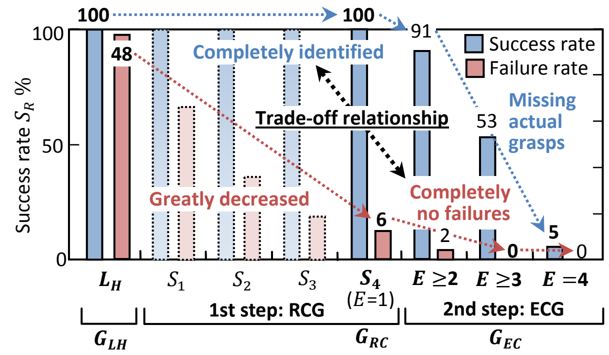

Fig. 10 Success and failure rate for each estimation method

Acknowledgment

This research was supported in part by Hitachi Construction Machinery Co., Ltd, in part by JSPS KAKENHI Grant Number 24760215, and in part by the Research Institute for Science and Engineering, Waseda Univ.

References

[1] D. Ryu, S. Kang, M. Kim, and J.B. Song, "Multi-modal user interface for teleoperation of ROBHAZ-DT2 field robot system," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, pp. 168–173, 2004.

[2] P.L. Hera, B.U. Rehman, and D.O, Morales, "Electro-hydraulically actuated forestry manipulator: modeling and identification," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, pp. 3399–3404, 2012.

[3] M. Kamezaki, H. Iwata, and S. Sugano, "Operator support system based on primitive static states in intelligent operated-work machines," *Advanced Robotics*, vol. 23, no. 10, pp. 1281–1297, 2009.

[4] M. Kamezaki, H. Iwata, and S. Sugano, "A framework to identify task-phase and attentional-condition for supporting complicated dual-arm operations", *Journal of Robotics and Mechatronics*, vol. 22, no. 4, pp. 447–455, 2010.

[5] M. Kamezaki, H. Iwata, and S. Sugano, "Primitive static states for intelligent operated-work machines," in *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 1334–1339, 2009.

[6] T. Hirabayashi, T. Yamamoto, J. Akizono, M. Iwasaki, and H. Yano, "Experimental land model of tele-operated underwater backhoe with AR technology," in *Proc. Int. Symp. Underwater Tech.*, pp. 339–344, 2004.

[7] G.L. Foresti and F.A. Pellegrino, "Automatic visual recognition of deformable objects for grasping and manipulation," *IEEE Trans. Systems, Man, and Cybernetics–Part C*, vol. 34, no. 3, pp. 325–333, 2004.

[8] V. Lippiello, F. Ruggiero, B. Siciliano, and L. Villani, "Visual grasp planning for unknown objects using a multifingered robotic hand," *IEEE/ASME Trans. on Mechatronics*, vol. 18, no. 3, pp. 1050–1059, 2013.

[9] S. Jagannathan and G. Galan, "Adaptive critic neural network-based object grasping control using a three-finger gripper," *IEEE Trans. Neural Networks*, vol. 15, no. 2, pp. 395–407, 2004.

[10] M. Kamezaki, H. Iwata, and S. Sugano, "Relative accuracy enhancement system based on internal error range estimation for external force measurement in construction manipulator," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, pp. 3734–3739, 2011.

[11] M. Kamezaki, S. Hashimoto, H. Iwata, and S. Sugano, "Development of a dual robotic arm system to evaluate intelligent system for advanced construction machinery," in *Proc. IEEE Int. Conf. Advanced Intelligent Mechatronics*, pp. 1299–1304, 2010.