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Abstract*—Robotic bin-picking is increasingly important in the order-picking process in intralogistics. However, many aspects of the robotic bin-picking process (object detection, grasping, manipulation) still require the research community's attention. Established methods are used to test robotic grippers, enabling comparability of the research community's results. This study presents a modified YCB Robotic Gripper Assessment Protocol that was used to evaluate the performance of four robotic grippers (two-fingered, vacuum, gecko, and soft gripper). During the testing, 45 objects from the modified YCB Object and Model Set from the packaging categories, tools, small objects, spherical objects, and deformable objects were grasped and manipulated. The results of the robotic gripper evaluation show that while some robotic grippers performed substantially well, there is an expressive grasp success variation over diverse objects. The results indicate that selecting the object grasp point next to selecting the most suitable robotic gripper is critical in successful object grasping. Therefore, we propose grasp point determination using mechanical software simulation with a model of a two-fingered gripper in an ADAMS/MATLAB co-simulation. Performing software simulations for this task can save time and give comparable results to real-world experiments.

***Keywords*—intralogistics, robotic bin-picking, YCB protocol, robotic gripper evaluation, mechanical software simulations, performance analysis.**

I. Introduction

Today's challenges of skilled labor shortages and unstable economic and environmental conditions require profound changes in production and warehousing processes. In connection with increasingly demanding customer needs associated with small order sizes, an extensive product range, short delivery times, and variable order quantities, warehouses face major challenges [1].

Satisfying these needs usually requires redesigning and optimizing existing processes or introducing new technologies, such as robotization and automation. One of the most important and cost-intensive processes in warehouses is the order-picking of individual items according to the order list.

The order-picking process is usually only partially automated, although most work is repetitive. This is due to the large assortment of items (various dimensions, shapes, weights, etc.), which can pose a problem for the robot order-picking, which in many ways cannot yet surpass human speed and dexterity [2]. However, with the development of collaborative robotics, advanced robotic grippers, 3D image processing systems, and deep-learning algorithms, new order-picking opportunities are emerging [3] that bridge the gap between human and robotic order-picking capabilities.

Many researchers are currently engaged in the research area of robotic bin-picking, focusing on the development of new object recognition and grasping algorithms [4, 5], the positioning and orientation of objects within SKUs [6], optimal object grasping algorithms [7], and the use of different robotic gripping devices [8].

Selection of the proper components for the optimal robot order-picking, such as a 3D vision system and robotic gripper, is a complex task. It requires a substantial amount of experimental work to be done before the actual bin-picking application. On the other hand, it provides benefits in terms of a fully automatic process, which can achieve higher overall picking performance compared to the human order picker.

Therefore, the researchers are working on providing different benchmarks and organizing challenges [9] to enable a fair comparison between different robotic workstations, including a robotic arm, 3D vision systems, and robotic grippers [9-11]. Furthermore, the precision of the 3D vision system combined with the appropriate robotic gripper plays an important role in the overall efficiency of robotic bin-picking.

With our research work, we aim to evaluate the importance of selecting the optimal robotic grippers, which can improve the bin-picking process related to the operational efficiency in warehousing.

The research questions used in our analysis are as follows:

- Can the selected robotic gripper be used effectively for a single group of objects?
- Is there a procedure in the research community to analyze the suitability of the robotic gripper?
- Can we contribute to the faster development of robotic bin-picking using the proper procedure?
- Can mechanical software simulations predict the most suitable robotic gripper and grasp points?

To answer the above research questions, a comparative analysis of individual robotic grippers for different types of picking objects was developed. In addition to the results, the cases in which an objects cannot be grasped are analyzed in detail.

II. A Brief Literature Overview

Research groups working on robotic grippers are proposing methods that allow objective and reproducible testing of different robotic grippers. Well-defined test conditions and well-defined robotic gripper evaluation procedures ensure impartiality and reproducibility. The purpose of using these methods is to make the results generated by the broader research community comparable, which allows researchers to progress faster [10, 12-14].

Calli, et al. [10] propose five methods or protocols for testing robotic manipulation systems within their YCB Object and Model Set. From the point of view of testing robotic grippers, the Gripper Assessment Protocol, the Table Setting Protocol, the Block Pick and Place Protocol, and the Box and Blocks Test are particularly interesting. The Gripper Assessment Protocol is presented in more detail in Chapter III.

Falco, et al. [13] propose several methods to test the elementary properties and capabilities of robotic finger grippers, such as grip force, finger force, slip resistance, touch sensing capability, grip force sensing capability, grip force control capability, etc. In contrast to the protocols proposed by Calli, et al. [10], which are based on manipulation tasks, the methods proposed by Falco, et al. [13] are based on force measurements. This approach is welcome from the point of view of the reproducibility of testing. The measurements are made using external data acquisition systems independent of the system under study. No other objects are used in the tests, thus eliminating an important source of potential variation in the test conditions. The exception is a so-called artifact that allows the measurement of gripping force and slip resistance. All researchers have access to the same artifact at the expense of using standard and 3D-printed components.

