Iterative Visual Recognition for Learning Based Randomized Bin-Picking

Kensuke Harada\textsuperscript{2,1}, Weiwei Wan\textsuperscript{1}, Tokuo Tsuji\textsuperscript{3,1}, Kohei Kikuchi\textsuperscript{4}, Kazuyuki Nagata\textsuperscript{1}, and Hiromu Onda\textsuperscript{1}

1: National Inst. of Advanced Industrial Science and Technology, Tsukuba, Japan, 2: Osaka Univ., Toyonaka, Japan, 3: Kanazawa Univ., Kanazawa, Japan, 4: Toyota Motors Co. Ltd., Toyota, Japan

Abstract. This paper proposes a iterative visual recognition system for learning based randomized bin-picking. Since the configuration on randomly stacked objects while executing the current picking trial is just partially different from the configuration while executing the previous picking trial, we consider detecting the poses of objects just by using a part of visual image taken at the current picking trial where it is different from the visual image taken at the previous picking trial. By using this method, we do not need to try to detect the poses of all objects included in the pile at every picking trial.

Assuming the 3D vision sensor attached at the wrist of a manipulator, we first explain a method to determine the pose of a 3D vision sensor maximizing the visibility of randomly stacked objects. Then, we explain a method for detecting the poses of randomly stacked objects. Effectiveness of our proposed approach is confirmed by experiments using a dual-arm manipulator where a 3D vision sensor and the two-fingered hand attached at the right and the left wrists, respectively.

Keywords: Bin-picking, Grasping, Motion Planning, Visual Recognition, Industrial Robot

1 Introduction

Randomized bin-picking refers to the problem of automatically picking an object that is randomly stored in a box. If randomized bin-picking is introduced to a production process, we do not need any parts-feeding machines or human workers to once arrange the objects to be picked by a robot. Although a number of researches have been done on randomized bin-picking \cite{1,2,3,4}, randomized bin-picking is still difficult and is not widely introduced to production processes. Since one of the main reasons is its low success rate of the pick, we have proposed a learning based approach which can automatically increase the success rate \cite{5}.

Fig. 1 illustrates the randomized bin-picking where we use a dual-arm manipulator with a vision sensor (3D depth sensor) and two-fingered grippers both attached at the wrist. We first detect the poses of randomly stacked objects by
using the visual information obtained from the 3D vision sensor attached at the wrist. Once the objects’ poses are obtained, we consider predicting whether the robot can successfully pick one of the objects from the pile. If it is predicted that the robot successfully picks an object, the robot tries to pick an object. In our approach, the success rate is expected to increase if the number of detected object increases. Here, in the conventional research on randomized bin-picking, we have tried to detect the poses of all objects at every picking experiment in spite of the fact that the configuration of object while executing the current picking trial is almost same as that while executing the previous picking trial. The configuration on objects while executing the current picking trial is usually just partially different from that while executing the previous picking trial since a finger usually contacts just a few objects during the previous picking trial. To cope with this problem, we propose a new method for object pose detection for the randomized bin-picking. In our proposed method, we consider detecting the objects’ poses at a portion of the pile where its visual information is different from the visual information obtained during the previous picking experiment.

In our proposed method, we first obtain the pose of 3D vision sensor attached at the wrist to capture the point cloud on the randomly stacked pile realizing its maximum visibility. Here, based on the occupancy grid map, the maximum visibility of the pile is realized by merging the point cloud captured during the current picking trial with the point cloud captured during the previous picking trial. Then, we show a method for detecting the poses of objects. We consider comparing each segment of the point cloud captured during current picking trial with that captured during the previously picking trial. If the difference is small, we do not estimate the poses of objects and can save the time needed for the estimation.

