Picking-and-placing food with vacuum pad and soft gripper for industrial robot arm

Mr. Wiwat Tulapornpipat

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Engineering in Cyber-Physical System
Department of Mechanical Engineering
FACULTY OF ENGINEERING
Chulalongkorn University
Academic Year 2020

การหยิบและวางอาหารด้วยแผ่นสุญญากาศและนิ้วจับแบบยืดหยุ่นสำหรับแขนหุ่นยนต์อุตสาหกรรม

นายวิวรรธน์ ตุลาภรณ์พิพัฒน์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต
สาขาวิชาระบบกายภาพที่เชื่อมประสานด้วยเครือข่ายไซเบอร์ ภาควิชาวิศวกรรมเครื่องกล
คณะวิศวกรรมศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2563

Thesis Title	Picking-and-placing food with vacuum pad and soft gripper for industrial robot arm
By	Mr. Wiwat Tulapornpipat
Field of Study	Cyber-Physical System
Thesis Advisor	Associate Professor ALONGKORN PIMPIN, Ph.D.
Thesis Co Advisor	Professor Hayashi Eiji, Ph.D.

Accepted by the FACULTY OF ENGINEERING, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Engineering

.... Dean of the FACULTY OF ENGINEERING

(Professor SUPOT TEACHAVORASINSKUN, D.Eng.)

THESIS COMMITTEE

.... Chairman

(Professor PAIROD SINGHATANADGID, Ph.D.)

.... Thesis Advisor

(Associate Professor ALONGKORN PIMPIN, Ph.D.)

.... Thesis Co-Advisor

(Professor Hayashi Eiji, Ph.D.)

.... Examiner

(NATTAPOL DAMRONGPLASIT, Ph.D.)

.... External Examiner

(Kakanand Srungboonmee, Ph.D.)

วิวรรธน์ ตุลาภรณ์พิพัฒน์ : การหยิบและวางอาหารด้วยแผ่นสุญญากาศและนิ้วจับแบบยืดหยุ่นสำหรับแขนหุ่นยนต์อุตสาหกรรม. (Picking-and-placing food with vacuum pad and soft gripper for industrial robot arm) อ.ที่ปรึกษาหลัก : รศ. ดร.อลงกรณ์ พิมพ์พิณ, อ.ที่ปรึกษาร่วม : ศ. ดร.ฮายาชิ อิจิ

