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Design and Evaluation of an Automatic Decision System for Gripper Selection in Order Picking

Design und Evaluation eines automatischen Entscheidungssystems für die Greiferauswahl bei der Kommissionierung

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Grasping objects poses a challenge in the automation of order picking due to the diverse types of objects and complex real-world scenarios, necessitating the selection of an appropriate gripper for each object type. Existing gripper selection methods focus on generalized gripper selection systems able to grasp a large variety of objects in non-cluttered scenarios for handling in industrial applications. Within this paper, a knowledge-based gripper selection method for e-grocery items in cluttered scenarios is implemented as a binary decision tree. The results are validated through empirical tests, demonstrating an overall accuracy of 90.7 %. As the percentage of true negatives is 81.6 %, it is necessary to combine grasping principles to reduce the percentage of True Negatives in the future.

[Keywords: Automation, Order picking, E-grocery, Gripper Selection]

Das Greifen von Objekten stellt aufgrund der vielfältigen Objektarten und komplexen realen Szenarien eine Herausforderung in der Automatisierung des Kommissionierens dar und erfordert die Wahl eines passenden Greifers für die jeweilige Objektart. Vorhandene Methoden zur Greiferauswahl konzentrieren sich auf Greifsysteme, die in der Lage sind, eine breite Vielfalt von Objekten in geordneten industriellen Anwendungen zu greifen. Innerhalb dieser Arbeit wird daher eine wissensbasierte Methode zur Greiferauswahl für E-Grocery Artikel in unordentlichen Szenarien als binärer Entscheidungsbaum implementiert. Die Ergebnisse werden durch empirische Tests validiert und zeigen eine Gesamtgenauigkeit von 90,7 %. Da der Prozentsatz der echten Negative bei 81,6 % liegt, ist es erforderlich, Greifprinzipien zu kombinieren, um zukünftig den Prozentsatz der echten Negativwerte zu reduzieren.

[Schlüsselwörter: Automatisierung, Kommissionierung, E-Grocery, Greiferauswahl]

1 INTRODUCTION

Order picking is a highly labor-intensive operation in e-commerce supply chains and requires cost-intensive manual labor. Thus, the performance of automated order picking systems is a significant aspect of company competitiveness [1]. Even though there was a drop in parcel deliveries in 2022, the level of parcel shipments is 14 % above the last pre-Covid-19 year [2]. The branch of e-grocery has anticipated this increase specifically the recent years and it is expected to have substantial growth in the upcoming decade [3]. For automating the order-picking process grippers are necessary, which can grasp a wide variety of goods. Even though multiple studies in the past decade have concentrated on creating automated picking systems, currently, distinct grippers are still being created for managing individual product types [4–8]. To grasp a range of products, large enough to make an automated system a viable solution for e-grocery, an automated selection method for grippers is desirable.

Existing gripper selection methods focus on creating a generalized gripper selection system that can grip a large variety of objects in non-cluttered scenarios for handling in industrial applications [1], [8]. Automated gripper selection methods for cluttered environments and with a focus on the branch of e-grocery are not available.

The contribution of the paper is a knowledge-based gripper selection method based on a binary decision tree for e-grocery items and a comparison of the performance of the results with empirically tested gripper configurations on a representative set of fruits and vegetables.

The structure of the paper is as follows. In Section 2, a review of the related work concerning knowledge-based gripper selections methods is presented. In Section 3, the methodology is explained which consists mainly of an iterative process to define a minimum set of product characteristics as basis for the decision tree. Afterward, the products

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for the validation are defined, product properties are derived by referring to existing publications, gripper principles are evaluated concerning their usability in order picking, the experimental setup is explained and the gripper-selection algorithm is presented. In Section 4, the results for the empirical evaluation of the grasping tests and the binary choices of the decision tree are stated and discussed. In Section 5 a conclusion is drawn.

