Design of Digital Planner and 3D Vision System for Robot Bin Picking

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***Abstract*— Robot bin picking plays an important role in modern manufacturing process. In order to make these manufacturing systems more efficient and productive, it is essential to make a valid grasping plan from gripper design, industrial part recognition, pose estimation, to grasping evaluation. This paper proposes such a planning framework that enables the robot to learn to grasp an industrial part and improve the performance in two phases. First, prior knowledge of 3D model is utilized for gripper selection, database generation and grasping point evaluation in a design phase. Next, attempts for single part grasping are made in a test phase, and grasping failures will trigger the redesign in the previous phase. The grasping plan is then used for grasping randomly distributed parts. A risk assessment is made per part for selection of best candidate of parts, taking both grasping efficiency and potential collision into account. At last, pose adjustment is applied on the robot to improve grasping capability. Through simulation and field test, we demonstrate that the two-phase planning framework is a practical solution for robot bin picking applications.**

Fig. 1: Manulab at NTNU Ålesund.

I. INTRODUCTION

Today, customer demands such as faster delivery time and customized products with higher quality are driving manufacturing companies toward Industry 4.0 [1]. The transition to Industry 4.0 requires the changes of physical infrastructure, sensor integration, as well as new technologies from manufacturing process improvement to operational performance optimization. Taking advantages of Industrial Internet of Things (IIoT), the concept of smart manufacturing is expected to change from traditional automation to advanced manufacturing systems, where the production processes can be adjusted for different types of products and changing conditions [2]. To this end, digitalization of physical objects, sensors and actuators in the manufacturing process becomes necessary. It not only refers to digital representation such as 3D models and physical behavior models of machine, but also includes virtual testing of the complete manufacturing system with advanced tools [3].

The last decade has witnessed different types of robots capable of responding to environmental changes [4], [5], [6]. The use of these intelligent robots in digital manufacturing in various fields from automotive aerospace to medical to food is promising [7]. Bin picking, as one of the manufacturing applications, has attracted a lot of attention in the robotics community [8]. Picking up industrial parts from a clustered scene and placing them in order in a box or on a conveyor belt is a challenging task. Generally, it requires manipulating one or two robot arms with multiple degrees of freedom (DOF) to approach a target part and grasp it in an appropriate manner. The robot arms are usually equipped with 2D/3D cameras for environmental perception, together with built-in sensors such as IMU and encoder for intrinsic perception. Many technical issues, such as industrial part recognition, localization [9], pose estimation [10], and collision avoidance should be considered in developing bin picking systems.

In the literature, many efforts have been made for developing bin picking technologies [11]. For example, Oh et al. proposed a geometric pattern matching method for 2D image pattern recognition and 3D pose estimation by using a stereo camera [12]. Martinez et al. developed a 3D bin picking system using a 3D camera with a focus on robust solution of randomly located parts [13]. Jonschkowski et al. used an RGB-D camera to obtain vision data and applied their proposed probabilistic multi-class segmentation method to a warehouse picking setting [14]. A benchmark was proposed by Mnyusiwalla et al, aiming for comparability and reproducibility of bin-pinking systems in an easy-to-reproduce environment [15]. There are also novel proposals implemented in picking tasks in competitions, e.g. the Amazon picking challenge held in 2015$\sim$2017 [8]. Focuses are more on efficient picking of unknown light-weighted objects. Besides the visual data obtained from 2D/3D cameras, various types of grippers using magnet, parallel jaw and vacuum have been exploited for efficiently grasping objects. Many machine learning based methods for grasp point detection [16] and pose estimation [17] using 2D/3D images have been proposed, which search in the image to find an optimal pose

