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Robotic General Parts Feeder: Bin-picking, Regrasping, and Kitting

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Abstract— **The automatic parts feeding of multiple objects is an unsolved problem in the manufacturing industry. In this paper, we tackle the problem by proposing a multi-robot system. The system comprises three sub-components which perform bin-picking, regrasping, and kitting. The three sub-components divide and conquer the automatic multiple parts feeding problem by considering a coarse-to-fine manipulation process. Multiple robot arms are connected in series as a pipeline. The robots are separated into three groups to perform the roles of each sub-component. The accuracy of the state and manipulation are getting higher along with the changes of the sub-components in the pipeline. In the experimental section, the performance of the system is evaluated by using the Mean Picks Per Hour (MPPH) metric and success rate, which are compared to traditional parts feeder and manual labor. The results show that the Mean Picks Per Hour (MPPH) of the proposed system is 351 with eleven various-shaped industrial parts, which is faster than the state-of-the-art robotic bin-picking system. The lead time of the proposed system for new parts is less than that of a traditional parts feeders and/or manual labor.**

I. INTRODUCTION

Automatic parts feeding of multiple objects is an unsolved challenge in robotic automation. Although combinations of traditional parts feeders are able to supply various parts, they require a special device for each of the part, making the design, deployment, and maintenance problematic. Also, parts feeders require customized engineering for each object's shape, and there might be no solution for parts with complicated shapes. Therefore, we develop a robotic parts feeding system to solve the multiple parts feeding problem. The system is shown in Fig. 1. It is made of four robots and two vision sensors. These robots and vision sensors recognize, pick and place, re-recognize, and change the pose of parts in a pipeline. The system looks like a robotic bin-picking system, except that the robotic bin-picking systems do not handle the regrasping problem and align the orientation of the parts for the final kitting task. In contrast, the proposed system is able to solve the whole pick-and-align problem.

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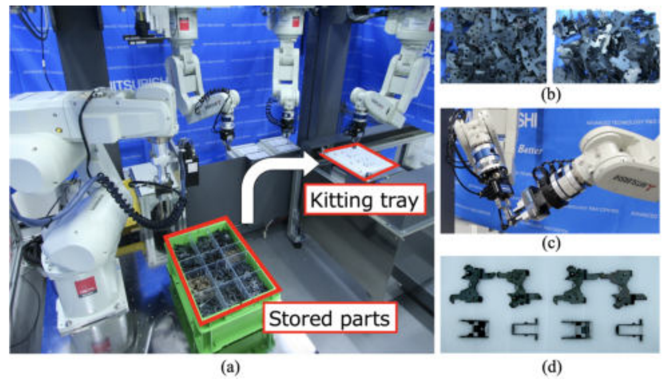

Fig. 1. The proposed robotic parts feeding system. In the beginning, multiple types of parts are stored in supply bins on the left. The goal of the system is to kit the parts to a kitting tray. The system is divided into three sub-components: isolation (bin-picking), regrasping, and kitting. Those are designed to solve the whole pick-and-align problem by using a coarse-to-fine approach. In subfigure: (a) System overview. Multiple robot arms are configured into a pipeline to play roles for each sub-component. In (b) Initial states of parts. Small parts are stacked with random poses in bins. The first robot in the system (left-most one) isolates a single part from the clutter. In (c) Regrasping by the second and third robots. After recognizing the pose of the placed single parts from bins, robots pick the parts and regrasp them using our efficient regrasp planning algorithm. Parts orientation is aligned for a next kitting task through the regrasp. In (d) Final states of parts. The fourth robot puts the parts into a tray. These correctly-aligned parts will be used in the next production processes, e.g. assembly.

The system includes three sub-components that execute bin-picking (isolation), regrasping, and kitting roles. These three sub-components are connected into a pipeline which divides and conquers the multiple parts feeding problem step by step. First, one robot picks up a part from bins and places it into a flat surface to isolate it from others. Second, three robots regrasp the part and align it to the goal pose. Third, the last robot in the regasping sub-component kits the object to a tray. The main contributions of the proposed system are:

- Redefinition of the random bin-picking problem by identifying the isolation, regrasping, and kitting sub-components.
- A pipeline system design for solving the whole pick-and-align problem by a coarse-to-fine approach along with a divide-and-conquer strategy.
- An efficient and robust regrasp planning algorithm to help multi-robot cooperation.