The Amazon Picking Challenge [4, 15] was a major competition in robot manipulation. The competition aimed to accelerate the development of robotic systems for warehouse automation. A key challenge in warehouse automation is picking objects from storage racks. The pick-up operation is also recognized as one of the logistical bottlenecks [12]. The benchmark for robotic systems is the performance of the people currently operating. Human operators take between 5 and 10 seconds to pick up an object, which is a challenge for robotic systems [4]. For the Amazon Picking Challenge, participants had to develop an autonomous robotic system that can pick as many objects as possible from a warehouse system in a limited time. A set of 25 objects from the Amazon Web shop is used, which are challenging to perceive and grasp due to their properties (shape, deformability, transparency, etc.).

Robotic manipulation is also a topic in the IROS Robotic Grasping and Manipulation Competition [16, 17]. The competition is divided into three sections. The first section deals separately with robotic grippers, an important subsystem of robotic manipulation systems. Different treatment from other subsystems, such as the manipulator and algorithms for path planning, grasp planning, perception, decision making, etc., is achieved by manual gripper control, where the operator holds and operates the robotic gripper. The operator must perform pick-and-place operations and ten predefined handling tasks. Using a sequence of pick-and-place operations, the operator must stack ten objects from a shopping bag. The objects used in the competition are from the YCB object and model set and from the Amazon Picking Challenge. The second part of the competition deals with complete robotic manipulation systems developed by the participants. Robotic manipulation systems must autonomously perform the same tasks as the operator in the first part of the competition. The third part of the competition is dedicated to simulations of manipulation tasks.

As seen from the brief literature overview, the robotic community is finding ways to compare various robotic gripper's performance efficiently. The key impact of testing protocols and benchmarks is to ensure repeatability and ease of use.

III. Yale-CMU-Berkeley (YCB) Object And Model Set For Benchmarking Robotic Grippers

This research study aims to evaluate the capabilities of selected robotic grippers. Our previous analysis shows that choosing the right robotic gripper for the selected items has a decisive influence on the bin-picking performance. Namely, not all items can be picked with a single robotic gripper.

When developing the method for testing the robotic grippers, our starting point was the YCB Object and Model Set [10]. YCB Object and Model Set and various protocols were proposed by Yale, Carnegie Mellon, and Berkeley Universities researchers. The YCB Object and Model Set aims to increase the comparability of results from studies carried out in robotic manipulation. The authors aim to provide researchers with a range of objects and models that is broad, accessible, robust, and affordable. The set consists of 86 objects, their digital models, a database of physical properties of the objects, and a collection of protocols representing possible uses of the set. The YCB Object and Model Set authors divide the objects into five categories, depending on the area or purpose of use: a) **Food items:** food in boxes (pudding, crisps), tins (coffee, tuna) and bottles (mayonnaise), and plastic fruit; b) **kitchen items:** objects used for cleaning (cleaning products, cleaning sponges) and preparing (dishes, scoops) and serving food (plates, cutlery); c) **tool items:** various tools (screwdrivers, clamps, hammer, drill) and objects used with the tools (screw, nut, nails, wooden block); d) **shape items:** objects of specific shapes (balls, marbles) and sizes (washers, credit cards) and deformable objects (rope, plastic chain); e) **task items:** objects used to carry out tasks (wooden blocks, LEGO bricks, Rubik's cube, T-shirt, magazine).

The YCB Gripper Assessment Protocol predicts using 28 objects from the standard 86 items, divided into the following categories: a) **Round objects:** balls (soccer, softball, tennis, racquetball, golf) and marbles (4 dimensions); b) **flat objects:** washers (7 dimensions) and credit card; c) **tools:** felt-tip pen, scissors, screwdriver, drill, hammer, and clamps (4 dimensions); d) **hinged objects:** rope and chain.

We have prepared a new division of objects from YCB object set, based on the characteristics of objects that affect their manipulation, such as shape, size, stiffness, etc: (1) **Packaging**: boxes, cans and bottles, and wooden logs and sponges for cleaning. These objects are characterized by simple shapes in which no dimension stands out and even mass distribution; (2) **Fruit:** plastic fruit characterized by various specific shapes; (3) **Tools:** workshop, office, and kitchen tools. These objects are characterized by complex shapes, in which one dimension often stands out, and uneven mass distribution; (4) **Spherical objects:** spheres of different diameters, stiffness, and surface structures. A common specific shape characterizes these objects; (5) **Cutlery:** flat and shell-shaped objects with openings and handles; (6) **Small objects:** objects of simple shapes, at least one dimension of which is distinctly small; (7) **Deformable objects:** objects whose shape changes under the influence of forces during their manipulation; (8) **Objects intended for the performance of tasks**.

Purchasing the original objects from the YCB Object Set from the US was associated with long delivery times and relatively high shipping costs. Therefore, we have created our object set using the best available substitutes. The robotic grippers were tested according to the modified YCB Gripper Assessment Protocol. The protocol is intended to evaluate robotic grippers in terms of their ability to manipulate objects of various shapes and dimensions. The protocol enables the evaluation of robotic grippers that use different grasping principles. Several examples of the use of this protocol are described in [10, 18].