2 Related Work

In recent years two methods emerged as most researched for tackling the issue of automatic selection of grippers in complex scenarios. The approaches are data-driven methods and analytical methods [9]. Data-driven methods are built to recognize and learn e.g. patterns of physical product properties and characteristics of the setup, without explicitly revealing the decision-making process [10]. This makes it difficult to adapt the automatic selection process once it is designed. In contrast, analytical methods use explicit rules and equations to achieve an automatic selection. Its key advantage is transparency, as they are not "black boxes", which facilitates to comprehend how the model selects a gripper [10]. This transparency allows experts to modify and refine the decision model. Among analytical methods, knowledge-based methods stand out as a promising approach. In the following paragraphs, various analytical methods for gripper selection are presented.

Among the first to tackle the problem are Pham et al. [8, 11, 12], who defined three knowledge-based selection methods. These methods are developed sequentially starting from a general selection of grasping principles chosen according to physical product characteristics [11]. Afterwards, they added sequentially a more sophisticated knowledge-based system, based on 200 rules to match a product to a grasping principle [12]. Finally, a more complete version named DBGRIP pinpointed the exact commercially available gripper most suited for a given application [8]. Despite the complexity of the methods developed by Pham et al., they do not consider the settings in which the objects have to be grasped.

More than two decades later, Fantoni et al. [1] established a comprehensive framework for planning and execution of grasping actions. Their work consists of three steps. First, they compile a set of parameters, derived from existing literature, that influences the grasping strategy. Second, they selected all grasping principles and third, they developed 200 rules to select suitable grasping principles considering the object characteristics and the gripper parameters [1]. Fantoni's work focuses on determining the grasping principle. The exact gripper configuration is not part of his research objective.

Pham et al. do not evaluate their selection in cluttered environments [8, 11, 12]. Fantoni remains on the level of automatic grasping principles selection and does not take gripper configurations into account. Finally, e-grocery items such as fruits and vegetables have specific product characteristics that do not fit the defined properties by Pham and Fantoni. This research gap is filled by this work.

3 Methodology

The goal of this work is to develop an automatic knowledge-based selection method for gripper configurations. The product range in this study is a subset of commercially available e-grocery products which corresponds to fruits and vegetables [2].

Initially, grasping principles were investigated, and from these, two suitable grasping principles for automatic grasping of the product range were selected. Subsequently, three steps were carried out iteratively (Figure 1):

- Definition of a minimum set of product characteristics that includes all necessary information, which is important for the gripper selection.

- Execution of preliminary grasping tests on seven representative products, each embodying distinct parameters to validate the selected parameters.

- Definition of suitable gripper configurations based on the chosen grasping principles. They are chosen according to the minimum and the maximum size of the products and their shape.

Afterwards, the rules for the decision tree are elaborated and a decision tree for the automated selection of gripper configurations is developed. It is executed for all the products in three different scenes: cluttered, semi-cluttered, and uncluttered. For a later comparison of the results, empirical tests on a representative set of goods with all used gripper configurations are executed. To validate the results of the decision tree, the results are compared with those from the empirical grasping tests.

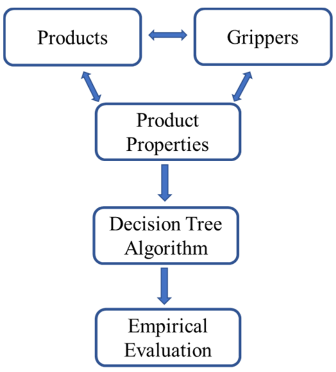

Figure 1. Process followed to execute the knowledge-based gripper selection.

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3.1 Products

The products used in this study are 51 of the 54 fruits and vegetables commercially available on the German market and listed by the *Bundesanstalt für Landwirtschaft und Ernährung* (German Federal Agency for Agriculture and Food) [13]. Of the 54 products truffle, annona, and ceps are not used because they are seldom commercially available in supermarkets. Fruits and vegetables are chosen as range of products of interest because of two main reasons:

- The complexity of handling fruits and vegetables compared to e-grocery items is high. This is due to their delicacy, their inclination to develop bruises and dents, as well as the variety of their physical characteristics and the irregularity of their shape.
- Fruits and vegetables share the same needs for conservation and, therefore, they are stored in the same warehousing sections.