Through experiments, the performance of the system is evaluated by using the Mean Picks Per Hour (MPPH) metric and success rate, which are compared to traditional parts feeder and manual labor. The results show that the proposed system is more advantageous than the state-of-the-art automatic or manual bin-picking approach. The proposed system with four robots can feed eleven types of parts one by one continuously with the same system efficiency, without manned reconfiguration and without pausing. The MPPHs from bulk bins to aligned into a tray, and from only picking up parts from bulk bins of the proposed system are 351, and 1116, respectively.

The rest of this paper is organized as follows. Related work of the proposed system is described in Section II. Our system design concept is explained in III. Our regrasping algorithm is summarized in IV. Experimental results are described in Section V. Finally, discussion on the system performance and conclusions are presented in Sections VI and VII, respectively.

II. Related Work

A. General parts feeder

The original parts feeder is said to be invented by Mr. William V. Spurlin of SYNTRON Company in 1940, a corporation of Delaware USA and launched in the 1950s[1].The principle of its operation is to use the traveling wave generated by a vibrator section to move parts over a narrow pathway section and to change the direction of parts to a desired one with tools set to protrude on their way in the pathway. The traditional parts feeder that follows these mechanisms requires custom designs especially in the tools section for each part shape. This tooling design is a typical knowledge-intensive business service. Thus, the lead time of a customized parts feeder to be delivered is commonly one month. To reduce the time cost, researchers studied the design of general parts feeders. For example, Goemans et al. [1] used blade-shape parts to feed primitive parts and combine the reorientation functionality of fences with the rejection functionality of traps. Carlisle et al. [2] proposed using a robot arm to pivot target parts. Brien's method is similar to our approach in terms of changing object poses by using a robot arm. Berkowitz and Canny [3] proposed a dynamic simulation to design the parts feeders. Although their generality is relatively higher, the targeted objects of these methods are still limited to some primitive shapes, and hard to be applied to various shapes of parts.

B. Bin-picking

Bin-picking is a classical but still state-of-the-art challenge in robotics. Marvel et al. [4] defined readiness level assessment for the bin-picking problem. Application to multiple parts types was ranked as the most difficult problem and is still challenging. One promised and practical approach is based on pose estimation by using a 3-D CAD model [5], [6], [7], [8]. Besl et al. proposed a registration method for point clouds [5]. Liu et al. used the edges in depth images to align the object poses efficiently [6]. Drost et al. [7] and Choi et al. [8] proposed simple feature pairs to represent object shapes efficiently for object pose estimation. Some methods use unraveling mechanisms to set bulk fed parts separately stand still on a table, then a 2D vision system to find the optimal one of them which can be picked up in a desired grasping pose, and a robot to pick it up, finally many parts in inappropriate poses are abandoned. Some of these methods are applied to parts feeder problems: picking parts from bins and kitting the parts into a tray directly. But applicable parts shapes are limited to plain or cylindrical, cases where either a back posture or a front one is acceptable, or cases where a stable posture of parts is appropriate for grasping. Besides, these methods require a rather high computational cost, thus, it becomes a problem for its application to multiple parts. Also, system operation efficiency is affected by probabilistic phenomena.

Grasp point detection takes place to determine the gripper pose to pick detected items. A method [9] which convolutes a binary image model of the gripper with the depth image and does not require pre-information of the object, is already being used in factory automation. Many methods for grasp point detection using machine learning from RGB images and depth images have been proposed. Jiang et al. proposed a method [10] which searches in an RGB image for a pose that is easy for a two-finger gripper to grasp and they were the first to make it practical [11] with deep learning. Pinto et al. proposed a grasp point detection method [12] from an RGB image based on 50,000 trials on actual robots. Moreover, Levine et al. achieved a method [13] where hand-eye coordination detects a grasp point from RGB data. A common feature among all these methods is that they can determine the grasp point using only images. Unfortunately, the physical correspondence between the gripper and the item in grasping [14] cannot be understood just from appearances in an image. Mahler et al. have defined a matrix which determines grasp points for several objects in advance from the relationship between the 3D object model and the 3D gripper model and proposed a method [15] which assumes a physical grasp point of unknown objects by learning from a vast amount of data. They achieved this with deep learning [16] and used it with vacuum and suction[2] type grippers [17]. In this method, bin picking is available based on the learned results when the learning becomes precise enough. Furthermore, Matsumura et al. succeeded in bin picking with real robots by learning exclusively from simulation data [18]. Team MIT-Princeton fitted for both suction and two-finger grippers by detecting grasp points with Fully Convolutional Network (FCN) on the base [19]. Matsumura et al. solved the picking of tangled objects from bins by combining a feature-based method with a learning based method [20]. Whether to use a learning method by providing data beforehand or to use a non-learning method which is more adaptive to unknown objects and environmental changes depends on the preconditions of the problem.

