Bin-Picking in the Industry 4.0 Era

Georgios Kyprianou, Lefteris Doitsidis, Athanasios Ch. Kapoutsis, Zinon Zinonos, and Savvas A. Chatzichristofis

2023 IEEE International Conference on Consumer Electronics (ICCE) | 978-1-6654-9130-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCE56470.2023.10043452

***Abstract*—In this paper, we are trying to examine the role of robots in the Industry 4.0 Era. After a brief chronology and an updated literature review on the field, we are trying to examine one of the biggest problems in today's industrial automation, namely in Robotic bin-picking. Its objective is to manage to control a robot with multiple sensory motors attached and be able to collect identified objects with random poses out of a bin, containing a collection of those objects, using any kind of robot-end effector and place it in a predetermined location in the working area. As we observe, the Robotic bin-picking task is divided into three main subcategories: i) perception of the environment, ii) the tooling and iii) the processing architecture. These subcategories are observed thoroughly in the paper and the state-of-the-art techniques used are presented.**

I. Introduction

DUring the last few decades, the industry field was changed dramatically to the benefit of humans. From the late 18th century and the first industrial revolution where mechanization of work was introduced, the early 20th century and the transformation caused by the introduction of electricity which made the use of assembly lines possible (and it marked the beginning of the 2nd industrial revolution), to the late 90s where the big advances of electronics and integrated circuits encouraged Industry 3.0 to make the next big step to the automation, has passed quite a few years.

Even though the improvements that brought Industry 3.0 made a big impact in the field, they also gave a boost to the industry to become even more automated using electronics and information technology, therefore making the usage of robots in factories more appealing. Moreover, the software systems that were keep on evolving and the rapid expansion of the internet and telecommunications, transformed the way information was exchanged. Cyber Physical Systems (CPS) made it possible to make machines smarter leading to Industry 4.0, by allowing the usage of Information and Communication Technology and simultaneous integration of thousands of sensors, working in real time to monitor and analyze data providing humans with the best possible outcome resulting in better manufacturing procedures, supply chain and life cycle control of any kind of products. Industry 4.0 key characteristics, include the capability of the systems involved to exchange and make use of information (interoperability), decentralization and real time operation. The combination of the aforementioned elements is leading to the completion of job humans cannot do in the effect robots can with no mistakes.

Nelles *et al.*[1], examined the possibilities "of human-centered design in assistance systems in production planning and control". The increased volume of networking and digital data make it possible to have access to any kind of information in daily life, let alone in the industry's huge data, and respond to that information. All the available technologies are transferred to industry and production planning and control. However, humans were not eliminated in the equation. Moreover, they are in place to use all the information coming from the machines and robots around to make the necessary decisions on the production line, in a more effective way. We see that man and machine are partners cooperating in a workplace they both share, in order to provide the best possible result, leading to the use of collaborative-robots (cobots). They are currently defined in *ISO 10218* that is described by five main features that allows human to interrupt or limit their usage routine for safety reasons [2].

The wide use of robots, cobots and mechatronics in the Industry 4.0 made people skeptical, since robotization is the key point, which may either turn humans obsolete in the industrial environment or in the best case scenario will make robots a necessity for them. As highlighted in [3], humans want robots to make their lives easier and safer, yet they lack trust in them. As a reaction metric it must be understood that as robots get smarter, more astute, agile and genius, more independent and autonomous, their goals and decisions have to be associated with human principles and ethics.

Besides the above, all the specialists in the field are now working in one common direction, a challenge that they have to fulfill: to move from cobots and mechatronics to smart microbots. They are striking to achieve the development of multi-purposed and all in one robotic platforms that are the smallest possible, in micro or milli scale. DARPA (Defense Advanced Research Projects Agency) already announced a program called short-range independent microrobotic platforms (SHRIMP), requiring from the candidates to develop and demonstrate multifunctional micro-to-milli robotic platforms for use in natural and critical disaster scenarios. The above to be achieved requires extensive research in the hardware that is the most complicated to engineer (like actuators and power supply). Furthermore, there has to be considered the control of these robots and the software to be used. In parallel to all the aforementioned, field experts are working to supply these microbots and cobots with clever algorithms and software that will allow them to attain equivalent targets.

