# Estimation of Robot Motion Parameters Based on Functional Consistency for Randomly Stacked Parts

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Keywords: Robot Motion Parameter Estimation, Function Recognition, Functional Consistency, Assembly, Bin Scene.

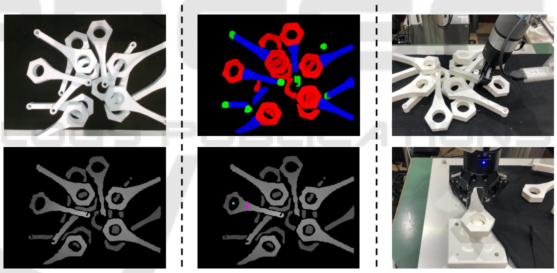
Abstract: In this paper, we propose a method for estimating robot motion parameters necessary for robots to automatically assemble objects. Generally, parts used in assembly are often randomly stacked. The proposed method estimates the robot motion parameters from this state. Each part has a role referred to as a "function" such as "to be grasped" or "to be assembled with other parts" for each region. Related works have defined functions for everyday objects, but in this paper, we defined a novel functional label for industrial parts. In addition, we proposed novel ideas which is the functional consistency of part. Functional consistency refers to the constraints that functional labels have. Functional consistency is used in adapting to various bin scene because it is invariant no matter what state the parts are placed in. Functional consistency is used in the proposed method as a cue, robot motion parameters are estimated on the basis of relationship between parameters and functions. In an experiment using connecting rods, the average success rate was 81.5%. The effectiveness of the proposed method was confirmed from the ablation studies and comparison with related work.

## 1 INTRODUCTION

In factories, there is an important task of grasping parts from a scene in which parts such as connecting rods, links, and gears are randomly stacked in boxes (bin). This type of "scene" is commonly referred to as a "bin scene" and "task" is commonly referred to as a "bin picking". In addition, parts grasped by a human or robot may be assembled with other parts. Automation of this task by robots is an important task in the robotics.

A common approach is to use object recognition methods(Redmon et al., 2016; Liu et al., 2016) to recognize objects. Next, the object is assembled by robot according to the motion parameters that were previously assigned for each part. However, this approach is time-consuming because model of each part must be assigned robot motion parameters in advance, and the workload needs to be reduced. The objective of this study is to significantly reduce the workload.

As a related works, there are methods(Domae et al., 2014; Zhang et al., 2021) for estimating robot motion parameters directly from the bin scene without using a model of the part. However, these methods use local information of the bin scene. The region that obstructs the assembly (e.g., threaded parts of bolts) may be estimated as grasping points, and smooth assembly cannot be performed. Furthermore, there are also methods(Turpin et al., 2021), for estimating the optimal robot motion parameters for assembly (e.g., grasping point, point of assembly to other parts, i.e., action point, etc.). These assume that the object to be manipulated is placed flat, and they cannot be applied to a bin scene.



(a) Bin scene (b) Parts functions & parameters (c) Assembly by robot

Figure 1: Abstract of proposed method for assembling an object from a bin scene by a robot. (a) (top) RGB and (bottom) depth images of a bin scene. (b) (top) recognizing the functions of parts and (bottom) estimating parameters. (c) (top) grasping parts and (bottom) assembling objects.

We propose a method for estimating robot motion parameters required for assembly from bin scenes (Figure 1). The proposed method reduces human assigning work.

The proposed method applies the "function"(Myers et al., 2015) of everyday objects to



Suzuki, T. and Hashimoto, M.
Estimation of Robot Motion Parameters Based on Functional Consistency for Randomly Stacked Parts.
DOI: 10.5220/0011683500003417
In *Proceedings of the 18th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2023) - Volume 4: VISAPP*, pages 519-528
ISBN: 978-989-758-634-7; ISSN: 2184-4321

industrial parts. Function refers to the roles for each part of an everyday object.

This is similar to a concept referred affordance(Yamanobe et al., 2017), which relates the part of an object to the robot motion. For example, for a hammer, the grip part is used to be grasped by a human or robot, and the head part is used to pound another object; therefore, the grip and head parts are referred to as the "grasp" and "pound" functions, respectively. Tasks to recognize the functions of everyday objects using 2D and 3D information and machine learning have been studied(Zhao et al., 2020; Minh et al., 2020; Chu et al., 2019a; Chu et al., 2019b; Iizuka and Hashimoto, 2018). In addition, there is dataset(Akizuki and Hashimoto, 2020) for machine learning to recognize functions.