As we described, some bin-picking problems include kitting as sub-problems. But in many cases, bin-picking problems were defined as picking from bins and placing (throwing) to other places. To avoid confusions in this

[1]History of Parts Feeders (in Japanese), http://www.jpf.ne.jp/index.html

[2]In this paper, we refer to the blower-based suction as *suction* and to the vacuum-pump-based suction as *vacuum*.

paper, instead of defining these problems (or approaches) as bin-picking, we redefine them as isolation from bins, to understand what kind of tasks were solved. This redefinition is essential to understand and solve this classic robotic challenge from the bulk feeding state of parts.

C. Regrasping

The very first study of regrasp planning was part of the HANDEY project [21]. It used a look-up table to switch between different grasp spaces [22]. Following studies using the same ideas include [23], [24], [25], [26], etc. Modern studies about regrasp use the concept of transit and transfer [27] to plan across multiple configuration spaces, where graph-like data structure is used to plan a sequence of key poses, then, motion planning is used in the low level to generate collision-free robot motion between key poses. For example, Simeon et al. [28] proposed a framework that uses transit and transfer paths to generate regrasp and motion for both stationary and mobile manipulators. Yoshida et al. [29] and Hauser et al. [30] adapted the approach to humanoid robots for transit and transfer pushing, respectively. Schmitt et al. [31] showed a reimplementation of the single-arm regrasp by using different contact modes to identify sub-configuration spaces. King et al. [32] simultaneously optimized regrasp and transport motion to implement a combined planning of preparing manipulation and transport. Both prehensile and non-prehensile grasps were considered in the study. Saut et al. [33], Xue et al. [34], and Wan et al. [35] adapted the approach to dual-arm robots.

More recently, regrasp is treated as part of the integrated task and motion planner (TAMP) [36]. Representative studies that perform regrasp under this framework include [37] and [38]. In [37], a robot can automatically determine the number of arms needed to perform a certain task. In [38], dynamic objects were considered. There are also very recently published studies which integrated regrasp with force sensing to meet the requirements of in-hand manipulation [39] or human-robot collaboration [40].

The regrasp part of our study follows the previous published graph-based planners. It is not a brand new regrasp planner, except for the system scale (three robots), and its efficient and robust searching. Especially, to make the regrasp robust, we forced the robot to do two times of non-parallel handover to eliminate the accumulated pose errors.

III. Pipeline System Design Considering a Coarse-to-Fine Manipulation Process

We propose a systematic approach to feed various parts by robots. The robotic parts feeding problem is divided into three sub-components: Isolation (bin-picking), regrasping, and kitting. By solving the sub-components, we develop a robotic parts feeding system as shown in Fig. 2. In the proposed system, four robots are configured into a pipeline. The first robot performs isolation. The remaining robots perform regrasping and kitting.

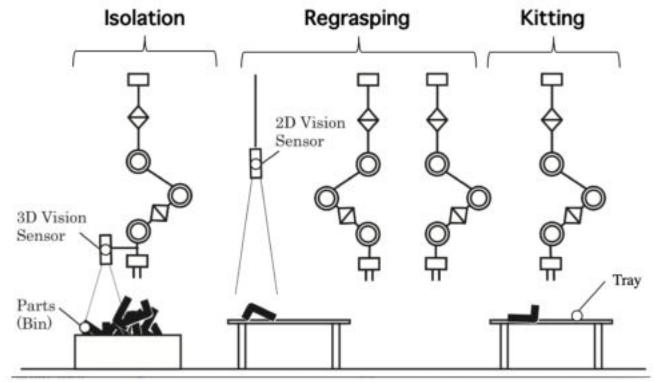

Fig. 2. Overview of the proposed robotic parts feeder.