2 Learning Based Bin-Picking Overview

We first briefly explain the leaning based bin-picking proposed previously [5]. As shown in Fig. 1, let us consider the case in which the same objects are randomly
stored in a box. To pick an object from the pile, a 3D vision sensor (e.g., Xtion PRO) first captures a point cloud of randomly stacked objects. Then, we try to estimate the poses of randomly stacked objects. Then, we try to pick one of the objects which poses were detected. First among multiple candidates of grasping postures, we solve IK to check the reachability of the robot. Then, for each reachable grasping posture, a discriminator trained through a number of picking trials estimates whether or not the robot can successfully pick an object. Here, the estimation is performed based on the distribution of point cloud included in the swept volume of finger motion as shown in Fig. 2. If there are multiple grasping postures which are estimated to successfully pick an object, we consider selecting a grasping posture from multiple candidates according to the value of an index function. Then, the robot actually picks an object according to the selected grasping posture.

![Finger swept volume](image)

**Fig. 2.** Finger swept volume

### 3 Sensor Pose Calculation

We assume that the manipulator has at least 6 DOF such that the wrist can make an arbitrary pose within its movable range. The pose of the 3D vision sensor is determined to maximize the visibility of randomly stacked objects so as to precisely estimate the poses of randomly stacked objects. As shown in Fig. 3, let us assume a $n$-faced regular polyhedron sharing its geometrical center with the geometrical center of box’s bottom surface. Let us also assume a line orthogonally intersecting a face of the polyhedron and passing through the geometrical center. Let us consider a point along the line where the distance measured from the geometrical center is $l$. We make a 3D vision sensor locating at this point and facing the geometrical center. By discretizing a position of a 3D vision sensor along the line as $l = l_1, l_2, \ldots, l_m$, we can totally assume $m \cdot n$ candidates of a 3D sensor’s pose. We consider imposing the following conditions for each candidate:

The 3D vision sensor is located above the box’s bottom surface.
IK (inverse kinematics) of the arm where the 3D vision sensor is attached at its wrist is solvable.

For a pose of the 3D vision sensor where IK is solvable, no collision occurs among the links and between a link and the environment.

Among a set of 3D sensor’s pose satisfying the above conditions, we consider selecting one maximizing the visibility of randomly stacked objects. Here, robotic bin-picking is usually iterated until there is no object remained in a box. For the first picking trial, we consider selecting a 3D sensor’s pose minimizing the occluded area of the box’s bottom surface as shown in Fig. 4(a). After the second picking trial, we consider using previous result of measurement to determine the pose of a 3D sensor as shown in Fig. 4(b) and (c). We consider partitioning the storage area into multiple grid cells. By using the point cloud captured in the previous picking experiment, we mark occupied to the grid cells including the point cloud. We also mark occluded to the grid cells occluded by the grid cells marked as occupied. Pose of a 3D sensor is determined to maximize the number of grid cells marked as occluded to be visible.

Here, through the previous picking experiment, configuration of stacked objects may change since the manipulator contacts the objects. However, the method explained in this subsection does not consider the change of configuration. Our method approximates the optimum pose of the 3D sensor by assuming the change of configuration is small.

Fig. 3. Regular polygon assumed at the geometrical center of bottom surface

4 Object Pose Detection

This section explains a method for detecting the pose of randomly stacked objects. For the first picking trial, we consider detecting the poses of as many objects as possible. After the second picking trial, we consider detecting the poses of objects which poses are changed.
Fig. 4. Determination of camera pose maximizing the visibility of stacked objects

4.1 Object Pose Detection for the First Picking Trial

To pick an object from the pile, the 3D vision sensor first captures a point cloud of randomly stored objects. Then, we segment the captured point cloud as shown in Fig. 5(a). In this research, we used a segmentation method based on the Euclidian cluster prepared in the PCL (Point Cloud Library) [9]. For each segment of point cloud which bounding-box size is similar to the bounding-box size of an object, we try to estimate the pose of an object using a two-step algorithm: first roughly detecting the pose by using the CVFH (Clustered Viewpoint Feature Histogram) [8] and the CRH (Camera Roll Histogram) estimation, and then detecting the precise pose by using the ICP (Iterative Closest Point) estimation method. In a preprocessing process before starting the detection, we prepared 42 partial view of the object model, and precompute the CVFH and CRH features of each view. During the detection, we extract the plenary surface from the point cloud, segment the remaining points cloud, and compute the CVFH and CRH features of each segmentation. Then, we match the precomputed features with
the features of each segment and estimate the orientation of the segmentations. The matched segments are further refined using ICP estimation method to ensure good matching. The segmentation that has highest ICP matches and smallest outlier points will be used as the output.