In this study, we apply the idea of conventional methods where each part of an everyday object has a role. New functional labels in industrial parts are defined by the proposed method. When the function is used as a cue, the grasping point can be estimated from the region that should be grasped during assembly, and the action point can be estimated from the region that should be assembled to other parts. In addition, we proposed novel ideas which is the functional consistency of part. Functional consistency refers to the constraints that functional labels have. For example, there are constraints on the geometric relationships among functional labels (geometric consistency), the number and types of functional labels a part can have and so on (semantic consistency). Functional consistency is important to use in adapting to various bin scene because it is invariant no matter what state the parts are placed in.

Figure 1 shows an abstract of the proposed method. First, the functions of a part are recognized from a depth image of a bin scene. Next, using functional consistency as a cue, the functions that constitute a part are determined. Finally, robot motion parameters are estimated on the basis of these.

The main contributions of this paper are as follows.

- We propose a method for estimating robot motion parameters required for assembly from a bin scene.
- We define new functional labels for parts used in a factory.
- We propose novel ideas which is the functional consistency of part.
- We reduce the workload of assigning robot motion parameters by human.

# 2 RELATED WORKS

## 2.1 Estimating the Robot Motion Parameters from a Bin-Scene

In this section, we discuss related works for estimating robot motion parameters from a bin scene.

Zhang et al.(Zhang et al., 2021) visualized the entanglement of objects in a bin scene using topological knowledge. From their results, they estimated the robot motion parameters for grasping only one object. Domae et al.(Domae et al., 2014) estimated robot motion parameters from depth image. First, contact and collision region templates $C_n, C_l$ are created on the basis of the pose of the robot hand. Next, the depth image $I$ is convolved with $C_t, C_l$. Finally, it is convolved with a Gaussian filter to detect parameters. Araki et al.(Araki et al., 2018) proposed a CNN-based method as an improvement to Domae et al.'s method. Song et al.(Song et al., 2020) proposed a 6DoF closed-loop grasping model for estimating the 6DoF pose of an object, enabling grasping in various environments. However, because these methods use local information of the bin scene, they cannot estimate optimal robot motion parameters for assembly. For instance, Grasping the threaded parts of bolts and inserting it into a hole or grasping the hole of connecting rod and inserting it into a shaft is contrary to functional use.

## 2.2 Estimating the Robot Motion Parameters Required for Assembly

In this section, we discuss related works for estimating the optimal robot motion parameters for assembly.

Qin et al.(Qin et al., 2020) built a self-supervised robot system consisting of a keypoint-generator that detects keypoints related to a task from a point cloud and an action-optimizer that generates actions. Turpin et al.(Turpin et al., 2021) proposed a reinforcement learning-based method that detects multiple candidate keypoints and selects the most appropriate one among them. The constraints on the grasping parameters between the objective task and the object types were formulated by Kokic et al(Kokic et al., 2017). They estimated an appropriate affordance map and object type for the task from the object point cloud and objective task using a Convolutional Neural Network (CNN), and detected parameters using this information. Suzuki et al.(Suzuki and Hashimoto, 2021) transferred the robot motion parameters assigned by humans to one part to another.

Other studies have been conducted to detect robot motion parameters for various everyday objects. Xu et al.(Xu et al., 2021) detected robot motion parameters from RGB images using their developed keypoint detection network. Liu et al.(Liu et al., 2020) detected grasp candidate points from a point cloud, and selected the optimal robot motion parameters from candidate grasp points on the basis of the object's material and state information using a wide & deep model. Hamalainen et al.(Hamalainen et al., 2019) generated robot motion from an RGB image using encoder-decoder network. Ardon et al.(Ardon et al., 2020) selected the optimal robot motion parameters among candidates by human motion assigning and self-assessment.

However, these studies assume that the object to be manipulated is placed flat. Therefore, they cannot be applied to a bin scene.