An expanded set of objects was used in evaluating the robotic grippers. Forty-five (45) objects from the previously introduced newly defined categories of the YCB set of objects and models were used (Fig. 1): packaging, tools, small objects, spherical objects, and deformable objects. The packaging category was selected because it contains objects relevant to logistics engineering. The categories of tools and small objects were selected because these objects are challenging from the point of view of grasping. The categories of spherical and deformable objects were selected to test all objects used in the original YCB Gripper Assessment Protocol Object Set. Not all objects from the listed categories were used in the testing of robotic grippers. Namely, a single object was used for multiple similar objects, as testing multiple similar objects would not provide additional information about the robotic grippers.

Fig. 1. The proposed five categories of objects to be grasped from the original YCB Gripper Assessment Protocol.

A. YCB Gripper Assessment Protocol

Four different positions of the manipulated objects are used in the YCB protocol to evaluate the robustness of the robotic grippers. The locations are defined by the points SP_1 (0, 0, 0), SP_2 (10, 0, 0), SP_3 (0, 10, 0), and SP_4 (0, 0, -10), considering the coordinate system shown in Fig. 2. Each object is positioned in front of the robot so that its center of gravity coincides with each point and its main axis coincides with the *X*-axis. Exceptions are flat objects, where only three points are used (SP_1, SP_2, and SP_3), and deformable objects, where no points are used, but these objects are positioned randomly in front of the robot. The coordinates units are in millimeters.

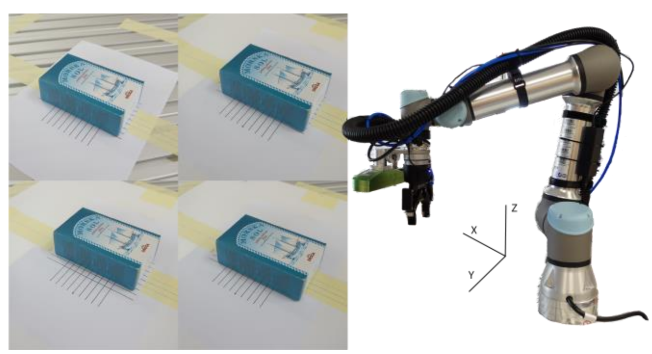

Fig. 2. The location of four points SP_1 (0, 0, 0), SP_2 (10, 0, 0), SP_3 (0, 10, 0), and SP_4 (0, 0, -10) of the packed salt object and the coordinate system of the robot used in the experiments.

For each object, the gripper's position is defined, which enables the object to be grasped, considering the position of the object defined by point SP_1. This gripper position is also used for the other positions of the object defined by points SP_2, SP_3 and SP_4. The protocol does not define the exact orientation of objects. When testing the robotic grippers, the objects were positioned following the YCB protocol instructions. In addition, such orientations of the objects were used that allow the maximum success of grasping with a certain gripper. With such an approach, the influence of object orientation on the gripper score was reduced. Otherwise, a particular way of orienting the objects could deliberately or undeliberate affect the gripper score.

The following testing procedure was used for objects from packaging, tools, small objects, and spherical objects.

1. The object is placed in the starting position to coincide with point SP_1.

2. The robotic gripper's position, which enables the object to be grasped, is defined.

3. The object is grasped.

4. The object is raised and held in this position for 3 seconds.

5. The object is rotated 90° in the *X*-axis direction and held in this position for 3 seconds.

6. The object is rotated 90° in the *Y*-axis direction and held in this position for 3 seconds.

7. The object is returned to its starting position.

Steps 3 to 7 are repeated for the other starting positions of the object defined by points SP_2, SP_3 and SP_4. If, in steps 3 to 6, the object's starting position defined by point SP_1 leads to the object's falling, the testing with this object is completed. If the object falls during steps 3 to 6, at the starting positions of the object defined by points SP_2, SP_3 and SP_4, the testing continues after step 7.

The described testing procedure differs from the classic YCB Gripper Assessment Protocol proposed by the additional 6th step, in which the manipulated object is rotated by 90° in the *Y*-axis direction. The testing steps are shown in Fig. 3.

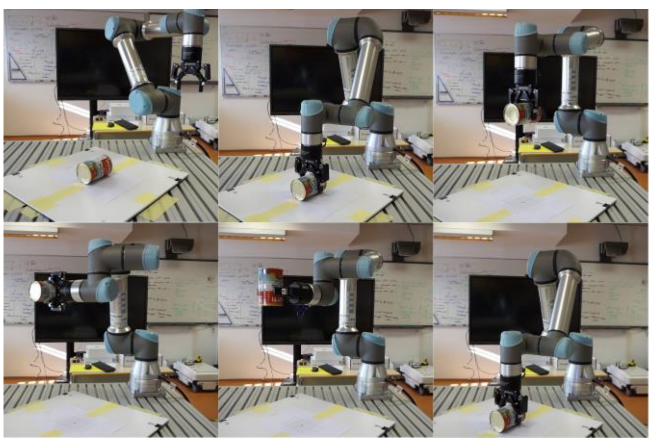

Fig. 3. The sequence of modified YCB Gripper Assessment protocol.

The following testing procedure was used for objects from the deformable objects category, which is the same as the procedure proposed by the original YCB Gripper Assessment Protocol.