Apart from robotics, machine learning is penetrating fast in the Industry 4.0 and at the same time though, after all this evolution on AI, machine learning and robotics, the industry still underestimates them and has doubts if these technologies

Georgios Kyprianou, Savvas A. Chatzichristofis, Zinon Zinonos: Intelligent Systems Laboratory (ISLab), Neapolis University Pafos, Department of Computer Science, Cyprus

Lefteris Doitsidis: School of Production Engineering and Management, Technical University of Crete, Chania, Greece

Athanasios Ch. Kapoutsis: Information Technologies Institute, The Centre for Research & Technology, Hellas

978-1-6654-9130-3/23/$31.00 ©2023 IEEE

will work in a consistent and reliable way, with a return on investment.

Deep learning networks, one of the most widely used tools of AI currently used in different applications, have been also adopted to tackle bin picking problems. A comprehensive review of the aforementioned approaches can be found in [4], where several approaches and learning methods based on specific domains are described.

Lee *et al.* [5], in order to form a roadmap and outline a structure of industrial AI have characterized some key elements in it, with ABCDE: including Analytics Technology (**A**), Big Data (**B**), Cloud and Cyber technology (**C**), Domain know-how (**D**) and Evidence (**E**). Moving forward, they designed an industrial AI ecosystem, that will help researchers to better understand and implement it, in an effort to define the requirements and challenges, and the required technologies for evolving metamorphic AI systems applicable for the industry.

Considering all the advances took place in Industry 4.0, someone would argue that most of the major problems are already addressed. While it indeed has been evolved to such a great extent, there is a field in industrial automation, where still the researches have a lot of work to do, namely in Robotic bin-picking. The objective of the Robotic bin-picking task is to have a robot with sensors and cameras attached to it to be able to pick-up known objects with random poses out of a bin using any kind of robot-end effector.

In a production line of a factory it is quite common to have a bin full of several, identical or not, machine parts. The human worker is able to find, distinguish and pick each one of them, even in an unordered environment quite easy and fast using two of his most used senses: sight and touch. Robots in contrary, are still struggling to complete these tasks correctly. While they excel in repetitive tasks and selecting items in an ordered and organized manner, they suffer on accuracy on this. It is required for the machine to act in a unique way for every part that is required to pick and place. It is required for it to locate the item in an amorphous situation where the items keep changing positions and orientations each time an item is detached from the bin. Among the above the robot must position its gripper (or other tool it uses) for every single item it needs to pick up, at the same time it is calculating the best way to take the item. Therefore, there is no way to pre-program the robot for each one of these situations.

Whilst the human does this even without thinking of it, a robot needs a huge quantity of data and processes to communicate and manage the bin-picking system. To achieve this, researchers are concentrating on the robots intelligence, focused on three main technologies: sensors, tooling and the processing architecture (that is the software).

Picking in the industry is a subject of high research and interest both from the science point of view but also from the companies, since the work currently done by humans is expected someday soon to be replaced by robots. This will increase effectiveness and at the same time will decrease the cost.

Amazon, in a way to increase the interest of researchers but also being in the spirit of organizing competitions as benchmarks for A.I., organized the Amazon Picking Challenge (APC), where researchers from around the world competed on whose robot will manage to complete first, a task requested. This was to locate, pick and replace into containers, specific items from a shelve, commonly sold in Amazon stores. Each item provided was of varying degrees of effort and difficulty for each robot to complete the task. Based on the APC, quite a few researches have been completed with interesting results. The researchers involved on the competition have published their findings making the community aware about the results and the problems arised during the completion of the challenges [6], [7]. Even though the challenge is not actually alike a real warehouse scenario, it highlighted the advances in the field and the high interest about the task by the community. Correll *et al.* [7], showed that picking and replacing items by robots is a combination of mechanism design, perception and motion planning algorithms.