In summary, these methods cannot be implemented in a robot system for assembly from a bin scene because they do not resolve all issues. To our knowledge, this is the first study to estimate the robot motion parameters required for assembly from a bin scene.

# 3 PROBLEM FORMULATION

In this section, we discuss the robot motion parameters to be estimated and how the estimation is formulated.

## 3.1 Definition

Given depth image $I$ of a bin scene, the goal is to estimate robot motion parameters (i.e., $G$: grasping point, $A$: action point).

## 3.2 Assumption

The following are assumptions in this study.

- The sensor's viewpoint is over the bin scene.
- The position and orientation of parts to be assembled are known.
- Only parts of the same type are randomly stacked.
- The types of parts (e.g., connecting rods, links) in the random stack are known.

## 3.3 Robot Motion Parameters to Be Estimated

There are two robot motion parameters to be estimated in this study (Figure 2).

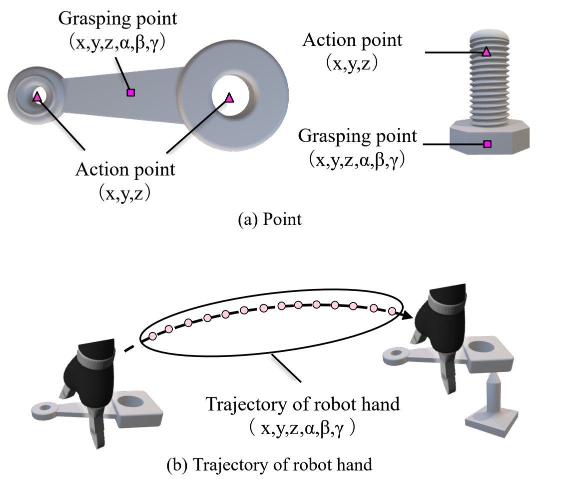



Figure 2: Robot motion parameters required for a robot to assemble an object.

The first parameter is related to the point (Figure 2 (a)). Assembly consists of two motions: a robot grasping a part and assembling it with other parts. That is, an object can be assembled if two points are known: 1) where the part is grasped (grasping point) and 2) where it is assembled with another part (action point). A grasping point consists of $x, y$ and $z$ in 3D space and α, β and γ, which are the grasping angles. An action point consists of $x, y$ and $z$ in 3D space.

The second parameter is related to the trajectory of the robot hand (Figure 2 (b)) between grasping the part and connecting it to another part. This consists of a sequence of points, each of which consist of $x, y$ and $z$ in 3D space. The data structure of this parameter is an array of points. Assembly requires precise movements for grasping and assembling parts. However, high accuracy is not required for the trajectories in between. This parameter is estimated by the robot's motion planner. If parameters can be estimated, the robot can assemble objects.

# 4 METHOD

In this section, we proposed a method for estimating robot motion parameters on the basis of functional consistency.

## 4.1 "Functions" and Functional Consistency of Industrial Parts

### 4.1.1 Functions

Related works have focused on recognizing the affordances of everyday objects to enable robots to use

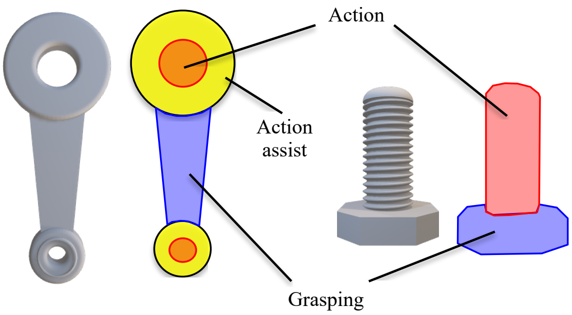



Figure 3: Functions of parts. A function refers to the role of each part of an industrial part. We defined three functions ("grasping," "action," and "action assist") for this study.

them(Minh et al., 2020; Chu et al., 2019b; Chu et al., 2019a; Zhao et al., 2020). On the basis of related works, we defined new functions of industrial parts. The novel idea of using functional consistency is implemented in the proposed method. Figure 3 shows an example of the parts used during assembly. A function refers to the role of each part of an industrial part. We defined three functions for this study.