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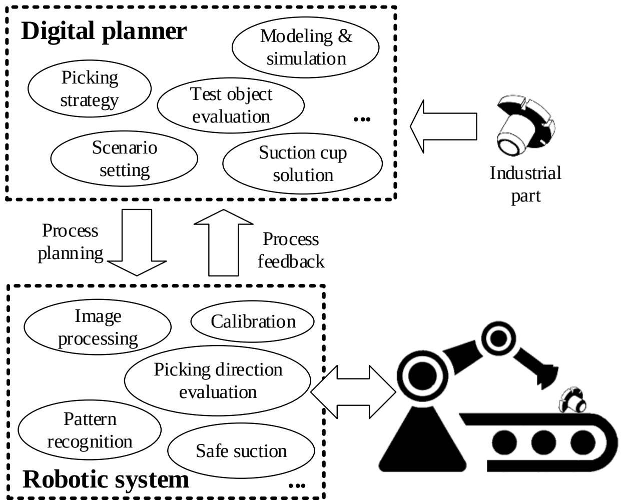


Fig. 2: Bin picking framework.

for grasping. Grasping planning is then used after the grasp pose is determined. Some manipulator motion planning tools such as MoveIt [18] and OMPL [19] are widely used in the robotic field.

Although recent works have addressed specific bin picking problems, there are still restrictions with respect to the bin picking technologies in real applications. For example, the computation time used in complex search algorithm and the big database used in deep learning for grasping point estimation hinder their use in industrial context. In practice, industrial parts are usually known in advance, e.g. in CAD format. Prior knowledge such as grasping point is therefore obtained before designing the bin picking system. Our research project aims to bridge the gap between academic results and industrial needs for fast development and verification of bin picking systems in manufacturing laboratory. The Manulab at NTNU in Ålesund plays such a role in testing different manufacturing solutions [20]. It consists of 3D printer, laser cutter, collaborative robots, mobile robots and delta robots etc., as shown in Fig. 1. In this paper, we use an Omron manipulator in the Manulab and focus on developing digital planner and 3D vision system for proof of concept of bin picking system.

The rest of the paper is organized as follows. First, an overview of a small-scale bin picking system implemented in Manulab will be introduced in Section II. Next, the key technologies about planning, 3D grasping will be presented in Section III. After that, Section IV presents a case study of bin picking task. Finally, conclusion and future work are drawn in Section V.

II. Robot Bin Picking System

This section introduces the framework of the proposed robot bin picking system and the Omron robot in Manulab used for verification.

A. Framework

Fig. 2 illustrates the framework of the bin picking system. It consists of a digital planner and a robotic system. In the

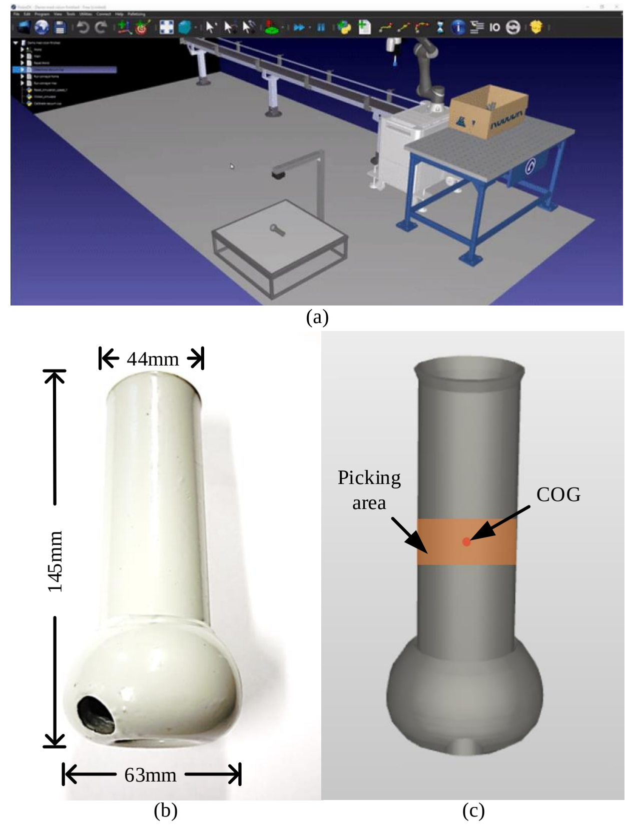


Fig. 3: Example of (a) scenario setting, (b) dimension of industrial part, and (c) suggested grasping area in a picking task.

planner, efforts are made to model and simulate the picking process, including modeling the robot, the industrial part, the calibration platform and the picking scenario. Considering in real applications the industrial parts are usually known beforehand, the digital planner could import their 3D models into simulation to evaluate the picking point/area, the gripper type and size, and design the grasping strategy for collision avoidance. We use RoboDK[1] in this study. Fig. 3 shows an example of a bin picking task implemented in RoboDK. The scenario includes an Omron robot, a box of industrial parts, a conveyor belt, a workstation, and a calibration table. By importing the CAD file of the part, the planner could evaluate the picking area based on the part's weight, dimension and center of gravity (COG).