1. An object is randomly placed in front of the robot.

2. The robotic gripper's position is defined, which enables the object to be grasped.

3. The object is grasped.

4. The object is raised by 150 mm and held in this position for 3 seconds.

5. The object is returned to its starting position.

While maintaining the grip position defined in step 2, the grasping is repeated twenty times.

Following the YCB Gripper Assessment Protocol, the robotic gripper's score was obtained based on grasping performance. The following evaluation procedure was used for objects from packaging, tools, small objects, and spherical objects. If the manipulated object is not released in the fourth step of testing and no free movement of the object inside the gripper is detected, two points are added to the robotic gripper. If the free movement of the manipulated object inside the robotic gripper is detected, one point is added to the robotic gripper. If the manipulated object is not released at the fifth or sixth step and the object's free movement inside the robotic gripper is not detected, two points are added to the robotic gripper. If the free movement of the manipulated object inside the robotic gripper is detected, one point is added. The described procedure is used for all starting positions of manipulated objects.

In the case of objects from the deformable objects category, grasping in which no part of the object touches the ground after the fourth step of testing is considered successful. Half a point is added to the grasp for a successful grasp.

B. *Robotic bin-picker setup*

The YCB Gripper Assessment Protocol is hardware independent and can be performed on industrial and collaborative robots. For the test environment, we chose the collaborative robot UR5e with four robotic grippers: (1) Robotiq 2F-85 two-finger gripper (parallel configuration), (2) OnRobot Gecko SP3 single-pad adhesive gripper, (3) Robotiq EPick vacuum gripper with a suction cup of diameter d = 40 mm, and (4) Soft Robotics mGrip P2 soft gripper.

IV. RESULTS

The YCB robotic gripper assessment protocol test results are presented in the diagrams in Fig. 4 and Fig. 5. Fig. 4 shows the percentages of points achieved, illustrating the effectiveness of individual robotic grippers. The maximum grasping efficiency of 72% is achieved with the two-fingered gripper and 71% with soft gripper, respectively. The overall grasping efficiencies of the other two grippers, vacuum, and gecko gripper, are significantly lower and amount to 26% and 17%. Fig. 5 shows the percentages of points achieved by individual grippers by category of manipulated objects.

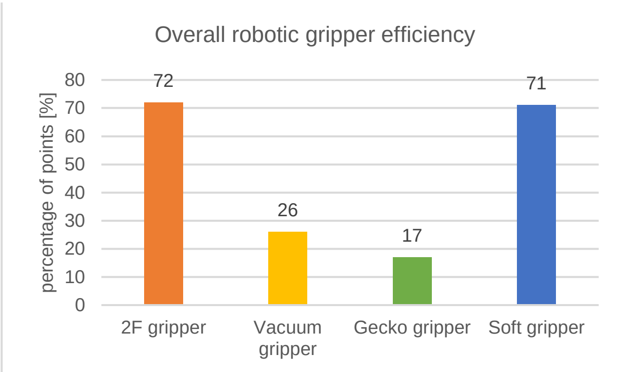

Fig. 4. Overall robotic gripper efficiency for selected objects.

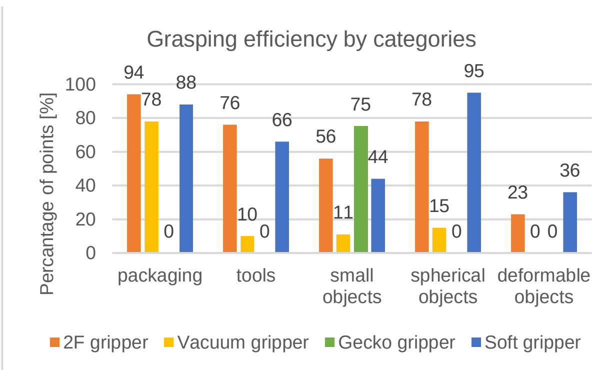

Fig. 5. Grasping efficiency of the robotic gripper by categories.

A. *Robotic Gripper analysis*

The following sections discuss the results and analysis for all four robotic grippers.

1) *Two-fingered robotic gripper*

With the two-fingered robotic gripper, the maximum grasping efficiency of 94% is achieved in the packaging category. The robotic gripper had the most trouble with the cereals box in this category (Fig. 6a). During grasping, the box was deformed, which resulted in the formation of contact between the gripper and the box only at the edges of the box (Fig. 6a). As a result, the box moved freely in the grasp during manipulation. A similar case also occurred when manipulating a bottle of glass cleaner (Fig. 6b). In the case of larger objects from the packaging category, the problem of a limited stroke width of robotic gripper fingers was observed. For larger objects and larger displacements, the grasp would be less successful.

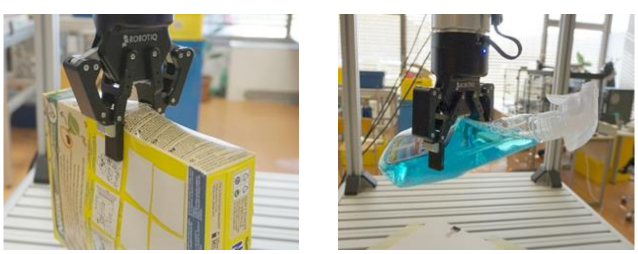

Fig. 6. Grasping of cereals box (a) and glass cleaner (b) with the two-fingered gripper.