All 51 fruits and vegetable packaging types were empirically collected by an extensive empirical study, that was conducted in common supermarket chains in Germany like ALDI Einkauf GmbH & Co KG, Lidl Dienstleistung GmbH & Co. KG, Edeka Zentrale AG & Co KG and Western Buying Co-operatives Auditing Association. All different packaging types are bags, nets, trails with plastic foil around, boxes with rigid top, trails wrapped with nets and plastic foil wrapping the product. 54 fruits and vegetables were observed in different product-packaging combinations. This leads finally to a total amount 94 product types and is the basis for this paper.

3.2 Product Properties

The work of Fantoni et al. [1] gives a baseline as they conducted a comprehensive review collecting product properties. For this paper, these product properties are adapted for fruits and vegetables by first eliminating unnecessary properties and afterward merging some properties into new property classes (Table 1). The properties considered irrelevant for grasping fruits and vegetables are hydrophobia, ferromagnetism, conductivity, stickiness, stiffness, and slipperiness [10]. In the following paragraphs all remaining categories and, if applicable, merging criteria are described. Each property description ends with examples from the 54 fruits and vegetables within this publication.

The list of UNECE-NORM for Fresh Fruits and Vegetables provided by the *Bundesanstalt für Landwirtschaft und Ernährung* [13] is used to assign average weight and size of all the products that are admitted to the German market with class A [13].

Weight (g): From the 94 products the nominal minimum value is 10 g (cherry), and the nominal maximum value is 5000 g (watermelon). If a packing type contains more than one product as in bundles or nets a representative weight of the observed product-packaging combination is used. None of them is above the maximum value of 5000 g.

Size (mm): The product dimensions (length, width, and height) range from 20 mm (cherries) to 400 mm (leeks). To define each of the dimensions, the products are considered in the orientation, in which the products normally lay in the boxes (Figure 2). The length is defined as the longest axis of the product on the visible 2D horizontal plane (x arrow in Figure 2) and the width is the shortest visible 2D horizontal plane (y arrow in Figure 2) and the height is represented by the dimension perpendicular to the picture.

Figure 2. Geometrical representation of the dimensions.

Shape (Categorical): Categorical values represent the six shapes chosen to approximate all products:

- Spherical (e.g., oranges, limes, apples)
- Ovoid (e.g., eggplants)
- Boxy (e.g., wild berries boxes, trails)
- Cylindrical (e.g., leek, cucumber)
- Pyramidal or conical (e.g., broccoli, savoy cabbage)
- Irregular (e.g., goods in nets)

This characteristic is defined by the 3D regular shape that best approximates the products' shape. The category shape merges symmetry and shape from Fantoni et al. [1] to one category. Symmetry is closely linked to the product shape, making it feasible and more precise to approximate the product form using a general shape.

Deformability (Boolean): The product or its packaging is deformable (1) or not deformable (0). Nets, plastic bags, and bundles, which wrap the products loosely are examples of deformable products. Single products like apples and oranges are not deformable.

Delicacy (Boolean): The product is delicate (1) or not delicate (0). Delicacy defines its vulnerability to bruises, cuts, or deformation when the product is being handled. The category toughness and sensitivity defined by Fantoni et al. [1] are merged into delicacy. When it comes to food

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products, delicacy holds more significance than toughness, as fruits and vegetables are not inherently tough. Sensitivity and delicacy encompass similar attributes, yet delicacy proves to be the more suitable term. Figs and grapes are delicate, while potatoes and carrots are not.

Shape Irregularity (Boolean): The product or its packaging shape is regular (0) or not regular (1). The categories irregularity, regular curved surface, and planar surface defined by Fantoni et al. [1] are merged in the property shape irregularity. This parameter includes different geometrical properties of the products. A shape is considered irregular when it detaches from the regular shape associated with the product. Lumps, uneven surfaces, and complex shapes make the shape of the product irregular. Examples of irregular products are artichokes, broccoli, and tomato vines. Examples of regular-shaped products are apples, oranges, and eggplants.