After planning, the prototype system could be tested on the real robot in Manulab. In this phase, efforts would be made to check how successful the grasp will be if the robot grasps the part from the grasping area. Failure of grasping will be fed back to the planner, resulting a new round of evaluation. Once safe grasping is achieved, recognition and localization of industrial parts are designed in the planner and tested in the physical system. As illustrated in Fig. 2, the design process and its implementation between the planner and the robotic system would be iterated and improved until

[1]https://robodk.com/

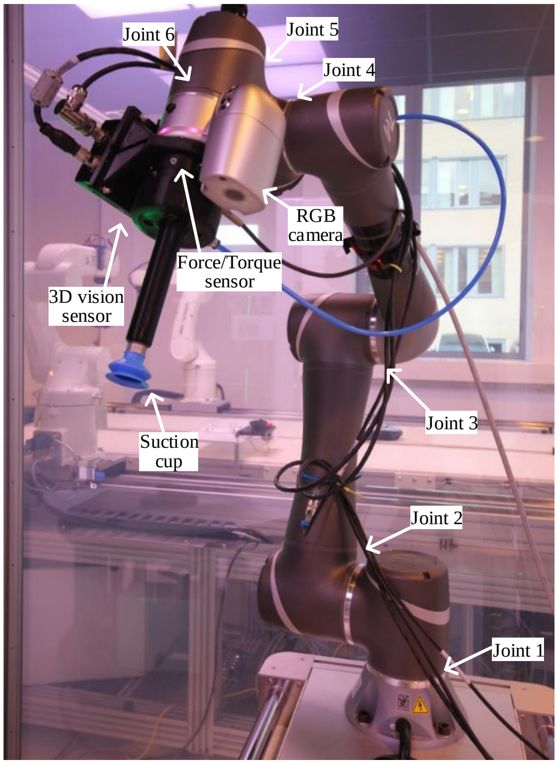


Fig. 4: Overview of a 6 DOF articulated manipulator with sensors.

TABLE I: Components used in the bin picking system

Component	Description
Omron TM5-900	Universal robot for manipulation
Robotiq FT300	Force sensor
FH-SMDA	3D vision sensor
Festo OVEM-10-H-B-QO-OE-N-2P	Vacuum generator
Festo VASB-40-1/4-PUR-B	Suction cup

the robot is able to pick the part in a clustered scene and place it to the target position.

B. Omron Robot

We use Omron TM5-900 for bin picking tasks. Fig. 4 shows the robot together with onboard sensors. The robot has a weight of 22.6 kg, and can reach up to 900 mm with max payload of 4 kg. There are six DOF with different joint range in the robot. Joint 1 and 6 can move $\pm 270°$; joint 2, 4, 5 have a smaller joint range of $\pm 180°$, and joint 3 can only rotate within $\pm 155°$. The robot has a flow chart based programming environment, called TMflow. It enables full control of the robot, safety setting, and built-in machine learning tools for vision jobs.