II. Problem definition - The bin-picking task

Random bin-picking challenge is a combination of different approaches and scientific fields. The scientific community dealing with the subject is divided into three main categories, based on their interests: (i) perception of the environment which includes scene understanding, object recognition and localization where different kind of sensors are used, (ii) the tooling, the ability to grasp and handle objects defined as object grasping and handling and finally (iii) the design of a proper algorithm, a processing architecture, to guide the mechanism to properly position the object to the goal position: motion/path planning.

A. Scene understanding / Object Recognition / Localization

In random bin-picking automation, especially in industrial applications, a key feature to be achieved is the pose estimation. This is the initial step that the robot will have to complete in order to be able to pick an object and manipulate it in an efficient way. There are plenty of algorithms around that are working to solve this problem, but what will make them applicable to the industry is not only their effectiveness but also the time they need to complete the task, therefore the online computation time needs to be short.

To enable the robot to interact with the full bin on object localization, specific steps have to be taken, based on data describing the scene. Usually an optical sensor is chosen for the data acquisition. For the object localization step, the quality of the sensor data is crucial; therefore a suitable sensor has to be chosen. One of the main tasks, if not the most important, in bin-picking is the determination of the objects' pose and grasping point. There has been many attempts to describe the problem using several range of sensor data. Bin-picking is a subject that has focus on complete autonomy of the robot in a dynamic changing environment in a factory. This makes the control functionality of the robot to be extremely complex and taking into consideration quite a few factors. There are major challenges in automation technology which restricts and put bog obstacles to the way of testing a candidate bin-picking system in a real environment. Having said the above, researchers are looking for a virtual representation of the

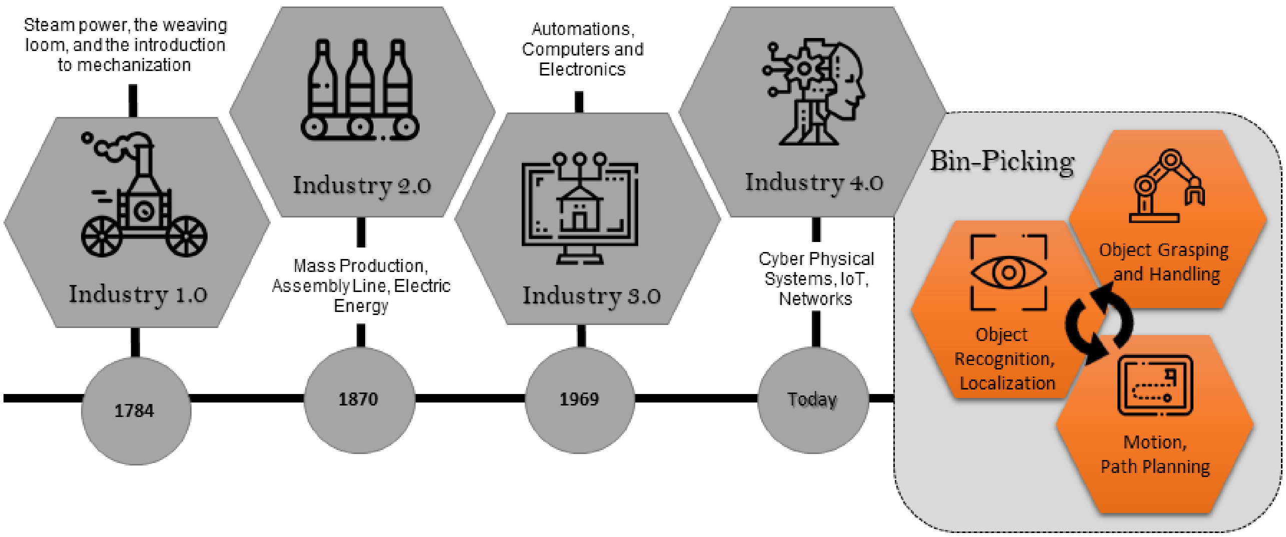

Fig. 1: Visualization of the Industrial Revolutions and Bin-Picking Components

automation solution, where the software could be tested with not any real risks.