Presence of grooves and/or holes (Boolean): The product has grooves and or holes (1) or does not have grooves and holes (0). The categories porosity and presence of holes defined by Fantoni et al. [1]. are merged to the presence of grooves and/or holes. Grooves and holes on the products' surface prevent the product from being grasped by suction. Ananas presents many grooves. Nets and holed bags present holes. Apples and oranges are examples of not grooved or holed products.

Table 1. Product properties from literature (left side) and derived product properties for this publication (right side).

Product Properties	
Fantoni et al. [1]	**This publication**
Weight	Weight
Size	Size
Shape	Shape
Symmetry	
Irregularity	Shape Irregularity
Regular curved surface	
Planar surface	
Shape can change	Deformability
Toughness	Delicacy
Sensitivity	
Porosity	Presence of grooves and/or holes
Presence of holes	
Stacked	Distance with other products and free sides
Tangled	

3.3 Scenario Description

The product arrangement in the boxes significantly affects the gripper selection. A cluttered scenario can be quite complex. However, the most crucial factor that affects successful grasping is related to the highest unobstructed product. The key point is whether this highest unobstructed product has open space around it within the arrangement.

Cluttering (Categorical): The product is not cluttered (0) the product is semi-cluttered (1), or the product is cluttered (2). A product is not cluttered if there is no obstacle within a frame of 30 mm around the product, a product is semi-cluttered if a minimum of two opposite sides are free accessible, a product is cluttered if all the sides of the products are not free accessible (Figure 3). Regarding oblong items, the grip is consistently applied perpendicular to the longest axis. Thus, if even one of the two sides along the longest axis is cluttered, it is automatically categorized as being in a cluttered state, instead of semi-cluttered.

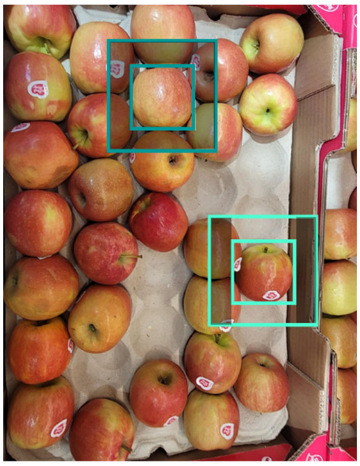

Figure 3. Example for semi-cluttered and cluttered scenarios. The darker sides around the fruits are not reachable, and therefore cluttered.

3.4 Grippers

Research has been conducted to explore suitable grasping principles for grasping fruits and vegetables. The following grasping principles were evaluated:

- Suction Grippers
- Pneumatic Finger Grippers
- Tendon Grippers
- Rigid Grippers
- Jamming Grippers
- Magnetic Grippers
- Electromagnetic Grippers

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The following requirements need to be fulfilled for the grasping principle to be suitable for the grasping of fruits and vegetables:

- Ability to handle fragile products without damaging them.
- Adaptability to grasp diverse and non-uniform shapes.
- Compatibility with the design and material guidelines essential for safe food handling.

The evaluation is done by asking experienced researchers in the field of automatic grasping. The only two grippers that satisfy all three fundamental requirements are the suction gripper and pneumatic finger gripper (Table 2).

Table 2. Evaluation of grasping principles for handling fruits and vegetables.

	Delicate	Shape compliant	Design and material compatibility
Suction Gripper	X	X	X
Pneumatic Finger Gripper	X	X	X
Tendon Gripper	X	X	
Rigid Gripper			X
Jamming Gripper		X	X
Magnetic Gripper			X
Electromagnetic Gripper			X

Suction grippers vary in their size and shape. For the evaluation in this paper two different types of suction grippers are used (Figure 4), which are provided by Schmalz GmbH:

- Circular: Ø 22 mm (SGC22), Ø 32 mm (SGC32) and Ø 43 mm (SGC43).
- Oval: 60 x 25 mm (SGO60) and 80 x 35 mm (SGO80).