Table I lists the involved components for the bin picking application. A 3D camera FH-SMDA with a dimension of $53 \times 110 \times 77$ mm is mounted on the robot. The camera with depth information is used for visual data acquisition. Its measurement range is $400 \times 300 \times 200$ mm. For each pick, the robot will take a picture to localize the best candidate part and then grasp. A Festo suction gripper is selected in this case. It works together with a Festo vacuum generator

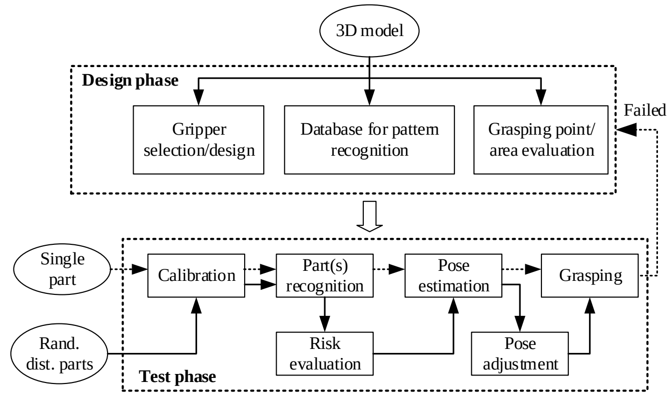


Fig. 5: Flow chart of the bin picking system development.

to provide suction while gripping. In addition, a force/torque sensor Robotiq FT300 is utilized for collision detection and safe grasping. The sensor has a force range ± 300 N and a torque range ± 30 N. By properly setting the force/torque threshold, the robot could detect collision with the part, activate the vacuum generator, and guild the suction tool to attach the part for grasping.

III. GRASPING PLANNING

The development of grasping planning consists of two phases: a design phase and a test phase, as shown in Fig. 5. As mentioned in Section II, prior knowledge of the industrial part including the dimension, weight and COG is beneficial for tool length and size determination, and gripper type selection. For example, regarding the industrial part illustrated in Fig. 3b, suction gripper is selected since safe grasping is of highest priority in the task. A 40 mm suction cup is selected based on the size of cross section of the part, so as to maximize the contact area and generate enough suction. Thanks to the 3D model of the part, the grasping point/area, as illustrated in Fig. 3c, could be evaluated for better balance when grasping. A data set with pictures of the part in different angles could be generated for training of part recognition. In addition, the tool length could be optimized for easy grasping in an upward-facing box where the depth is the largest dimension in this phase.

In the test phase, grasping of a single part is conducted at the beginning. First, the single part is calibrated on the calibration table as shown in Fig. 3a. By using OpenCV, part contour could be detected to obtain its location coordinates in frame, and further to calculate the conversion rate from pixels in the image to millimetres. After calibration, pattern recognition of random placement of the single part is performed, based on which we can locate the part and estimate its pose using the conversion rate for grasping. However, grasping may be failed due to improper design in the previous phase. For example, the failure of recognition may result from insufficient pictures of different poses for training; wrong type of gripper, or unbalanced grasping due to improper grasping point yield grasping failure. All types of failures will be fed back to the design phase, requiring for design improvement for stable grasping.

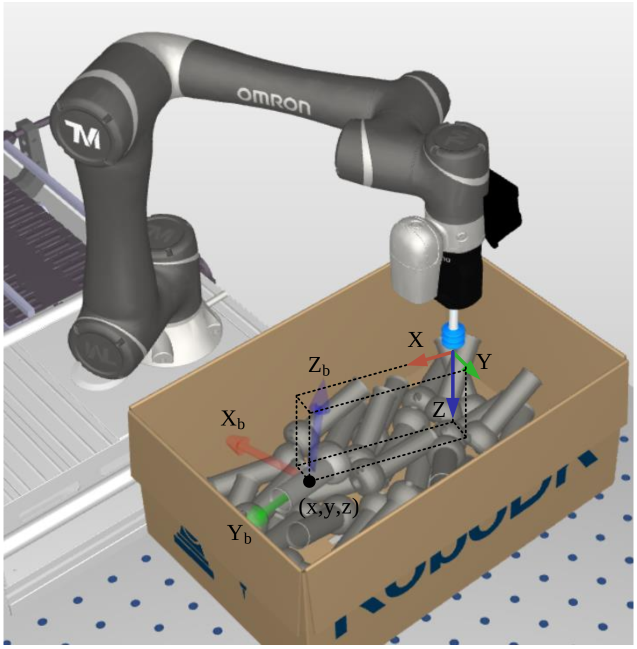


Fig. 6: Pose estimation for part grasping.