Fur *et al.* [8], developed a framework (Software on the Loop/SiL) to provide a virtual environment for testing software focusing on the bin-picking process and proposed a virtual data generation method that uses a laser range finder. Even though there exist other simulation tools, they lack of an adequate method for generating sensor data.

The presence of obstructions (like noise and edge distortions,) forces pose estimation to use 2D image, instead of 3D, especially in random bin-picking systems which work better when their poses are confined to a few cases. To bowl over these types of matters, using data coming directly from a RGB-D camera the 3D pose of objects is estimated. Then, a 2D camera will be used to estimate with better results the pose of the object. The latter are then conveyed to a robot to complete the grasping task.

Bin-picking methods using 2D-features to recognize objects and estimate their position, do not work efficiently on environments with different lighting conditions but also to unequal objects [9]. In contrary the newly developed techniques using 3D-vision, they require both high computational power but also composite calculation for object modeling and feature extraction. As about the use of deep learning algorithms, they are used to learn the image trajectory but it is difficult to accurately guess the rotation angle, which will be used to estimate the position of the objects to be picked. Pyo *et al.* [10], presented a method for pose estimation that is irrelevant to the pose of the object using affine transformation, which "preprocessed the image for invariance to object posture".

Yan *et al.* [11], presented a fast pose estimation pipeline for random bin-picking, in which the pipeline is capable of recognizing different types of objects in various cluttered scenarios and uses an adaptive threshold segment strategy to accelerate estimation and matching for the robot picking task.

In a recent paper [12], the impact of using depth maps from multiple viewpoints on robotic bin-picking tasks such as 6D object pose estimation, is investigated. In their work, the authors, propose a novel probabilistic framework for scene reconstruction in robotic bin-picking. They initially estimate the uncertainty of depth measurements for mitigating the adverse effects of both noise and outliers. The derived estimates are then incorporated into a probabilistic model for incrementally updating the scene.

Dyrstad *et al.* [13], presented a new method for bin-picking based on a dual resolution convolutional neural network trained entirely in a simulated environment. They tried to solve the problems come up when the bin-picking algorithm deals with every reflective objects but also the algorithm to be able to automatically be modified for several objects.

At the same time, some groups of researchers tried to examine the issue of bin-picking, as whole and therefore designing architectures for automated grasping tasks, consisting of all the three main categories of the subject. Kouskouridas *et al.* [14], tried to create such a framework that will be able to answer all the three critical questions when dealing with bin-picking: What, Where and How. To be precise, What the robot needs to grasp, Where should it grasp it from, and How to grasp it. As stated, the majority of times there is not a single question to answer to an approach to the general bin-picking challenge, but it needs a combination of them to handle it. Their attempt is considered successful since not only managed to outperformed likewise methods but it can also be adapted to unknown object manipulation tasks (similar to the ones already learned by the system), without further training on the new datasets or target goals. They managed to obtain precise detection outcomes for the recognition task, using a Bag-of-Features (BoF) classification procedure and the grasping task, was defined using an ontology where the acknowledged objects via inheritance they acquire grasping coordinates from the related class of objects. Wong *et al.* [15], propose another holistic approach were ROS was used to integrate an object perception module and a pick-and-place module.

The major challenge for perception systems is their ability to distinguish objects in a fast changing environment and in fast changing object sets. In order to achieve this lot of training must be done a priori and huge datasets must be provided to the system. To be applicable though in a warehouse scenario with object categories differing daily, the extended training times needs to be kept away and the training examples needs to be kept as few as possible. To overcome this kind of problems Schwarz *et al.* [16], used deep learning with a combination of object detection and semantic segmentation. They have used RGB-D cameras for object recognition and pose estimation with combination to a depth fusion technique they developed. With the usage of pretrained features they managed to acquire knowledge to their system, from small datasets, whenever possible. They have put their solution in action for the *Amazon Picking Challenge 2016*, with quite promising results.