The first function is "grasping" as shown by the blue region in Figure 3. This function has the role of being grasped by a human or robot. For the connecting rod, this function is the bar-shaped region between the two ring-shaped regions. For the bolt, this function is the head region.

The second function is "action" as shown by the red region in Figure 3. This function has the role of being assembled with another part. For the connecting rod, this function is the two ring-shaped regions. For the bolt, this function is the threaded rod-shaped region.

The third function is "action assist" as shown by the yellow region in Figure 3. This function has the role of assisting an action with another part. For the connecting rod, the region has action function in a hole shape. Therefore, there is a region that have role for making hole, which has this function. Parts that do not have holes (e.g., connectors, bolts, etc.) do not have this function.

#### 4.1.2 Functional Consistency

We proposed novel ideas which is the functional consistency of part. Functional consistency refers to the constraints that functional labels have. There are two types of functional consistency. First functional consistency is geometric consistency. This refers to the geometric constraints among the functional labels of a part. For example, the functional labels of connecting rods have constraints such as the normals of all functional regions being match, the grasping function being close to the action assist function, the action assist function being close to the action function, and so on.

Second functional consistency is semantic consistency. This refers to the constraints on the number and type of functional labels a part has and on the composition of functional labels. For example, the constraints that the connecting rod has are as follows.

- Connecting rod has grasping, action, action assist function.
- The grasping function is often in the form of a rod, on top of which is an action assist function.
- There is an action function in the action assist function.

Functional consistency is invariant no matter what state the part is placed in, because it is a relative constraint within a part. Therefore, it is important to use functional consistency to adapt the bin scene.

### 4.2 Estimation of Robot Motion Parameters

The flow of the proposed method is shown in Figure 4 and Figure 5. The proposed method inputs a depth image of a bin scene and outputs the robot motion parameters of assembly.

#### 4.2.1 Function Recognition and Object Recognition

In function recognition, a depth image of a bin scene $I$ is input to Mask R-CNN(He et al., 2017). Next, a segmentation depth image of each functional labels $I_f$ is generated by Mask R-CNN. In object recognition, $I$ is segmented by object. The segmentation depth image of each part $O$ is segmented by Mask R-CNN. Because each part is assigned a different functional label, an instance segmentation method (i.e., Mask R-CNN) was implemented.

#### 4.2.2 Action Function Detection

For action detection, the internal action function of an action assist function is detected. First, an image with only one action assist function label is generated. White pixels in this image are functional labels. Next, a label is assigned to the black region of each image (i.e., labeling). If the label number is 2, the interior of the region of action assist function is detected as the region of action function. If the part does not have an action assist function, this process is skipped.

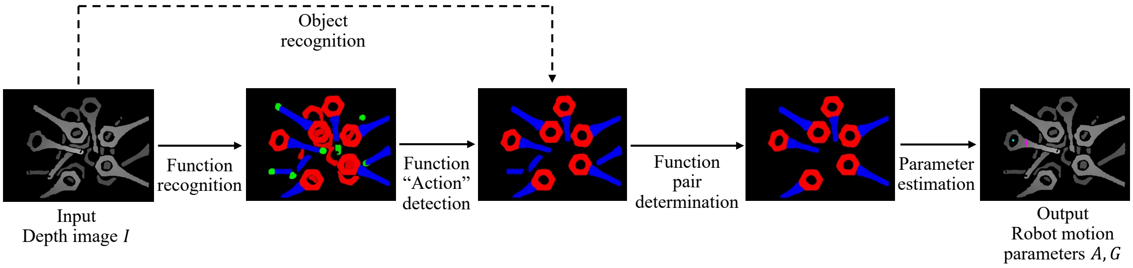



Figure 4: Flow of proposed method. The system inputs a depth image of a bin scene and outputs the robot motion parameters of assembly. Object recognition, which is not required in the process, is indicated by the dotted line.