A lower grasping efficiency can be seen in the tool (76%) and spherical objects (78%) categories. In the tool category, the grasp was less successful for lower objects (spoon, knife, scissors, etc.) and objects with an uneven mass distribution (hammer, drill). In the case of lower objects, the grasping was unsuccessful when the objects slipped in *Z*-axis direction, as the robotic gripper did not reach the objects, or the objects fell out of the grip due to insufficient contact surface (Fig. 7a). Objects with unevenly distributed mass (e.g., hammer) moved freely inside the gripper during manipulation (Fig. 7b). In the spherical objects category, the robotic gripper failed to grasp the soccer ball due to limited finger stroke width. The grasping of smaller marbles was also unsuccessful in case of deviations in the *X*-and *Z*-axis directions.

Fig. 7. Grasping of (a) spoon and (b) hammer with the two-fingered robotic gripper.

The two-fingered robotic gripper achieved 56% efficiency in the small objects category. Two-fingered gripper had problems with objects with a distinctly small height, such as credit cards and small washers. Grasping was unsuccessful due to the shape of the fingertips, as the rounded edges did not allow the formation of adequate contact between the robotic gripper and the objects.

The deformable objects category achieved the lowest grasping efficiency of 23%. The robotic gripper could not successfully grasp the plastic chain and magazine in any of the 20 trials. In the case of a plastic chain, a problem for grasping is the free movement of its joints, which causes the chain to slip out of the grip partially or completely. The magazine is problematic to grasp due to its dimensions. If the magazine is not deformed (bent, twisted), it is impossible to grasp it due to the insufficient stroke width of robotic gripper fingers. The small finger stroke width was also a problem when gripping the T–shirt, where a 35% grasp success rate was achieved. The highest success rate of 55% among deformable objects was achieved for the rope.

2) *Vacuum robotic gripper*

As with the two-fingered robotic gripper, the vacuum gripper has the highest grasping efficiency of 78% for objects in the packaging category. Grasping was unsuccessful for a can of tomatoes and a cleaning sponge. In both cases, it was not possible to ensure sealing between the vacuum suction cup and the object. In the first case due to the shape of the can (Fig. 8a), while in the case of the sponge due to the porosity of the surface.

In other categories of objects, the efficiency of the vacuum robotic gripper is significantly lower. The efficiency of grasping spherical objects is 15%. Grasping is successful with larger balls with a smooth surface (soccer, baseball, racquetball). With marbles and balls with a surface structure (tennis, golf), the grasp is unsuccessful (Fig. 8b). In case of marbles, the lack of success is due to insufficient contact area between the vacuum gripper and the object.

Fig. 8. Grasping of (a) tomato can and (b) golf ball with vacuum gripper.

The problem of the insufficient contact surface is even more evident in the case of small objects (Fig. 9a). The grasping efficiency of these objects is 11%. The grasp was successful only in the case of the credit card and the lock in the starting position without slipping. Using a smaller vacuum suction cup, it would be possible to successfully grasp all objects from the category of small objects except for screws and nails.

An even lower grasping efficiency of 10% is noticed in the tool category. Grasping is successful only with a spoon. The rest of the objects are characterized by expressively uneven surfaces and surfaces with different structures, making it impossible to ensure sealing as seen in Fig. 9b.

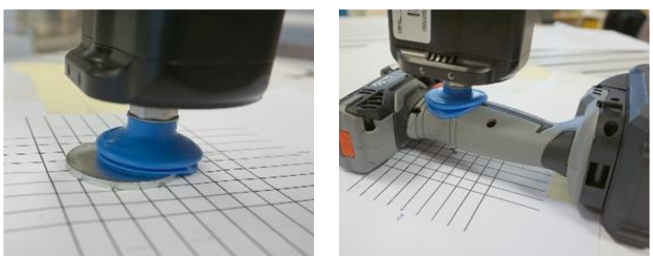

Fig. 9. Grasping of (a) washer and (b) drill with vacuum gripper.

Sealing also cannot be ensured between the vacuum gripper and the deformable objects category. The exception to this is the magazine, which opens and bends during manipulation. Therefore, the manipulation cannot be performed successfully.

3) Gecko robotic gripper

The gecko robotic gripper achieves a minimum grasping efficiency of 15%. The robotic gripper efficiency was higher than 0% only in the case of the small objects category. Robotic gripper efficiency in this category of 75% is the highest among all tested robotic grippers. We can conclude that the gecko robotic gripper is intended for a narrow set of specific objects. The operation of the robotic gripper was very efficient in these objects but expressively inefficient in all the others. Rigid, flat, and smooth surfaces are necessary for successful grasping. Due to deformation, objects with deformable surfaces, such as boxes, bottles, and balls, are separated from the gripper (Fig. 10a).

The application of this robotic gripper for manipulating deformable and sensitive objects is questionable, as objects can be damaged during preloading (Fig. 10a). With uneven surfaces, typical of tools, insufficient adhesion forces are formed between the robotic gripper and the objects. Therefore, the grasp is unsuccessful (Fig. 10b). Also, the grasp is unsuccessful on surfaces that are not perfectly smooth, e.g., on wooden surfaces. In addition, the robotic gripper is moment sensitive. When the manipulated object is loaded with a moment, it separates from the gripper, which is good when dropping objects, but unfavorable when grasping objects at a higher distance from their center of gravity.