Lee *et al.* [17], identified the disadvantages that past researchers had in pose estimation and tried to address them by recommending a method that guesses the 3D pose of objects in stack using an RGB-D camera and deep learning and the pose estimation using an ICP (Iterative Closest Point) algorithm. Plane fitting is also used to deal with the insufficient 3D point data acquisition problem.

B. Object Grasping and Handling

Real time grasp planning for robotic hands is a real challenge. A detailed survey of methods and strategies for high-precision robotic grasping and assembly tasks is presented in [18]. Manual teaching of different type of grasps for every part in several environments is non efficient for industrial environments and also time consuming. Shi and Koonjul [19] managed to overcome the real time grasping planning problem, without using any predefined grasp database, but by decomposing time consuming grasp planning problems (i.e. collision checking, distance calculations) using the volume of the objects and palms grasp volume they managed to plan quickly, the way that the gripper or palm will handle the item. Moreover they managed to decompose complicated grasp planning problems that use 3D shapes into multiple but simpler grasp planning ones that use 2D plannar polygons.

Grasping does not only deals with the software and algorithmic problems but also it has to deal with hardware ones. That is to decide what kind of grasp policy or mechanism to use. Usually this is related to the items to be collected, but in RBP problems this must be eliminated by using a universal kind of grasping mechanism that will be good for several items. The choice is quite complex since sensing and control but also the type or shape of items are critical. Moreover there are some physics factors (like friction, gravity, etc.) that cannot be directly detected and be taken into consideration through the grasping function.

Different kinds of grasping mechanisms do exist in the industry, varying from finger grippers, to granular jamming and caging grippers, to inflatable needles and suction caps. Their ability to grasp is task specific and not universal. For example in cases where distorted objects need to be grasped, like sacks or meat [20], a finger gripper is not suitable, because the grasping points actually change among each grasp. Therefore the grasping tool needs to be adjustable and flexible to deal with this change. A suction cup is an ideal solution for the above mentioned scenario

Mahler *et al.* [21], experimented using two specific kind of grasping mechanisms: a parallel jaw gripper and a vacuum based sanction cup gripper. They introduced an ambidextrous grasping policy that decides online on the type of grasp, each time to use and at the same time it plans the grasp so to extend the quality provided.

C. Motion / Path Planning

Bin-picking is verged on by putting the objects in an ordered and predefined pattern, so all the sub problems and tasks to be simplified (object recognition, motion planning and object manipulation). This makes the general problem easily solvable since the objects are always at the same position. In real life problems though, there is not usually met such a condition, but the objects are most likely to be randomly placed in the bins. Moving forwards, from the moment the object is located and its pose was estimated, a path should be calculated in order for it to be placed to its goal location. This is though a not easy task since the manipulator needs to take into consideration both the objects shape or specific restrictions (e.g. an open can or bottle must be kept vertical at all times), but also several obstacles found on its way to the destination. Among all the problems need to be solved, all these need to be computed online, in the fastest possible way. Motion planning in the bin-picking scenario is the process that a robot follows after it identifies any possible obstacles or obstructions on the work space and after, it calculates trajectories in order to complete the pick and place task. In the modern smart factories, due to the great demand of fast changing environments, especially when people or other robots or cobots are present there is the necessity of fast online planning of the above mentioned trajectories.

Vonasek *et al.* [22], proposed a unique technique that uses an extension of Rapidly-exploring Random Tree (RRT) that uses motion primitives. These are short trajectories in the space which the end-effector (manipulator) tries to achieve throughout every expansion step of the RRT. The usage of these motion primitives causes acceleration for the planning process. Motion planners like the RRT and PRM (Probabilistic Roadmaps) are usually used to solve planning problems. Coming to real time (online) planning, a common solution is to allocate the estimation on virtual machines: in the cloud. The method proposed in [23] seems to be more applicable for cloud computing, since it does not claim communication between the computational nodes, but rather that they run in parallel.