Pneumatic finger grippers can be either parallel or circular, parallel finger grippers need two free sides around the product, while circular finger grippers envelop the product on every side. For the evaluation in this paper, two different types of pneumatic fingers are used (Figure 4), which are provided by SoftGripping GmbH. Pneumatic finger grippers differing in the size:

- Normal finger (67 mm in length and 20 mm in width): 3, 4, and 8 finger grippers (3FG, 4FG, 8FG), 3 in circular gripper configuration, 4 and 8 are in parallel gripper configuration.
- Gorilla Finger® (98 mm in length and 33 mm in width): 4 and 6 Gorilla Finger® grippers (4GFG, 6GFG), 4 is in parallel gripper configuration, 6 in circular configuration.

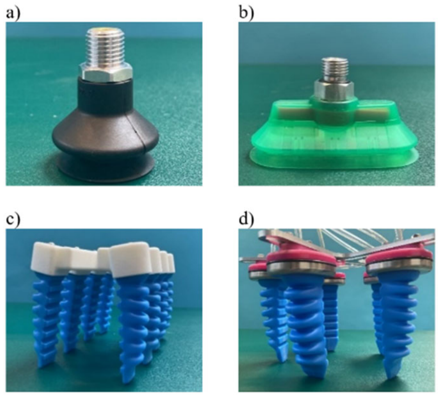

Figure 4. Suction grippers, circular a) and oval shape b) Finger grippers c) and Gorilla Finger ® grippers d).

3.5 Preliminary Tests

Preliminary tests are conducted to test both the validity and the reliability of the defined parameters and to provide evidence that the defined parameters fit the gripper's capabilities. The preliminary tests are conducted with the most suitable gripper configuration for each of the chosen grasping principles. For each product property, a product was chosen randomly, and 100 grasping tests were conducted both in cluttered and non-cluttered environments.

The tests have been carried out with a UR 10 robotic arm, run at 100 % speed. The grasping point detection is executed with the camera rc_Visard 65 from Roboception. This software of the camera determines grasping points by employing segmentation to isolate objects, then defines the depth information to find the highest object to be grasped, and finally identifies the center of this object as grasping point.

A grasp is considered successful when the product is put correctly in the receiving box. A grasp is considered unsuccessful when falling or colliding with the environment. Furthermore, grasping point detection does not always deliver optimal grasping points, and occasionally leads to grasping points that are not in the middle of the product. These grasping attempts are not considered. The decision if a grasping point is not optimal is made during the experiments by the performer of the experiments.

For evaluation of the preliminary tests, the success rate is computed. The success rate is computed for each test case independently and is the ratio between the number of successful grasping tests and the total amount of conducted grasping tests. A gripper configuration is appropriate for a product, if the success rate is higher than 90 %. From all 28 preliminary test cases, 11 (39.2 %) are successful and 17 (60.7 %) are unsuccessful. Table 3 shows the related success rate in cluttered and non-cluttered environments. The first column displays the test scenario, the second the evaluated property, and the third column the chosen product for preliminary tests. The last columns state the results, if the success rate is higher than 90% the font is bold.

Table 3. Results of the preliminary tests (Numbers are reported in bold if grasping is considered successful).

Test scenario	Property	Product	Success Rate	
			Suction Gripper	Pneumatic Gripper
Non-cluttered scenario	Deformable	Bag of carrots	12%	78%
	Not deformable	Lemons	**94%**	**91%**
	Irregular shape	Tomato vine	16%	**90%**
	Regular surface	Orange	**98%**	**93%**
	Presence of holes and grooves	Net of lemons	55%	81%
	Absence of holes and grooves	Pears	**96%**	**96%**
	Delicate	Tomatoes	7%	**96%**
Cluttered scenario	Deformable	Bag of carrots	9%	3%
	Non-deformable	Lemons	**92%**	15%
	Irregular shape	Tomato vine	13%	0%
	Regular surface	Orange	**95%**	12%
	Presence of holes and grooves	Net of lemons	48%	7%
	Absence of holes and grooves	Pears	**90%**	8%
	Delicate	Tomatoes	6%	0%