**Require:** Depth image $I$
**Ensure:** Robot motion parameters are calculated by the proposed method $(A(Actionpoint), G(Graspingpoint))$

$I_f \leftarrow$ Function_recognition($I$)
**if** Function "action assist" is exist in $I_f$ **then**
  $I_f \leftarrow$ Action_function_detection($I_f$)
**end if**
$O \leftarrow$ Object_recognition($I$)
$P_f \leftarrow$ Point_cloud_conversion($I_f$)
**for** Each function "action" $x \in P_f$ **do**
  **for** Each function "grasping" $y \in P_f$ **do**
    $score[y] \leftarrow \mathrm{SC}(x, y, O)$
  **end for**
  $max\_id[x] \leftarrow \max(score)$
  $A[x], G[x], score\_grasp[x] \leftarrow$ Parameter_estimation($P_f, max\_id[x]$)
**end for**
$A, G \leftarrow \max(A, G, score\_grasp)$

Figure 5: Estimation of robot motion parameters.

### 4.2.3 Point Cloud Conversion

For point cloud conversion, a point cloud in 3D space is generated from the segmentation depth image of each functional labels. This point cloud has functional labels. A point cloud is generated as

$$
\begin{aligned}
P_z &= \frac{p_{max} - p_{min}}{255} I_v + p_{min} \\
P_x &= \frac{I_x - (c_x/2)}{f_x} P_z \\
P_y &= \frac{I_y - (c_y/2)}{f_y} P_z \\
P_r &= I_r \\
P_g &= I_g \\
P_b &= I_b
\end{aligned} \tag{1}
$$

where $P_x, P_y, P_z$ denote $x, y$ and $z$ in 3D space for each point in the point cloud, $P_r, P_g, P_b$ denote RGB value (i.e., functional labels) for each point, $P_{max}, P_{min}$ denote maximum and minimum values of the depth normalization range when generating the depth image, $I_x, I_y$ denote pixel position of depth image, $I_v$ denotes pixel value of depth image, $I_r, I_g, I_b$ denote pixel value of the segmentation depth image for each functional label, $c_x, c_y$ denote size of depth image, $f_x, f_y$ denote focal length of sensor. However, if the pixel value is 0, point is not generated from the pixel.

### 4.2.4 Function Pair Determination

The optimal grasp/action function pair of a part is determined by score calculation(SC). Functional consistency is used to determine for pairs. As discussed in 4.1.2, there are several elements of functional consistency, but for the proposed method the following three will be used.

- The normals of regions with grasping and action functions in one part match.
- The regions with grasping and action functions in one part are close.
- Each part has at least one grasping and one action function.

Using functional consistency, the optimal grasping function $max\_id[x]$ is determined for each action function $x$. The optimal grasping function is the region where the score output by the formula 2 is maximized.

$$
\begin{aligned}
SC(x, y, O) = w_1 (1.0 - &\frac{2.0 * \cos^{-1}(\mathbf{x_n}, \mathbf{y_n})}{\pi}) \\
&+ w_2 (1.0 - \|\mathbf{x_p} - \mathbf{y_p}\|) \\
&+ w_3 object\_recog(x, y)
\end{aligned} \tag{2}
$$

Where $w_1, w_2, w_3$ denote weight, $\mathbf{x_n}$, $\mathbf{y_n}$ denotes the normal of a region with an action function and grasping function, $\mathbf{x_p}$, $\mathbf{y_p}$ denotes the nearest neighbor between two regions, $x$ denotes the region with an action function, $y$ denotes region with the grasping function.

Note that if $object\_recog$ is implemented in Formula 2, additional learning is required and processing speed is reduced. Therefore, $object\_recog$ should be implemented as needed.

#### 4.2.5 Parameter Estimation

In parameter estimation, robot motion parameters are estimated from the optimal function pair determined in 4.2.4.

The grasping point $G[x]$ is estimated from the region of the grasping function $max\_id[x]$ using Graspability(Domae et al., 2014). In this method, contact and collision region templates $C_n$, $C_l$ are first created on the basis of the pose of the robot hand. Next, the depth image $I$ is convolved with $C_t$, $C_l$. Finally, it is convolved with a Gaussian filter to detect the parameters. In the proposed method, $I$ is changed to the image of the grasping function. The pixel with the highest grasp confidence $score\_grasp[x]$ is detected in the output image. On the basis of the pixel, the grasping point $G[x]$ is estimated.

The center of gravity of the region with the action function $x$ is estimated to be the action point $A[x]$.

The final output grasp point $G$ is the grasp point with the highest grasp confidence among $G[x]$, and the action point $A$ is the point paired with $G$.