Different motion planning algorithms do exist, each one most applicable to a certain domain. The choise depends explicitly on the specific use case. Older planners like PRM that proved to be accurate to static environments and more recent and faster ones (RRT and Fast Marching Tree - FMT [24]) give some choices but at the same time questions arise about which one to chose. Iversen and Ellekilde [25] put several planner algorithms to the test on bin-picking explicit scenarios and defined benchmarks. Their results shown significant outcomes about the performance and speed of the algorithms.

III. Conclusion

In this paper, we formally discuss the problem of random bin-picking in the industry. The process as a whole is divided into three subcategories, which may be themselves three different areas of investigation from the community depending on the researchers' interests:

1) Scene understanding / Object Recognition / Localization,
2) Object Grasping and Handling and
3) Motion / Path Planning.

Making a literature review we examined the current trends and viewpoints of the researchers in the field. The task is not yet fully solved in a way that could be deployed in an industrial environment and let work unsupervised by any human factor, or at a faster or more efficient and reliable pace than the human worker can do.

We've seen that, even though the subcategories as independent scenarios have found several solutions, when they are combined all together to solve the bin-picking task, either they lag behind human or they find difficulties on completing it. For instance, not only a system needs to identify an object in a stack and have a proper understanding of the scene, but also this have to be done online and quick enough. We've also seen that more and more groups who are dealing with this specific task to make use of RGB-D cameras and both 2D and 3D images. There is a variety of unsolved problems yet to overcome.

On the other hand, object grasping and handling might be of different kind of problems and already been solved for specific tasks, in bin-picking though, where there is the need the grasping mechanism to be universal we lack of solutions. The robot to complete a grasp needs to know how to do it and what policy to follow and this requires a lot of a priori knowledge.

On motion planning part, the trajectories, the mechanism has to go through, need to be computed on line on the fastest possible way. This requires both high computational power but also the correct algorithm that will take into consideration different values and possible occlusions.

References

[1] J. Nelles, S. Kuz, A. Mertens, and C. M. Schlick, "Human-centered design of assistance systems for production planning and control: The role of the human in industry 4.0," in *2016 IEEE International Conference on Industrial Technology (ICIT)*. IEEE, 2016, pp. 2099–2104.

[2] P. Markillie, "Collaborative manufacturing: all together now," *The advantages of crowdsourcing. The Economist Special Report: Manufacturing and Innovation*, 2012.

[3] J. Fiaidhi, S. Mohammed, and S. Mohammed, "The robotization of extreme automation: The balance between fear and courage," *IT Professional*, vol. 20, no. 6, pp. 87–93, 2018.

[4] A. Cordeiro, L. F. Rocha, C. Costa, P. Costa, and M. F. Silva, "Bin picking approaches based on deep learning techniques: A state-of-the-art survey," in *2022 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, 2022, pp. 110–117.

[5] J. Lee, H. Davari, J. Singh, and V. Pandhare, "Industrial artificial intelligence for industry 4.0-based manufacturing systems," *Manufacturing letters*, vol. 18, pp. 20–23, 2018.

[6] M. Schwarz and S. Behnke, "Data-efficient deep learning for rgb-d object perception in cluttered bin picking," in *Warehouse Picking Automation Workshop (WPAW), IEEE International Conference on Robotics and Automation (ICRA)*, 2017.

[7] N. Correll, K. E. Bekris, D. Berenson, O. Brock, A. Causo, K. Hauser, K. Okada, A. Rodriguez, J. M. Romano, and P. R. Wurman, "Analysis and observations from the first amazon picking challenge," *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 1, pp. 172–188, 2018.

[8] S. Fur, A. Verl, and A. Pott, "Simulation of industrial bin picking: An application of laser range finder simulation," in *2018 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, June 2018, pp. 1–6.

[9] K. Rahardja and A. Kosaka, "Vision-based bin-picking: recognition and localization of multiple complex objects using simple visual cues," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems. IROS '96*, vol. 3, Nov 1996, pp. 1448–1457 vol.3.