3.6 KNOWLEDGE-BASED ALGORITHM

A decision tree is employed for the knowledge-based gripper selection. The decision tree is carried out on a dataset generated with the properties defined in Section 3.2 and the results of the preliminary tests in Section 3.5. Nodes correspond to parameters and branches to conditions. Parameters encompass both numerical and Boolean types, resulting in a hybrid decision tree. The tree is composed of 10 nodes that correspond to the parameters and rules presented in Section 3.2. The structure of the decision tree is the same for each product since all the parameters previously defined can be applied to each of them. The rules for the decision tree are individually defined for each gripper configuration based on experience and preliminary tests. The tree presents only exclusion rules; therefore, the output is represented by Boolean values, attached to each gripper. The decision tree was implemented using the Python library Pandas.

3.7 PRODUCT CLUSTERING

Product clustering is used to choose representative products for empirical tests. To achieve this a five-dimensional cluster analysis according to five properties defined in Section 3.2 is done (shape, shape irregularity, deformability, delicacy, presence of grooves and/or holes). Weight and size are not considered as they are independent of the grasping principle.

The choice for the optimal number of clusters is made by using the silhouette score. The silhouette score quantifies how well-separated the clusters are, considering both the cohesion within each cluster and the separation between different clusters. The silhouette score was calculated for the five-dimensional cluster analysis with clusters from 1 to 15. The highest score was 0.38 achieved with six clusters. With a close examination of the clusters, products with rather similar properties are in each cluster. The six cluster names are chosen according to the most representative property:

- Unpackaged spherical products (e.g., cantaloupe, limes)
- Unpackaged elongated products (e.g., cucumber, carrots)
- Bundles (e.g., spring onion, parsley)
- Bags (e.g., apples in bags, carrots in bags)
- Nets (e.g., lemons in net, onions in net)
- Boxes (e.g., berries boxes)

Two products are extracted randomly from the first five of the six clusters. Due to the small size of the sixth cluster, only one representative product was chosen. The validation of the knowledge-based selection is performed on these 11 products (cantaloupe, limes, cucumber, carrots, spring onion, parsley, apples, carrots, lemon, onion, and berries boxes).

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4 Results

The setup for the tests was designed with the scope of recreating realistic order picking scenarios. Euro-boxes (300 mm x 400 mm x 120 mm) are used to store the goods in the same manner in which the fruits and vegetables are stored in boxes in supermarkets (Figure 5).

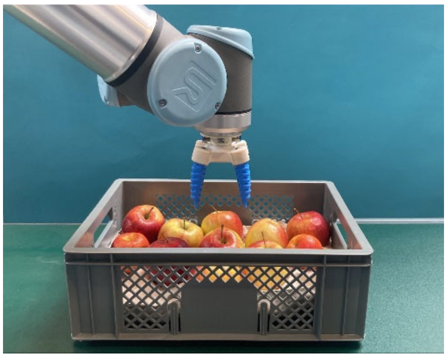

Figure 5. The experimental setup for the empirical tests.

4.1 Empirical Results

The tests have been carried out with a UR 10 robotic arm, run at 100 % speed. The grasping point detection is executed with a rc_Visard 65 from Roboception. This software of the camera determines grasping points by employing segmentation to isolate objects, then defines the depth information to find the highest object to be grasped, and finally identifies the center of this object as the grasping point.

A grasp is considered successful when the product is put correctly in the receiving box. A grasp is considered unsuccessful when falling or colliding with the environment. Furthermore, grasping point detection does not always deliver optimal grasping points, and occasionally leads to points that are not in the middle of the product. These attempts are not considered. The decision if a grasping point is not optimal is made during the experiments by the performer of the experiments.

For evaluation of the empirical tests, the success rate is computed. The success rate is computed for each test case independently and is the ratio between the number of successful grasping tests and the total amount of conducted grasping tests. A gripper configuration is appropriate for a product if the success rate is higher than 90 % percent.