Fig. 10. Grasping of the (a) cereals box, and (b) spoon with the gecko robotic gripper.

4) Soft robotic gripper

With the soft robotic gripper, a maximum grasping efficiency of 95% is achieved in spherical objects category. This gripper is the most effective of all the grippers tested in this category due to how the fingers move and deform. The robotic gripper allows the fingers to be locked and unlocked by applying an overpressure or under pressure to the fingers. This gives the fingers enough stroke width needed to grasp larger objects such as a football (Fig. 11a). Due to deformable fingers, smaller objects such as marbles can be successfully grasped (Fig. 11b).

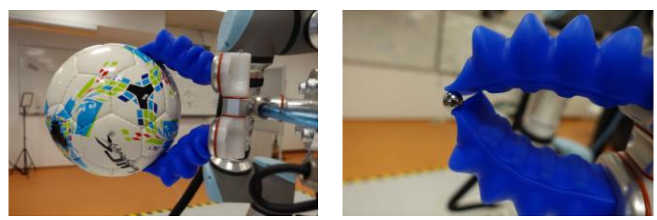

Fig. 11. Grasping of (a) football and (b) marbles with soft robotic gripper.

A high grasping efficiency of 88% is also achieved for objects in the packaging category. In these cases, the robotic gripper had problems with smooth surfaces (Fig. 12a). Problems were particularly evident for heavier objects and for *Y*-axis displacements. The displacement in the *Y*-axis direction causes the object to apply a moment to the gripper. It can be concluded that the problems are due to the low maximum grasping force and the unfavorable frictional conditions between the objects and the robotic gripper.

The low grasping force and friction conditions also prevented the successful manipulation of some objects in the tool category, resulting in 66% grasping efficiency. The manipulation of the drill (Fig. 12b) and hammer failed due to the low grasping force. The manipulation of spoon and knife failed due to unfavorable friction conditions. Further, the low friction and deformability of the fingers grasping the spoon and the wrench resulted in a twisting of the objects inside the gripper. Like the classic two-fingered gripper, the soft gripper had problems with lower objects (spoon, knife, scissors, etc.) in this category when they were displaced in the *Z*-axis direction.

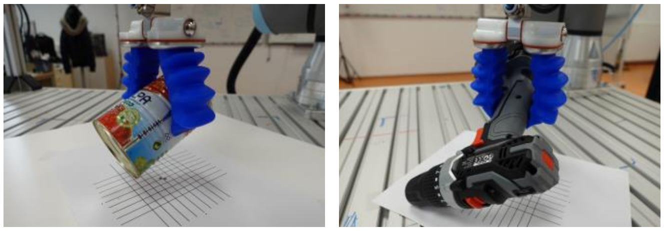

Fig. 12. Grasping of (a) can of tomatoes and (b) drill with soft robotic gripper.

The soft robotic gripper achieves a 44% grasping efficiency in the small object category (Fig. 13a). The low efficiency is due to limited control over fingertip movements. On the gripper tested, the two fingers did not deform in the same way, resulting in a tip offset (Fig. 11b). This was particularly a problem when grasping objects with a distinctly low height, such as credit cards and small washers.

A minimum grasping efficiency of 36% is achieved for deformable objects category. However, for this category of objects, it is the most effective of all the robotic grippers tested. This is due to the flexibility of the robotic gripper fingers, which is significantly higher compared to the two-fingered gripper (Fig. 13b). The robotic gripper can grasp the rope, the chain, and the T-shirt with 70%, 40%, and 35% of success, respectively. At the same time, it is not able to grasp the magazine.

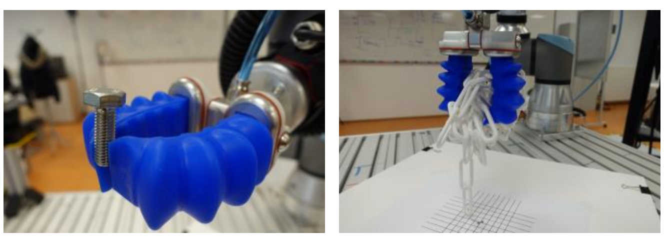

Fig. 13. Grasping of (a) bolt and (b) chain with soft robotic gripper.

V. Mechanical Software Simulations For Determining Optimal Grasp Points

The selection of grasp points has a major influence on bin-picking performance. Since determining object grasp points is not always trivial, as in the case of simple objects, a systematic approach should be used. Therefore, an offline model based on ADAMS/MATLAB co-simulation was developed by Bencak, et al. [19]. The model, presented schematically in Fig. 14, has been designed to select the optimal grasp points for an arbitrary object with a two-fingered robotic gripper.