[10] J. Pyo, J. Cho, S. Kang, and K. Kim, "Precise pose estimation using landmark feature extraction and blob analysis for bin picking," in *2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)*, June 2017, pp. 494–496.

[11] W. Yan, Z. Xu, X. Zhou, Q. Su, S. Li, and H. Wu, "Fast object pose estimation using adaptive threshold for bin-picking," *IEEE Access*, vol. 8, pp. 63 055–63 064, 2020.

[12] J. Yang, D. Li, and S. L. Waslander, "Probabilistic multi-view fusion of active stereo depth maps for robotic bin-picking," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 4472–4479, 2021.

[13] J. S. Dyrstad, M. Bakken, E. I. Grøtli, H. Schulerud, and J. R. Mathiassen, "Bin picking of reflective steel parts using a dual-resolution convolutional neural network trained in a simulated environment," in *IEEE International Conference on Robotics and Biomimetics, ROBIO 2018, Kuala Lumpur, Malaysia, December 12-15, 2018*, 2018, pp. 530–537.

[14] R. Kouskouridas, A. Amanatiadis, S. Chatzichristofis, and G. A., "What, where and how? introducing pose manifolds for industrial object manipulation," *Expert Systems with Applications*, vol. 42, p. 81238133, 11 2015.

[15] C.-C. Wong, C.-Y. Tsai, R.-J. Chen, S.-Y. Chien, Y.-H. Yang, S.-W. Wong, and C.-A. Yeh, "Generic development of bin pick-and-place system based on robot operating system," *IEEE Access*, vol. 10, pp. 65 257–65 270, 2022.

[16] M. Schwarz, A. Milan, A. S. Periyasamy, and S. Behnke, "Rgb-d object detection and semantic segmentation for autonomous manipulation in clutter," *The International Journal of Robotics Research*, vol. 37, no. 4-5, pp. 437–451, 2018.

[17] J. Lee, S. Kang, and S.-Y. Park, "3d pose estimation of bin picking object using deep learning and 3d matching," 01 2018, pp. 318–324.

[18] R. Li and H. Qiao, "A survey of methods and strategies for high-precision robotic grasping and assembly taskssome new trends," *IEEE/ASME Transactions on Mechatronics*, vol. 24, no. 6, pp. 2718–2732, 2019.

[19] J. Shi and G. S. Koonjul, "Real-time grasping planning for robotic bin-picking and kitting applications," *IEEE Transactions on Automation Science and Engineering*, vol. 14, no. 2, pp. 809–819, April 2017.

[20] T. B. Jørgensen, N. Krüger, M. M. Pedersen, N. W. Hansen, and B. R. Hansen, "Designing a flexible grasp tool and associated grasping strategies for handling multiple meat products in an industrial setting," *International Journal of Mechanical Engineering and Robotics Research*, vol. 8, no. 2, pp. 220–227, 2019.

[21] J. Mahler, M. Matl, V. Satish, M. Danielczuk, B. DeRose, S. McKinley, and K. Goldberg, "Learning ambidextrous robot grasping policies," *Science Robotics*, vol. 4, p. eaau4984, 01 2019.

[22] V. Vonasek, A. Vick, and M. Saska, "Motion planning with motion primitives for industrial bin picking," in *2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, Sep. 2017, pp. 1–4.

[23] V. Vonásek, A. Vick, and J. Krüger, "Distributed motion planning for industrial random bin picking," *Procedia CIRP*, vol. 76, pp. 121–126, 2018.

[24] L. Janson, E. Schmerling, A. Clark, and M. Pavone, "Fast marching tree: A fast marching sampling-based method for optimal motion planning in many dimensions," *The International journal of robotics research*, vol. 34, no. 7, pp. 883–921, 2015.

[25] T. F. Iversen and L.-P. Ellekilde, "Benchmarking motion planning algorithms for bin-picking applications," *Industrial Robot: An International Journal*, vol. 44, no. 2, pp. 189–197, 2017.