For each product in a specific scenario, each gripper was tested. Initially, 10 grasping attempts are executed on each test case. If the success rate is higher than 20 % 90 more tests are executed resulting in 100 grasping attempts. If the success rate is lower than 20 % no further tests were conducted.

For empirical tests, the eleven products from Section 3.7 are used. As long products such as cucumber, carrots, and bundles of parsley are automatically packed cluttered for these products only not cluttered and cluttered test scenarios were considered. For all other products also the third (semi-cluttered) test scenario is considered. Overall, 29 empirical test cases were conducted with all the 10 gripper configurations chosen, resulting in 290 decisions evaluated. Summarizing the empirical results 26 (9.1 %) of the test cases have a success rate higher than 90 % and the remaining 264 (90.9 %) have a success rate lower than 90 % and are classified as not reliably graspable.

The empirical test results are reported in Table 5. The table represents the grippers in the first column and all the possible products and scenarios in the top rows. The percentages represent the success rate of the empirical test results. A dash indicates that the first 10 grasping attempts have a success rate lower than 20 % and no further grasping attempts were conducted.

Table 4. Empirical test results and the knowledge-based selection result.

	Spherical Products						Elongated Products				Bundle				Bags						Nets						Boxes		
	Canalupe			Limes			Cucumber		Carrots		Spring Onions		Parsley		Carrots bag			Apples Bag			Lemon net			Onion net			Berries box		
	NC	SC	C	NC	SC	C	NC	C	NC	C	NC	C	NC	C	NC	SC	C	NC	SC	C	NC	SC	C	NC	SC	C	NC	SC	C
3FG	-	-	-	94%	43%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4FG	-	-	-	89%	81%	-	-	-	-	-	49%	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6GFG	93%	-	-	-	-	-	-	-	-	-	-	-	-	-	39%	-	-	32%	-	-	83%	-	-	88%	-	-	74%	-	-
8FG	-	-	-	-	-	-	93%	-	90%	-	76%	-	81%	-	-	-	-	-	-	-	-	-	-	-	-	-	84%	62%	-
4GFG	67%	45%	-	-	-	-			81%		83%	-	87%	-	44%	-	-	-	-	-	78%	47%	-	82%	63%	-	91%		-
SCR22	-	-	-	94%	90%	95%	-	-	57%	48%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	82%	84%	71%
SCR32	74%	78%	74%	89%	90%	87%	32%	30%	48%	53%	-	-	-	-	-	-	-	-	-	-	43%	49%	-	-	-	-	92%	90%	89%
SCR43	80%	83%	89%	-	-	-	86%	86%	-	-	-	-	-	-	-	-	-	-	-	-	55%	56%	39%	51%	53%	48%	97%	92%	89%
SCO65	95%	90%	83%	-	-	-	96%	87%	81%	85%	-	-	-	-	-	-	-	-	-	-	61%	59%	53%	69%	72%	63%	99%	95%	92%
SCO80	95%	92%	92%	-	-	-	91%	89%	56%	50%	-	-	-	-	-	-	-	-	-	-	39%	-	31%	49%	42%	-	98%	97%	91%

4.2 Knowledge-based selection results

By analyzing 94 different fruits and vegetables with their packaging types within the three distinct scenarios – cluttered, semi-cluttered, and uncluttered – a total of 282 different test cases were generated. Applying the decision tree to each of the 10 predefined gripping configurations yields a cumulative outcome of 2820 binary decisions. 548 (19.4%) of the 2820 decisions output positive results, which means that the gripper can grasp the product in the given scenario, in 2272 (80.6%) the gripper evaluated is not able to grasp the product in the given scenario.

Considering all 282 different test cases, the automatic knowledge-based selection method results in 184 (64.9 %) successfully grasped by at least one of the gripper configurations, while 98 (35.1 %) test cases remained ungraspable by any of the gripper configurations. The results differ highly according to the scenario. Among the 184 products that are graspable by at least one gripper, 85 products (46.7 %) in not cluttered test scenarios, 57 products (31.0 %) in semi-cluttered test scenarios, and 41 products (22.3 %) in cluttered test scenarios.