For the first picking trial, we usually detect the poses of a number of objects. In such cases, since we have to solve ICP estimation for a number of times, we consider using multiple threads and solving multiple ICP estimation in parallel.

For the second picking trial, we consider using the current point cloud together with the previously captured one. If a part of the previously captured point cloud is similar to the current one, we do not need to calculate the object’s pose belonging to the part of point cloud and can save the time needed to calculate the objects’ poses. In a picking task, after a 3D sensor capture a point cloud of randomly stacked objects, a robot manipulator tries to pick an object from the pile. The configuration of objects after a robot manipulator tries to pick an object is usually partially different from the configuration before the picking trial. If the previously captured point cloud is partially similar to the current point cloud, we consider merging the part of previously captured point cloud to the current one. By merging a part of the previous point cloud to the current one, the occluded area of the point cloud is expected to be smaller.

**Fig. 5.** Segmentation of point cloud after the second picking trial

### 4.2 Object Pose Detection after the Second Picking Trial

After the second picking trial, we consider using the current point cloud together with the previously captured one. If a part of the previously captured point cloud is similar to the current one, we do not need to calculate the object’s pose belonging to the part of point cloud and can save the time needed to calculate the objects’ poses. In a picking task, after a 3D sensor capture a point cloud of randomly stacked objects, a robot manipulator tries to pick an object from the pile. The configuration of objects after a robot manipulator tries to pick an object is usually partially different from the configuration before the picking trial. If the previously captured point cloud is partially similar to the current point cloud, we consider merging the part of previously captured point cloud to the current one. By merging a part of the previous point cloud to the current one, the occluded area of the point cloud is expected to be smaller.
The algorithm of merging the point cloud is outlined in Fig. 5 and Algorithm 1. Let \( \bar{P} = (\bar{p}_1, \bar{p}_2, \cdots, \bar{p}_m) \) and \( P = (p_1, p_2, \cdots, p_n) \) be the previously captured point cloud and the current one, respectively. Let also \( \bar{P}_1, \bar{P}_2, \cdots, \) and \( \bar{P}_s \) be the segments of previous point cloud. The overview of the merging algorithm is explained in the following. Fig. 5 (a) shows the segmented point cloud obtained during the previous picking trial. On the other hand, Fig. 5 (b) shows the current point cloud where the configuration of object is partially different from the previous one. As shown in Fig. 5 (c), for each point included in the current point cloud, we search for the point included in the previous point cloud making the minimum distance between them (lines 6 and 7). We further find a segment of previous point cloud where the point making the minimum distance belongs to (line 8). For each segment of previous point cloud, we introduce two integer numbers \( \text{near}(i) \) and \( \text{far}(i) \) expressing the number of points included in the segment \( P_i \) where the minimum distance is smaller and larger, respectively, than the threshold MinDistance (lines 9 and 10). We determine whether or not we merge the segment \( \bar{P}_i \) into the point cloud \( P \) depending on the ratio between \( \text{far}(i) \) and \( \text{near}(i) \).