## 5 EXPERIMENT

### 5.1 Setup

The experimental setup was as follows. The OS was Ubuntu 18.04, CPU was an Intel CORE i9, GPU was GeForce GTX1660Ti, Robot Operating System (ROS) was Melodic, robot was UR5, and robot hand was Robotiq 2F-85.

In the experiment, a connecting rod was inserted into the shaft. The parts used in the experiment are shown in Figure 6. We used four types of connecting rod of different shapes and sizes. These parts were fabricated using 3D-CAD software and a 3D printer. The sizes of the connecting rods were 15 to 22 cm in length, 5 to 10 cm in width, and 4 or 6 cm in hole diameter. The hole diameter of the shaft into which the parts were inserted was 3.5 or 5.5cm, with a clearance of 0.5cm between the hole and shaft.

In Mask R-CNN training data generation, depth images of the bin scene were generated by a physics simulation. The point cloud of the bin scene was generated by dropping 15 parts from above, and a depth image was generated from it. In ground truth data generation, part model is assigned functional label by human. This model was dropped and automatically generated ground truth data.

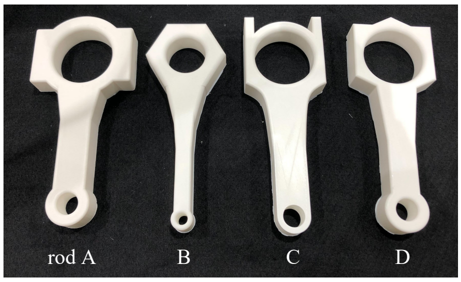



Figure 6: Parts used in the experiment. Four types of connecting rods of different shapes and sizes were used.

For the learning parameters of Mask R-CNN, the number of epochs was 30, the batch size was 16, and the number of data was 4000. The weights of Formula 2 are $w_1 = 1.0, w_2 = 5.0, w_3 = 0.0 or 1.0$. Ten to fifteen parts were randomly stacked in the bin scene.

The motion procedure of the robot was as follows. First, the robot moved over the parts. Then, it grasped the grasping point of the part estimated with the proposed method. Next, it moved the part so that the action point was on the shaft. Finally, it inserted the part into the shaft.

The proposed method was compared to method in which robot motion parameters are estimated by Mask-RCNN, Graspability and hole detection. This method is often used in the estimation of grasping point from a bin scene. The process step are as follows. First, parts are detected by Mask R-CNN. Next, the grasping point on the parts are estimated by Graspability and the action point is estimated by hole detection. In order to confirm the effectiveness of the function used in the proposed method, a method without the function was used as a comparison method. We determined the success or failure on whether the robot was able to insert the part into the shaft.

In the other experiments, we conducted ablation studies for Formula 2. For each pattern, we operated the robot for 50 trials per part.

### 5.2 Experimental Result

The results from the experiment using the proposed method with function and comparison method without function are shown in Table 1, robot motion parameters are estimated by the proposed method and comparison method are shown in Figure 7, 8 and the motions of the robot inserting a connecting rod into a shaft using the proposed method are shown in Figure 9.

The Table 1 confirms the importance of the function in the proposed method. The red point in Figure 7 shows the result to estimate using the proposed method and the blue point show the result using the

Figure 7: Estimation results of robot motion parameters by the comparison method and the proposed method. The red point shows the result to estimate using the proposed method and the blue point show the result using the comparison method. If robot grasp blue point on the part, assembly will fail because of collision between robot hand and shaft. If the center of gravity of a small hole is estimated as the point of action, it is not possible to insert the part into the shaft. However, the proposed method estimates the optimal robot motion parameters (red point) for assembly.

Table 1: Success rate of assembly using the connecting-rod.

| | Without function (Object recognition + Graspability + Hole detection) | With function (**Ours**) |
|---|---|---|
| rod A | 40% | **86%** |
| rod B | 34% | **78%** |
| rod C | 38% | **88%** |
| rod D | 34% | **74%** |
| Mean | 36.5% | **81.5%** |

comparison method. Comparison method estimated the grasping point around the hole as shown in the upper left image in Figure 7. If robot grasp this point on the part, assembly will fail because of collision between robot hand and shaft. And, the center of gravity of the small hole was estimated as the action point, as shown in the lower right image in Figure 7. These error occur because the point with the highest grasp confidence is estimated as the grasp point and center of gravity of the hole as the action point without considering the function. However, because the proposed method uses function, the optimal robot motion parameters for assembly are estimated.