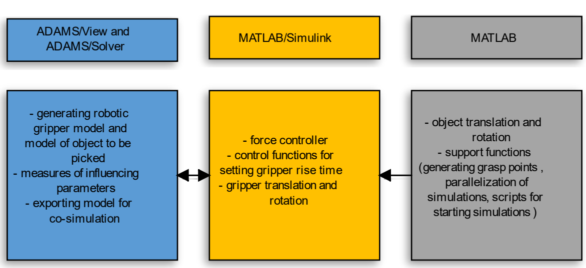

Fig. 14. Shematic of ADAMS/MATLAB co-simulation model.

A model of the two-fingered robotic gripper Robotiq FT-85 has been developed in ADAMS, where the main gripper mechanical parameters have been considered. A model of the object has been obtained by 3D scanning and importing it into the ADAMS. Contacts and forces were set according to the materials used and based on the actual response from grasp evaluation. A P-force controller modeled in MATLAB/Simulink ensures that the gripper grasps the object with the prescribed force. The simulation model is controlled by a user interface developed in MATLAB/App Designer. A grasp-point generator generates grasp-point pairs, which coincide with the actual robotic gripper location and orientation. The user selects the number of desired grasp points, corresponding to the grasp simulation performance. For higher execution speed, they are executed parallelly using the local MATLAB *parallel pool.* The models' main limitations are only considering rigid objects and setting up the correct contact parameters.

Since the original model only considers a single height (the object is always picked at half its height), this proved problematic in some cases. Also, if the objects are randomly placed in the bin, they cannot always be picked at that position. Therefore, the model has been further developed to ensure picking at almost any desired height. The model of the object to be grasped is imported into the GUI using a top-down picture of the object. Since the object does not always have a constant height across its entire surface (Fig. 15), it is not always practical to grasp the object at half of the height, but only where it proves necessary.

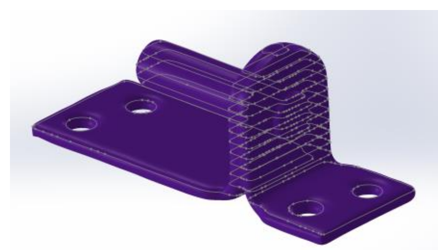

Fig. 15. Sliced door hinge model by layers in SolidWorks.

This ensures that only feasible grasps are evaluated. The 3D model is therefore sliced in the *SolidWorks* program imported slice by slice into the GUI. The process of saving the slices into pictures to be imported into GUI has not been automated yet and will be the work of future studies. Further, grasp success is now graphically shown on the simulated object, which enables quick evaluation of grasp points (Fig. 16).

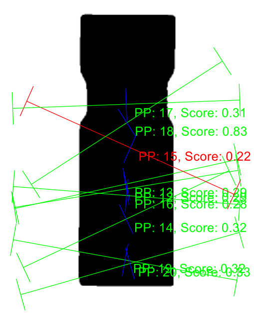

Fig. 16. Grasping score of the two-fingered robotic gripper for the door hinge object on selected object height h = 17.5 mm.

The output of the co-simulation model is in the form of a table, where *X*, *Y*, *Z* coordinates of grasp points, and gripper rotation (α) along with the grasp score (*S*) are presented. Coupled with the remote control of the collaborative robot, the simulated grasp points can be verified on the actual system.

VI. Conclusions

The results of extensive benchmarking show, that robotic grippers behave very differently for each of the object category. The grasp points in this experiment were selected according to the user experience of the possible grasp success. Therefore, it would be beneficial to first perform mechanical software simulations in the proposed ADAMS/MATLAB co-simulation to elaborate on the grasp success. However, the model is still limited to grasp-point evaluation of the two-fingered gripper.

The two-fingered robotic gripper had difficulty manipulating small objects and lower objects especially in the vertical direction. The weakness of the two-fingered robotic gripper is also the limited stroke width of the fingers, which limits the size of the objects that the robotic gripper can manipulate.

The success of grasping with a vacuum robotic gripper mainly depends on sealing between the manipulated object and the vacuum cup of the vacuum gripper. The characteristics of the surfaces of the objects, such as porosity, structure, shape and size, influence sealing. By using a smaller diameter of the vacuum cup, it would be easier to ensure sealing and thus increase the success of gripping, especially smaller objects.

The gecko robotic gripper is sensitive to properties of surfaces of the manipulated objects and is only suitable for completely flat, smooth, and rigid surfaces. The gecko robotic gripper is intended for a narrow set of specific objects where the robotic gripper works very efficiently. In all other cases, the operation of this robotic gripper was markedly inefficient.

Soft gripper achieves high performance in picking spherical and deformable objects due to the flexibility of the fingers. For the packaging and tools categories, the lower performance is due to a combination of low grasping force and unfavorable frictional conditions. Imprecise fingertip movements reduce performance in small objects category.

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References

[1] N. Boysen, R. de Koster, and F. Weidinger, "Warehousing in the e-commerce era: A survey," *European Journal of Operational Research,* vol. 277, no. 2, pp. 396-411, 2019/09/01/ 2019, doi: https://doi.org/10.1016/j.ejor.2018.08.023.

[2] A. S. Morgan *et al.*, "Benchmarking Cluttered Robot Pick-and-Place Manipulation With the Box and Blocks Test," *IEEE Robotics and Automation Letters,* Article vol. 5, no. 2, pp. 454-461, 2020, Art no. 8936856, doi: 10.1109/lra.2019.2961053.