Until a single part is grasped successfully, the test scene becomes a random distribution of parts. From Fig. 5, the process is the same as the single part grasping except a 'risk evaluation' module and a 'pose adjustment' module. Among the recognized parts, the 'risk evaluation' module plays a role in identifying which part is most suitable for grasping. First, those parts that are hindered by other parts are neglected. Then, the eligible parts are assessed and ranked by the following criteria:

- the vertical distance from the tool position to the grasping point of the part;
- the closest distance between the grasping point projected to the box plane and the edges of the box.

The first criterion considers the grasping efficiency, while the second one takes collision with the box into consideration. After that, the pose of the top ranked part will be calculated. As illustrated in Fig. 6, given the estimated pick position $P = [x, y, z]^T$, and its pose $\theta = [\theta_x, \theta_y, \theta_z]^T$, the transformation for the robot to grasp the part can be expressed as:

$$T = Trans(x, y, z) \cdot R(\theta_x) \cdot R(\theta_y) \cdot R(\theta_z) \tag{1}$$

where $Trans$ stands for the translation matrix and R represents the rotation matrix.

In order to guarantee the part is safely grasped, the 'pose adjustment' module utilizing the force/torque sensor is proposed, as shown in Algorithm 1. A threshold of 15 N is used to ensure that the suction cup is in contact with the part without causing the part to displace. A strategy of small rotation about the suction tool's x and y axes is applied to the part, aiming to enhance grip adhesion. As a result, the part can be successfully picked up, and placed to a desired position afterward.

Algorithm 1 Safe grasping using force/torque sensor

Parameters: $pickPos$ – the pick position of the part; $picturePos$ – the position for taking a new picture; $vaccumOutput$ – turn on/off the vacuum generator; $vaccumInput$ – binary signal from vacuum sensor for safe grasping; $actionStp$ – action steps.

Move to $pickPos$
$vaccumOutput = True$
$actionStp = 0$
while not $vaccumInput$ **do**
  if $forceInput \leq 15N$
    $z- = 5mm$
  else if $forceInput > 15N$ **AND** $actionStp == 0$
    θ_x += $5°$
  else if $forceInput > 15N$ **AND** $actionStp == 1$
    θ_x −= $10°$
  else if $forceInput > 15N$ **AND** $actionStp == 2$
    θ_x += $5°$
    θ_y += $5°$
  else if $forceInput > 15N$ **AND** $actionStp == 3$
    θ_y −= $5°$
  else
    $actionStp = 0$
    $vaccumOutput = False$
    Move to $picturePos$
  end if
  $actionStp$ ++
end while

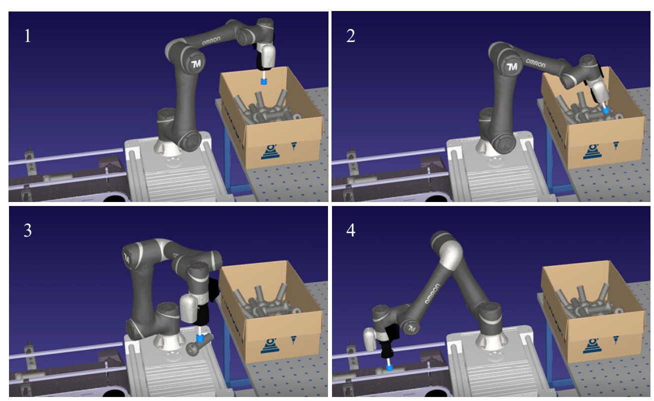
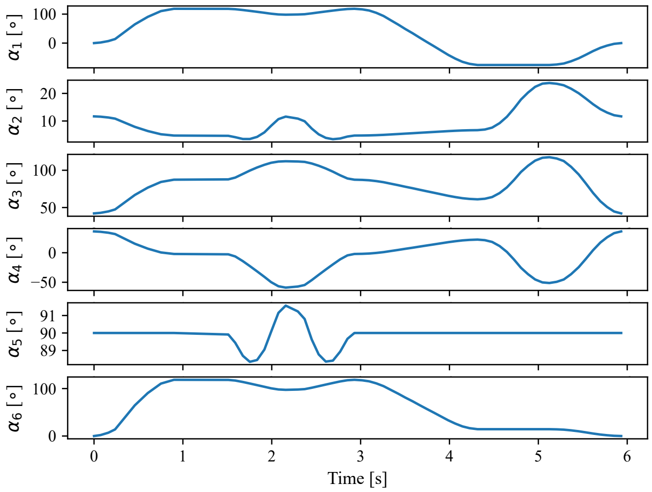


Fig. 7: Simulation of a bin picking task in RoboDK.