Figure 8(c) shows the result of function recognition, Figure 8(d) shows the result of robot motion parameters being estimated. The red point and line show the grasping point and the blue point shows the action point. Figure 9 can be confirmed that the proposed method enables the robot to assembly from a bin scene.

The results of ablation study from the experiment using connecting rods are shown in Table 2. The components of Formula 2 are shown in the left two columns of Table 2. The success rate of assembly with each part is shown in columns 3-6 from left of Table 2. The mean of the success rate using each score calculation formula is shown in the rightmost column of Table 2.

The average success rate is 81.5% for the formula that combined object recognition and a module evaluating functional consistency, 77.5% for those with only the module of evaluating functional consistency, and 76.5% for those with only object recognition. The formula in which the two modules were combined had the highest success rate. Therefore, introducing object recognition into functional consistency improves the success rate. However, functional consistency alone can still obtain a near success rate. That is, functional consistency is important in determining the grasping/action function pair. The need for object recognition should be determined on the basis of processing speed and cost of generating training data.

For functional consistency only, there were failures when determining the grasping/action function pair. This is caused when there were two or more grasping functions with similar normals near the action function. For object recognition only, there were failures when a part was dropped when the robot grasped a lower part which became that was entangled with another part. This is cased because Formula 2 cannot rank the grasping function that outputs 1 because the output of Formula 2 is binary.

The most common failure was robot motion when the inserting the parts into the shaft. This is caused because the estimated action point was incorrect. This error often occurred when a part that was not opposite the sensor was estimated. This is because 3D sensors are less accurate in acquiring point clouds of surfaces that are not opposite to them. Introducing force control of the robot to the system and acquiring point clouds from multiple viewpoints are potential solutions to this problem.

There are two scenes in which the proposed method underperforms. The first is when the region with a grasp or action function is blinded by self-occlusion. In this case, the grasp and action points cannot be estimated simultaneously. A solution is to have the robot grasp the part where the grasping point is estimated, and then estimate the action point of the