[3] J. Park, M. B. G. Jun, and H. Yun, "Development of robotic bin picking platform with cluttered objects using human guidance and convolutional neural network (CNN)," *Journal of Manufacturing Systems,* Article vol. 63, pp. 539-549, 2022, doi: 10.1016/j.jmsy.2022.05.011.

[4] N. Correll *et al.*, "Analysis and Observations From the First Amazon Picking Challenge," *IEEE Transactions on Automation Science and Engineering,* vol. 15, no. 1, pp. 172-188, 2018, doi: 10.1109/TASE.2016.2600527.

[5] J. Mahler *et al.*, "Learning ambidextrous robot grasping policies," *Sci Robot,* Article vol. 4, no. 26, Jan 16 2019, Art no. eaau4984, doi: 10.1126/scirobotics.aau4984.

[6] X. Li *et al.*, "A Sim-to-Real Object Recognition and Localization Framework for Industrial Robotic Bin Picking," *IEEE Robotics and Automation Letters,* Article vol. 7, no. 2, pp. 3961-3968, 2022, doi: 10.1109/LRA.2022.3149026.

[7] F. Spenrath and A. Pott, "Gripping Point Determination for Bin Picking Using Heuristic Search," in *Procedia CIRP*, 2017, vol. 62, pp. 606-611, doi: 10.1016/j.procir.2016.06.015.

[8] S. Hasegawa, K. Wada, Y. Niitani, K. Okada, and M. Inaba, "A three-fingered hand with a suction gripping system for picking various objects in cluttered narrow space," in *IEEE International Conference on Intelligent Robots and Systems*, 2017, vol. 2017-September, pp. 1164-1171, doi: 10.1109/IROS.2017.8202288.

[9] Y. Bekiroglu *et al.*, "Benchmarking protocol for grasp planning algorithms," *IEEE Robotics and Automation Letters,* vol. 5, no. 2, pp. 315-322, 2020, Art no. 8917672, doi: 10.1109/LRA.2019.2956411.

[10] B. Calli, A. Walsman, A. Singh, S. Srinivasa, P. Abbeel, and A. M. Dollar, "Benchmarking in Manipulation Research: Using the Yale-CMU-Berkeley Object and Model Set," *IEEE Robotics & Automation Magazine,* Article vol. 22, no. 3, pp. 36-52, 2015, Art no. 7254318, doi: 10.1109/mra.2015.2448951.

[11] T. F. Iversen and L. P. Ellekilde, "Benchmarking motion planning algorithms for bin-picking applications," *Industrial Robot,* vol. 44, no. 2, pp. 189-197, 2017, doi: 10.1108/IR-06-2016-0166.

[12] T. Watanabe, K. Yamazaki, and Y. Yokokohji, "Survey of robotic manipulation studies intending practical applications in real environments -object recognition, soft robot hand, and challenge program and benchmarking," *Adv .Rob.,* Article vol. 31, no. 19-20, pp. 1114-1132, 2017, doi: 10.1080/01691864.2017.1365010.

[13] J. Falco, K. V. Wyk, S. Liu, and S. Carpin, "Grasping the Performance: Facilitating Replicable Performance Measures via Benchmarking and Standardized Methodologies," *IEEE Robotics & Automation Magazine,* vol. 22, no. 4, pp. 125-136, 2015, doi: 10.1109/MRA.2015.2460891.

[14] Y. Yokokohji, Y. Iida, and T. Yoshikawa, "'Toy problem' as the benchmark test for teleoperation systems," (in English), *Adv .Rob.,* Article vol. 17, no. 3, pp. 253-273, 2003, doi: 10.1163/156855303764018495.

[15] C. Eppner *et al.*, "Lessons from the amazon picking challenge: Four aspects of building robotic systems," in *Robotics: Science and Systems,* D. Hsu, N. Amato, S. Berman, and S. Jacobs, Eds., 2016, vol. 12: MIT Press Journals, doi: 10.15607/rss.2016.xii.036.

[16] Y. Sun *et al.*, "Robotic grasping and manipulation competition: Task pool," in *Communications in Computer and Information Science*, J. Falco and Y. Sun, Eds., 2018, vol. 816: Springer Verlag, pp. 1-18, doi: 10.1007/978-3-319-94568-2_1.

[17] J. Falco, Y. Sun, and M. Roa, "Robotic grasping and manipulation competition: Competitor feedback and lessons learned," in *Communications in Computer and Information Science*, J. Falco and Y. Sun, Eds., 2018, vol. 816: Springer Verlag, pp. 180-189, doi: 10.1007/978-3-319-94568-2_12.

[18] S. B. Backus and A. M. Dollar, "An Adaptive Three-Fingered Prismatic Gripper with Passive Rotational Joints," *IEEE Robotics and Automation Letters,* Article vol. 1, no. 2, pp. 668-675, 2016, Art no. 7378287, doi: 10.1109/LRA.2016.2516506.

[19] P. Bencak, D. Hercog, and T. Lerher, "Simulation Model for Robotic Pick-Point Evaluation for 2-F Robotic Gripper," *Applied Sciences (Switzerland),* Article vol. 13, no. 4, 2023, Art no. 2599, doi: 10.3390/app13042599.