A. Isolation (bin-picking)

In the beginning, various parts are piled randomly in each bin. As a first step, a robot picks a single part from each bin and places the parts on a flat surface. This problem is often called bin-picking. Nevertheless, as we have shown in Section II, the goal of the sub-component is not aligning the parts' poses. Instead, it is to isolate an object. Therefore, we simply detect the grasping point in the first sub-component. The exact poses of the parts are not considered. The robot can efficiently find the grasping points and pick a single part from the bin and place (throw) it on a flat surface, whereas the pose of the part remains arbitrary. This approach in the sub-component is called isolation, as we described in Section II.

B. Regrasping

After a single part is isolated on a flat surface, as a second step, its pose is estimated. Compared to pose estimation in cluttered bins, the problem becomes easy. Because part poses on a flat surface are limited to small numbers, poses can be estimated by using simple sensors, for example, an industrial 2D camera. Then, robots may plan how to pick and regrasp a part by using the estimated pose. In the proposed system, the second robot picks a part. The third robot regrasp the part from the second robot. The fourth robot regrasp the part from the third robot. By regrasping the part sequentially, the pose of the part is regulated gradually. The details of this sub-component will be discussed in the next section.

C. Kitting

The fourth robot kit the parts to the tray. It receives the part from the third robot in its goal pose (the reception is part of regrasping), and places it precisely onto the kitting tray.

We consider a coarse-to-fine manipulation process in the design of the pipeline system: The first isolation problem does not need much accuracy of manipulation. It only limits the pose of isolated parts roughly. The second step plans regrasping from the limited poses of the parts. The poses of the part in the grippers might have a little uncertainty in the beginning but are updated gradually through regrasp. The final kitting problem is like a peg-in-hole problem. It requires high precision. The accuracy of the state and manipulation are getting higher along with the changes of the sub-components in the pipeline. The precision problem is solved gradually by orchestrating the sub-components considering the coarse-to-fine manipulation process. The robotic system can precisely manipulate parts like feeders by: preserving parts, aligning parts poses, and kitting them to the final destinations.

It should be noted that the proposed system does not always require four robot arms. The proposed system design can be applied to one or two robot arm(s) system. The number of robot arms depends on the required working speed (throughput) and precision of the system.

IV. Efficient and Robust Regrasp Planning

In the first sub-component, the parts are isolated on a flat surface. They can be in various stable poses, as it is shown in Fig. 3(a). These stable poses will be used for single-arm regrasps considering its placement on a flat surface.

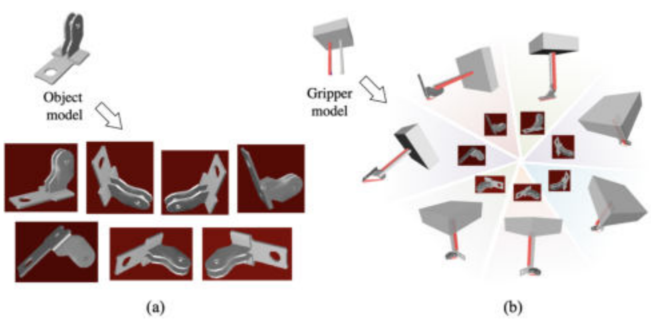

Fig. 3. State definition for regrasp planning – I. (a) Stable poses on a flat surface. (b) Accessible grasp configurations associated with the stable poses.