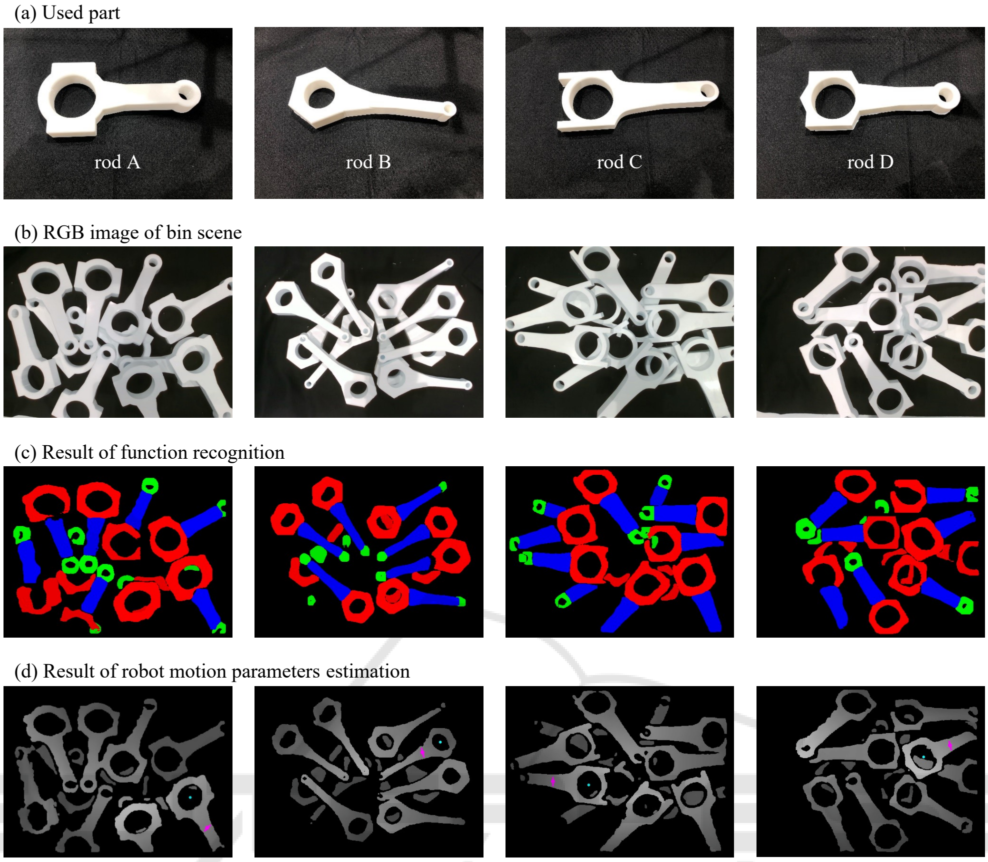



Figure 8: Experimental result of robot motion parameters estimation. (a) Parts used in the experiment. (b) RGB image of bin scene. (c) Result of function recognition. Blue refers to grasping function, red refers to big action assist function, green refers to small action assist function. There are a few recognition errors, but most of them are correctly recognized. (d) Result of robot motion parameters estimation. Red point and line show grasping point and blue point shows action point. This is the estimation result when all components are included in Formula 2. The robot motion parameters were correctly estimated by the proposed method.

Table 2: Result of ablation study.

| Component of Formula 1 | | Success rate | | | | |
|---|---|---|---|---|---|---|
| Functional consistency | Object recognition | rod A | rod B | rod C | rod D | Mean |
| ✓ | ✓ | **86%** | **78%** | **88%** | 74% | **81.5%** |
| ✓ | | 78% | 74% | 80% | **78%** | 77.5% |
| | ✓ | 78% | 74% | 76% | 78% | 76.5% |

part in that state. The second point is when the parts are intricately entangled with other parts. In this case, when robot lifts a part, the entanglement causes the part to drop. It is necessary to solve the problem using related work(Zhang et al., 2021) or to devise grasping strategies such as grasping the parts on top.

In future work, we will propose a method for estimating grasping points for parts that are easy to assemble from a bin scene. The grasping point is estimated by our current method without considering the ease of assembly, unlike humans. Ease of assembly will be defined by us and the grasping point will be estimated accordingly.

## 6 CONCLUSION

In this paper, we proposed a method for estimating robot motion parameters required for parts assembly from a bin scene. Each part has a role referred to as

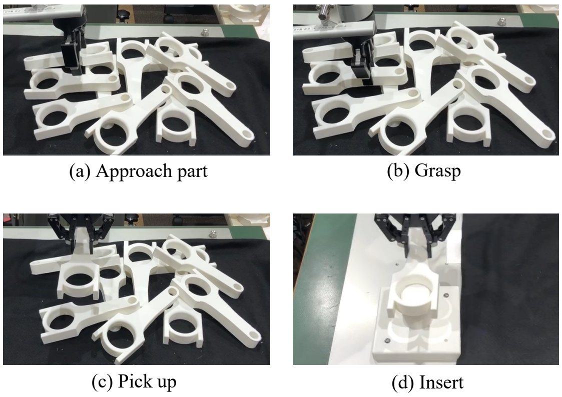


Figure 9: State of object assembled by robot. (a) Robot approaches the grasping point estimated by the proposed method. (b) The part is grasped by the robot. (c) Robot pick up the part. (d) The robot inserts the carried parts into the shaft.

a "function" such as "to be grasped" or "to be assembled with other parts" for each region. We defined a novel idea of functional labels and their consistency in industrial parts. Functional consistency is used in the proposed method as a cue, robot motion parameters are estimated on the basis of relationship between parameters and functions. In an experiment using connecting rods, the average success rate was 81.5%. The effectiveness of the proposed method was confirmed from the ablation studies and comparison with related work. The proposed method has a higher success rate than methods that do not use function and functional consistency, these are especially important concepts. In future work, we will propose a method for estimating grasping points for parts that are easy to assemble from a bin scene.

## ACKNOWLEDGEMENTS

This paper is based on results obtained from a project, JPNP20006, commissioned by the New Energy and Industrial Technology Development Organization (NEDO).

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