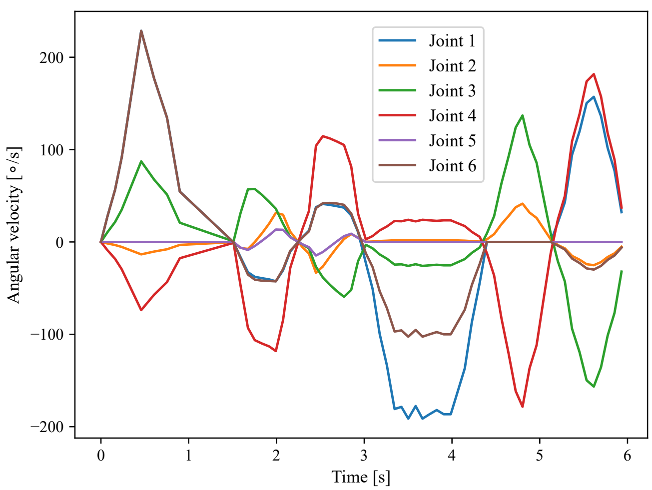
IV. EXPERIMENT

We conducted a simulation in RoboDK environment and a field test in Manulab to verified the proposed planning framework.

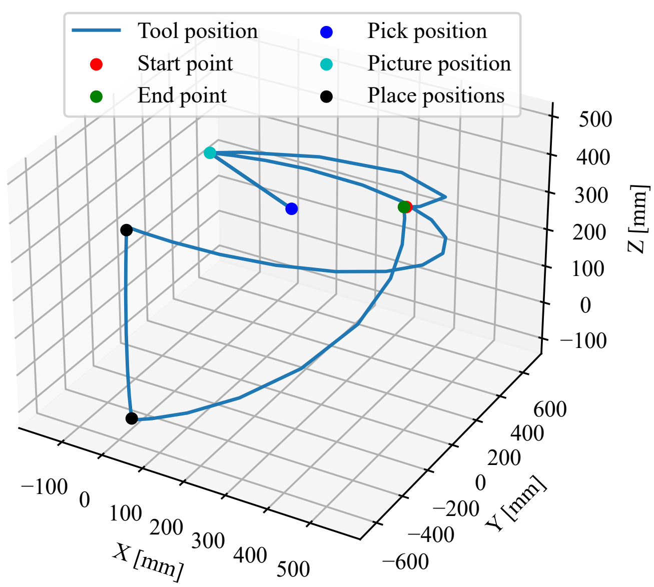
The simulation scenario is the same as the one illustrated in Fig. 3a. The task is to pick up randomly distributed parts as shown in Fig. 3b from a box and place it on to the conveyor belt. Fig. 7 shows a complete picking process from part recognition, evaluation, grasping, to placement. In the simulation, since the simulated camera is a 2D camera, we cannot obtain the desired distance for approaching the part. An alternative is to use RoboDK's collision detection



(a)

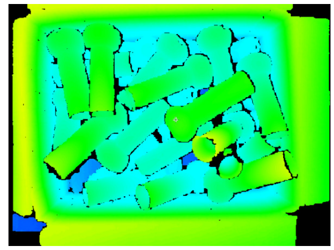


(b)

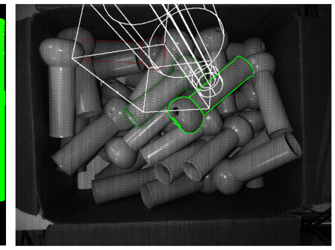


(c)

Fig. 8: The variation of (a) joint angle and (b) angular velocity over time, and (c) the corresponding gripper tool trajectory in the picking process in simulation.