**Algorithm 1** Merging method between two point clouds

1. for \( i \leftarrow 1 : s \)
2. \( \text{near}(i) = 0 \)
3. \( \text{far}(i) = 0 \)
4. end for
5. for \( j \leftarrow 1 : m \)
6. \( d \leftarrow \min(|\bar{p}_1 - p_j|, \cdots, |\bar{p}_m - p_j|) \)
7. \( k \leftarrow \arg\min(|\bar{p}_1 - p_j|, \cdots, |\bar{p}_m - p_j|) \)
8. \( t \leftarrow \text{SegmentNumber}(\bar{p}_k) \)
9. if \( d < \text{MinDistance} \) then : \( \text{near}(t) \leftarrow \text{near}(t) + 1 \)
10. else : \( \text{far}(t) \leftarrow \text{far}(t) + 1 \)
11. end for
12. for \( i \leftarrow 1 : s \)
13. if \( \frac{\text{far}(i)}{\text{near}(i)} < \text{Threshold} \), then \( P \leftarrow \text{Merge}(P, \bar{P}_i) \)
14. end for

We further segment the merged point cloud. For each segment of point cloud, we calculate the distance between a point in the segment and the object which pose is estimated during the previous picking trial. If the distance is less than the threshold, we use the result of pose estimation during the previous pick. On the other hand, if the distance is larger than the threshold, we newly estimate the pose of an object by using two step algorithm using the CVFH and CRF estimation and the ICP algorithm.
5 Experiment

We performed experiments on bin-picking. As shown in Fig. 6(a), we randomly placed nine objects in a box. We put nine objects close to each other such that the finger contacts a neighboring object when picking the target one. In the experiment, we performed the picking trial for three times. After the three times picking trial, we additionally captured the visual information. Fig. 7 shows the grid cells of captured point cloud during a series of picking tasks where the red cells include the newly captured point cloud while the green cells include the previously captured point cloud. We can see that object recognition is performed only for the object where red cells are included. Fig. 8 shows the pose of 3D vision sensor during a series of picking task by using the dual-arm industrial manipulator HiroNX.

![Image](image.png)

**Fig. 6.** Estimation of objects’ pose

6 Conclusions

In this paper, we discussed the visual recognition system for learning based randomized bin-picking. We first explained the view planning method to maximize the visibility of randomly stacked objects. Then, since randomized bin-picking usually estimates the pose of a number of objects, we relaxed the computational cost of the object pose detection by using the visual information on randomly stacked objects captured during the current picking task together with the visual information captured during the previous picking tasks. Through experimental results, we confirmed that the computational cost of the object recognition is reduced.

Here, in our visual recognition of randomly stacked objects, we used the conventional Euclidian cluster based method to segment the stacked objects. Using more advanced method on segmentation is considered to be our future topic. Also, performing experiment for different shaped objects is also considered to be our future research topic.
Fig. 7. Grid cells of captured point cloud
Fig. 8. Pose of 3D sensor during a series of picking task

References

1. Y. Domae et al., “Fast Graspability Evaluation on Single Depth Maps for Bin Picking with General Grippers”, Proc. of IEEE Int. Conf. on Robotics and Automation, 2014.
2. K. Harada et al., “Project on Development of a Robot System for Random Picking – Grasp/Manipulation Planner for a Dual-arm Manipulator –”, Proc. of IEEE/SICE Int. Symposium on System Integration, 2014.
3. D.C. Dupuis et al., “Two-Fingered Grasp Planning for Randomized Bin-Picking”, Proc. of RSS 2008 Manipulation Workshop, 2008.
4. K. Harada et al., “Probabilistic Approach for Object Bin Picking Approximated by Cylinders”, Proc. of IEEE Int. Conf. on Robotics and Automation, 2013.
5. K. Harada et al., “Initial Experiments on Learning Based Randomized Bin-Picking Allowing Contact with Neighboring Objects”, Proc. of IEEE Int. Conf. on Automation Science and Engineering, 2016.
6. S. Thrun, W. Burgard, and D. Fox, Probabilistic Robotics, MIT Press, 2005.
7. K. Nagata et al., “Picking up and Indicated Object in a Complex Environment”, Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, 2010.
8. A. Aldoma et al., “OUR-CVFH - Oriented, Unique and Repeatable Clustered View-point Feature Histogram for Object Recognition and 6DOF Pose Estimation”, Pattern Recognition, Springer, 2012.
9. Point Cloud Library, http://pointclouds.org