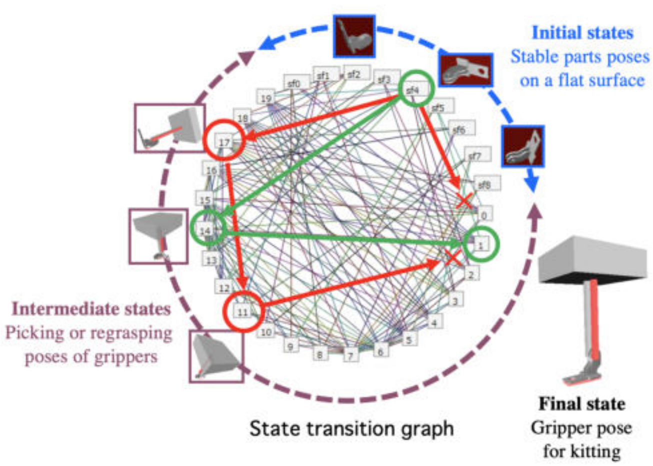

Fig. 4. Connecting the grasp configurations into a graph for regrasp planning. Each grasping configuration (identified by a pose) is treated as a node. Two nodes are connected if they share a common grasp configuration.

We can find the accessible grasping configurations for each stable pose of the parts, by using the model of a robot arm, a gripper, the parts, and the stable poses. The small pictures in the right part of Fig. 3(b) show the grasp configurations for specific part poses. These part poses and grasp configurations are connected into a graph for grasp planning. Each grasping configuration (identified by a pose) is treated as a node. If two poses of the parts have a common grasping configuration, i.e. a grasp configuration that is the same in the local coordinate system of the parts, they are connected using an edge. In this way, we can build the graph structure shown in Fig. 4.

On the other hand, each object can be held in the air in another set of poses, as shown in Fig. 5. These poses will be used for dual-arm handover. We also find the accessible grasping configurations for each of these poses, and connect them to the graph structure for later searches.

Fig. 5. State definition for regrasp planning – II. Handover poses and their associated grasp configurations.

After that, we use the graph structure to generate a sequence of robot motions for pose preparation. Given an initial part pose on a table surface and a goal part pose on a kitting tray, our algorithm finds their grasps, converts them to a starting node and a goal node, and connects them to the graph structure. A graph search method is then employed to find a path across the graph and generate the robot motion considering the found path.

A. *Efficiency*

During graph search, we require the algorithm to find the shortest collision-free path. Shortest collision-free path means it has the smallest number of regrasps, which will potentially increase the efficiency of the regrasping sub-component.

However, efficiency is not the only factor we need to consider. Since the uncertainty of the parts accumulates during the regrasp process, we have to further consider the accumulation of errors, i.e. robustness.

B. *Robustness*

An important problem during regrasp is the accumulated errors. Each grasp and release are uncertain, thus, adding errors to the poses of the parts. To avoid the accumulation of errors, we force the grasp configurations to be perpendicular with each other during dual-arm handover. Since the robotic grippers are parallel, perpendicular grasp configurations during handover add geometric constraints to the parts, thus, reducing the changeable Degrees of Freedom (DoFs) of the parts to the central axis of the perpendicular cross. The errors in the other DoFs are automatically eliminated.

Also, we arrange the robots carefully so that at least two times of regrasp are needed in a plan. The planner is forced to find a regrasp sequence with two non-parallel handovers among the three robots. That is, the central axes of the perpendicular cross of the two handovers have a certain angle with each other. In this way, the remaining uncertain axis left by the first handover is consequentially reduced by the second handover, and all accumulated errors are removed.

Note that in the middle state of a path, we are able to allow or inhibit a part to be placed on a table surface again, which means we can also generate a path for a system that uses only one robot. However, the path is ignored since it cannot deal with uncertainty.

V. Experiments

A. System settings

Our experimental system is shown in Fig. 6. Here, the 6-DoF industrial robot arms are made by Mitsubishi Electric Corporation. The 3D sensor is a structured light based stereo vision sensor. VGA-sized depth image can be captured by the 3D sensor. The capturing time is about one second. The 3D sensor is used in fast graspability evaluation and grasping point detection, using an algorithm previously developed by Domae et al. [9]. The 2D sensor is made by Cognex Corporation. It is used in detecting the poses of a part on a flat surface. PatMax, an edge-based object pose estimation method developed by the same company, is used in the pose estimation. All the grippers installed at the end of the manipulators are parallel two-finger grippers. The shape of the fingers are simply flat plates.