(a)



(b)

Fig. 9: Parts evaluation from (a) depth image and (b) estimated grasping pose in the Omron TMflow system.

method. Thus, once the robot moves towards a part and collides with it, it can be assumed that a successful grasp has occurred. The robot then can rotate about $180°$ and place the part onto the conveyor belt.

Fig. 8 shows the changes of the six joint angles and their angular velocities of the robot, as well as its tool trajectory in one complete picking process. The whole picking process lasts about 6 s. It is noted from joint 5 in Fig. 8a that approaching the part and grasping occurs around $1.5 \sim 3.0$ s. Combining with the same time period shown in Fig. 8b, the successful grasp happens at 2.3 s, where all the joints' angular velocities are close to $0\ ^\circ/s$, indicating a stationary state at that moment. From Fig. 8b, it is also noted that there are 6 such stationary states in the whole process. They correspond to the positions highlighted in Fig. 8c. The pick position in Fig. 8c is determined by the position of the top ranked part after risk evaluation. Except for that, the other positions are predefined in the case study. For example, the first sub-figure of Fig. 7 is the position for taking pictures for grasping, and the the last sub-figure of Fig. 7 is the position for placing the part. The simulation result shows the feasibility of the bin picking application.

The proposed planner was further tested on the Omron robot in Manulab. Fig. 9 is an example of industrial part evaluation. By taking pictures from the 3D camera on the Omron robot, a depth image was obtained and the parts were segmented and recognized, as shown in Fig. 9a. According to the risk evaluation criteria, the top ranked part was highlighted and the corresponding grasping pose was estimated, as shown in Fig. 9b. Then a grasping can be conducted. Fig. 10 shows the screenshots from a video of bin picking. Note that we simplified the process by replacing placement of the parts on the conveyor belt with dropping them in another box. It should be noted from the second and the third sub-figures that a pose adjustment was performed by using Algorithm 1. The robot twisted the suction gripper a little bit about the x and y axes of the gripper. As a result, the part stuck to the suction cup better and the robot successfully grasped it and placed it to the other box. The results shows the effectiveness of the proposed method in bin picking applications.

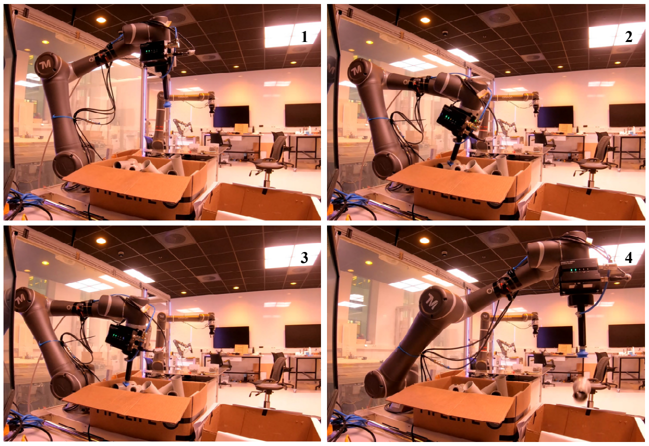


Fig. 10: Bin picking example using Omron robot.

V. CONCLUSIONS

Robot bin picking is widely used in industrial automation scenes. In this study, we propose a framework for designing and testing of robotic grasping system using 3D vision. By making use of 3D model of the part, grasping strategy and recognition database could be generated, followed by a single part testing from calibration, recognition, pose estimation to grasping. Success of single part grasping supports the development of grasping among randomly distributed parts. A risk evaluation method and a pose adjustment method are proposed in this phase for part selection and stable grasping, respectively. A simulation in RoboDK and field test on Omron robot in Manulab were conducted. The results shows that the proposed framework is efficient in grasping planning in bin picking applications.

For future work, focus will be on enhancing the risk evaluation method, especially for assessing unstable parts due to interaction of parts in the box. In addition, efforts will be made to improve the design of the gripper to accommodate any potential changes to the part.

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