4.3 Evaluation of the knowledge-based selection with empirical tests

An evaluation of the performance of the knowledge-based selection method is done by comparing the results of the decision tree with the empirical tests.

The output of the knowledge-based selection method and the empirical tests are not directly comparable. The knowledge-based selection method yields a binary output (a gripper is either suitable for a specific product in a test case or not suitable), whereas the empirical tests yield success rates in percentage. Therefore, test cases with success rates higher than 90 % are defined to be successful (1), and test cases with success rates lower than 90 % are defined to be unsuccessful (0).

Table 5. Combination of the possible results from the knowledge-based selection and the empirical tests.

		Knowledge-based predicted Results	
	Total Results	Positive	Negative
Condition derived from epirical results	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

Applying the results to the empirical test results and the results of the knowledge-based selection method led to 4 classes: true positives, true negatives, false positives, and false negatives (Table 5). The evaluation of these results leads to:

- 26 test cases are true positives (9.1 %)
- 27 test cases are false positives (9.3 %)
- 237 test cases are true negatives (81.6 %)
- No test case is false negative (0 %)

The results are shown in **Fehler! Verweisquelle konnte nicht gefunden werden.**. In the first column, all the grippers are listed by using the abbreviations introduced in Section 3.4. The following columns are grouped on the first level concerning their cluster, on the second level concerning their representative products (see Section 3.7**Fehler! Verweisquelle konnte nicht gefunden werden.**) and, finally, for each product, the three test scenarios are displayed (cluttered (C), semi-cluttered (SC) and non-cluttered (NC)). The success rates of the empirical tests are stated in percentages. The underlying color represents green for true positives, light green for true negatives, red for false positives, and light red for false negatives.

Accuracy is the fraction of correct classifications divided by the total amount of classifications. The accuracy of the knowledge-based selection method is 27 divided by 290 resulting in 90.7 %.

The tests' success rates are generally lower than those forecasted by the proposed knowledge-based selection method. This is mainly due to inherent gripper limitations. Despite the pneumatic finger gripper and the suction grippers being the optimal choice for handling fruits and vegetables, their reliability is limited to values comprised between 80 % and 99 %, with an average of 88.1 %. The knowledge-based selection method relies solely on exclusion rules. This restricts the ability to create a comprehensive model that fully captures the complexity and variability of the grasping action. Enhancing accuracy could be achieved by incorporating more rules beyond simple exclusion within the knowledge-based selection.

Concerning the grasping principles finger grippers are not able to envelop the product when located in a highly cluttered scenario. Suction grippers do not reliably grasp types of products, such as deformable and air-permeable products like bags, nets, and bundles. The combination of these characteristics, deformable or holed or grooved products in highly cluttered scenarios gives the lowest success rate considering both pneumatic finger grippers and suction grippers.

Lastly, a limitation of this study, arising from their practical nature, involves the execution of the tests. As mentioned, the decision on whether a grasp is unsuccessful

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due to the failed grasping or due to camera detection failure.

5 Conclusion

This study demonstrates the promising application of a knowledge-based decision system for the automatic selection of gripper configurations within a subset of e-grocery items.

The inability to grasp many of the products in real scenarios underscores the necessity for continued research and innovation in the development of new grippers for cluttered delicate products. To achieve reliable knowledge-based selection methods for industrial applications all products should be grasped by at least one gripper. A solution could be to merge several grasping principles. Therefore, the presented knowledge-based decision system can be easily used to find a suitable gripper that can be combined for a given product range.

In addition to the grippers investigated in this study, further grasping systems should be implemented to be able to grip all these products in cluttered environments. This will be crucial for the successful integration of robotic automation in the fruit and vegetable handling industry, leading to increased productivity, reduced waste, and improved overall efficiency of food e-commerce.

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