The kitting tray has holes and pins to hold the kitted parts in a desired posture for latter assembly processes, as shown in Fig. 7. The required accuracy for kitting is about 1 millimeter. Eleven industrial parts as shown in Fig. 8 are stored and piled separately in each bin. Stored parts are shown in Fig. 1. The sizes of the target parts are from about 10 millimeters to about 50 millimeters. The parts have complicated shapes, making it possible to identify their front, back, and orientation. Also, the parts cannot be grasped by inside holes (which is a widely used trick in bin-picking industry). During the feeding process, the parts suffer from visual occlusion, flicking in motion, and entangled gripping, these problems are the basic challenges of robotic bin-picking.

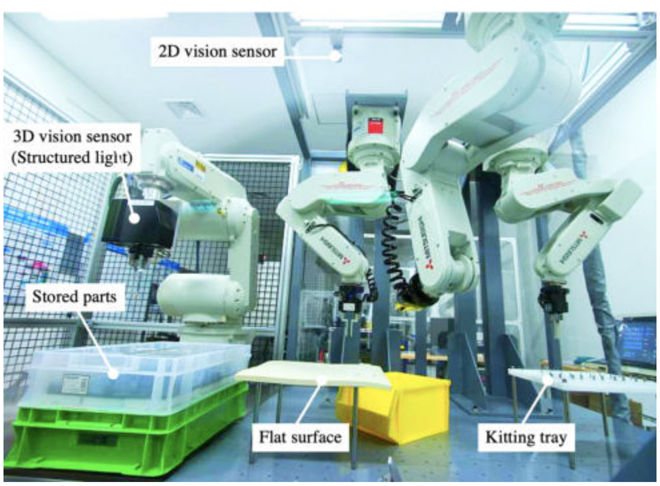

Fig. 6. Experimental system. The system is made of four 6-DoF industrial arms made by Mistsubishi Electric Corporation, one structured light based 3D vision sensor for bin-picking, and one 2D vision sensor for recognizing the pose of an isolated part.

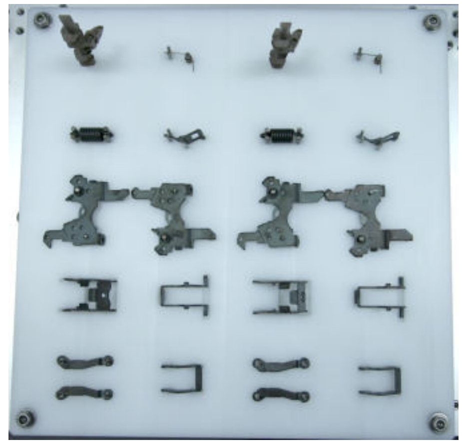

Fig. 7. Aligned parts by the proposed system in the kitting tray.

Fig. 8. Eleven types of target parts. These parts are used to assemble an industrial breaker. The parts sizes range from about 5 millimeters to 40 millimeters. The shapes are various, including plain, cylindrical, box, and more complicated types.

B. Experimental results

We evaluate the system performance by using the Mean Picks Per Hour (MPPH) metric [15] and success rate of the system. The results are shown in Table I. The number of kitting tries executed was 64. The results indicate that the MPPH of the proposed system is higher than the state-of-the-art bin-picking system [41]. The results demonstrate that our proposed system design and methods are effective and efficient.

TABLE I
Success rate and MPPH of the proposed system.

	Only bin-picking	System total
Success Rate [%]	96.9	90.6
MPPH	1116	351

A sequence of snapshots showing how the system behaves is shown in Fig. 9. Fig. 9(a)-(b) show the isolation process. In (a) the picking robot isolates some parts. The isolated results are dropped to a flat surface and are examined by a 2D vision sensor in (b) to exactly determine its pose. Fig. 9(c)-(f) show the regrasp process. In (c), the first regrasping robot picks up a part from the flat surface. In (d) and (e) two handovers were performed to change the pose of the part. In (f) the part is finally placed to its goal pose in the kitting tray.

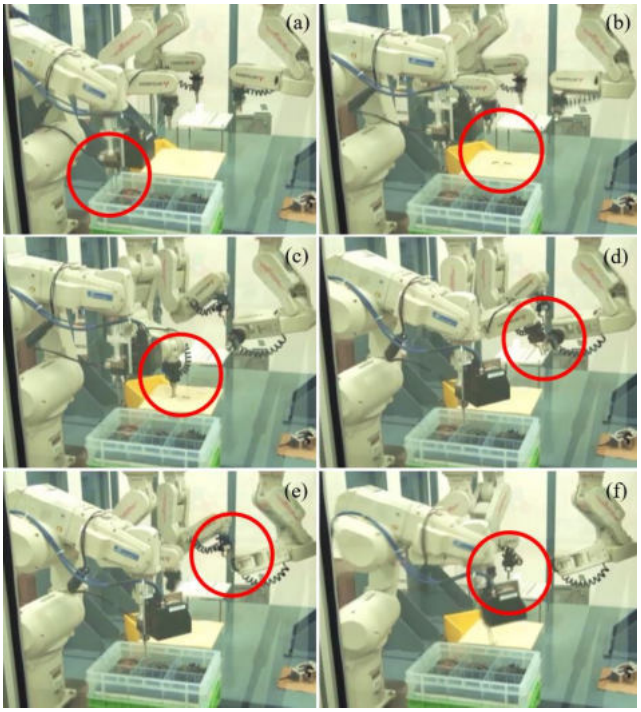

Fig. 9. Sequence of snapshots showing the real-world executions. (a) The first robot isolates some parts. (b) Pose estimation using the 2D vision sensor. (c)-(e) Regrasping. (f) Kitting. For more details, please watch the attached video.

VI. Comparison, Analysis, and Discussion

A. Other feeding methods

We compare the performance of the proposed system with traditional parts feeders and manual labor. The results are shown in Table II.

TABLE II

Performance comparison of different parts feeding methods.

	Proposed	Parts feeders	Manual labor
Applicable parts	11/11	6/11	11/11
Cycle time [sec]	3.7	1.5	1.9
Lead time	3 days	1 month	1 hour (starting) 2 weeks (mastership)

An important drawback of the traditional parts feeders is they do not apply to all parts, due to complicated part shapes. Experienced engineers are needed to design mechanisms for each part shape. For this reason, the lead time of the traditional parts feeders is costly. In contrast, the average cycle time of the proposed robotic feeding system is not faster than others. But the lead time during product change is shorter. As for manual labor, workers can start working instantly, but they need several weeks (two weeks in this task) for mastership. Considering all these factors, our proposed method is more advantageous for the feeding of various-shaped parts, which is heavily needed in cell-production systems.

B. Available robotic bin-picking systems

There are already many robotic bin-picking systems in both industry and academia. These systems have been mostly applied to inside-graspable objects with inside type holes, vacuum graspable types, and cylindrical types. Also, most of the parts are axis symmetrical or surface symmetrical, therefore, they do not need to be rotated and regrasped. Furthermore, the parts cannot avoid the interference with the robotic hands at the kitting stage. Compared with the available robotic bin-picking systems, the proposed system is the first one which can handle and prepare complicated objects that can only be grasped from outside and that have to be rotated. Also, the proposed divide-and-conquer strategy is a breakthrough for bulk parts feeding and redefines the bin-picking problem. The applicable range of robotic bulk parts feedings is believed to be highly expanded by using the proposed strategy.

C. Limitations

One limitation of the proposed system is, it is only applicable to rigid objects. Flexible objects remain a challenge. Also, the types and materials of the graspable objects are limited by the parallel grippers. The proposed system cannot handle heavy objects since there might be a large moment/force that is beyond the maximum static friction force at the small gripping areas between the thin metal gripper and the object. Easily entangled objects like springs are challenging too. These objects are difficult to isolate, as well as difficult to rotate and insert in the following regrasping and kitting process. In our recent work [20], we proposed a bin-picking (isolation) method to deal with entangled objects. Including this method into our system is considered to be future work.

VII. Conclusions and Future Work

In this paper, we proposed a robotic parts feeding system for various shaped industrial small parts. The system is made of three sub-robotic systems that execute picking, regrasping, and kitting roles. The performance of the system is compared to parts feeders and conventional manual methods. The results showed that the proposed system is fast, robust, and has high adaptability. Future work includes reducing the number of robots by using in-hand pose estimation and manipulation methods, fully automating the regrasp planners, as well as dealing with entangled objects.

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