มนุษย์มีความต้องการอาหารที่แตกต่างกันด้วยสาเหตุหลายอย่าง เช่น โรคประจำตัว, ภูมิแพ้, อายุ, เพศโดยกำเนิด, เชื้อชาติหรือศาสนา เป็นต้น นอกจากนั้นในปัจจุบันผู้คนนิยมเลือกรับประทานอาหารตามคุณค่าทางสารอาหารมากกว่าราคา ดังนั้นอาหารเฉพาะสภาวะบุคคล หรืออาหารที่มีการปรับเปลี่ยนวัตถุดิบให้เหมาะสม จะได้รับความสนใจภายในระยะเวลาอันใกล้นี้ ในแง่มุมที่กล่าวมานี้หุ่นยนต์อัตโนมัติสำหรับประกอบอาหารเป็นตัวเลือกที่ดีในการผลิตชุดอาหารกล่องจำนวนน้อย แต่มีความสามารถในการปรับเปลี่ยนวัตถุดิบได้สูง เพื่อให้เข้ากับความต้องการที่กำหนดได้ โดยระบบอัตโนมัติสามารถลดระยะเวลาและต้นทุนในการปรุงอาหาร รวมไปถึงลดการปนเปื้อน แล้วยังมาพร้อมกับการตรวจสอบย้อนกลับที่ดีในเหตุการณ์ที่ผิดปกติได้ อย่างไรก็ตามหุ่นยนต์ที่สามารถทำงานได้ดังที่กล่าวมายังคงอยู่ในช่วงเริ่มต้นของการพัฒนา ประเด็นหนึ่งคือการออกแบบส่วนประกอบมือจับของหุ่นยนต์ที่ใช้ในกระบวนการจับและวางอาหาร ที่ควรจะมีความสามารถในการปรับเปลี่ยนได้อย่างรวดเร็วเพื่อให้ใช้ได้กับอาหารประเภทต่างๆได้ดี ในวิทยานิพนธ์นี้ได้มีการสร้างและประเมินระบบแขนหุ่นยนต์ประกอบอาหารชุดที่มีความยืดหยุ่นสูง หุ่นยนต์สามารถจดจำและกำหนดตำแหน่งของอาหารญี่ปุ่นและจับวางลงในกล่องได้ โดยส่วนประกอบที่ใช้จับอาหารได้ถูกออกแบบตามหลักโมดูลาร์เพื่อติดตั้งมือจับแบบยืดหยุ่นและแผ่นสุญญากาศร่วมกัน สมรรถนะของระบบได้รับการประเมินโดย กระบวนการหยิบและวางในสถานการณ์ต่างๆ การทดลองได้ใช้ไก่ทอด ข้าวปั้น และโบโลน่า โดยการจับและวางใส่กล่องอาหาร ผลการทดลองสำหรับอาหารประเภทเดียว ระบบสามารถเลือกและวางอาหารลงในกล่องอาหารได้สำเร็จร้อยละ 90 อย่างไรก็ตามอัตราความสำเร็จจะลดต่ำกว่าร้อยละ 50 เมื่อระบบทำการหยิบและวางอาหารหลายประเภทลงในกล่องอาหาร

สาขาวิชา	ระบบกายภาพที่เชื่อมประสานด้วยเครือข่ายไซเบอร์	ลายมือชื่อนิสิต ....
ปีการศึกษา	2563	ลายมือชื่อ อ.ที่ปรึกษาหลัก ....
		ลายมือชื่อ อ.ที่ปรึกษาร่วม ....

6270373021 : MAJOR CYBER-PHYSICAL SYSTEM
KEYWORD: food automation, soft gripper

Wiwat Tulapornpipat : Picking-and-placing food with vacuum pad and soft gripper for industrial robot arm. Advisor: Assoc. Prof. ALONGKORN PIMPIN, Ph.D. Co-advisor: Prof. Hayashi Eiji, Ph.D.

Human with different conditions such as disease, allergy, gender, ethnicity, or religion need different types of food. Nowadays, people prefer to choose diet based on nutrition value over price such as composition of food or the impact on body, so personalized or customized food could potentially be a big market in few years. With this aspect, the assembly robot becomes a good choice in the food industry to produce the small amount of packed meal with highly adjustable ingredients to match with the requirements. With the automation system, the cooking process is faster, cheaper and safer, yet coming with good traceability in unusual incidents. However, the robot that overall works practically is still in an early stage of development. One issue is a design of the end-effectors that should be interchangeable to match with different types of food. In this thesis, a highly flexible food assembling framework has been realized and evaluated. The robot with designed end-effector could recognize and localize objects to assemble Japanese lunch box. A modular end-effector using soft gripper and vacuum pad in the single unit was designed, prototyped, and installed. The performance has been evaluated by the pick-and-place process with various scenarios. For a single type of food, the system could successfully pick-and-place karaage, onigiri, and bologna into a meal box with a 90% success rate. However, when picking and placing multiple types of food, the success rate is reduced lower than 50%.

Field of Study:	Cyber-Physical System	Student's Signature ....
Academic Year:	2020	Advisor's Signature ....
		Co-advisor's Signature ....

ACKNOWLEDGEMENTS

First of all, I would like to express my gratitude to Assoc. Prof. Ratchatin Chancharoen, Ph.D., Head of Program Master of Engineering in Cyber-Physical System, Chulalongkorn University, Thailand, for his intuitive to keep up with the situation and develop the first Cyber-Physical System (CPS) in Thailand.

I want to express my deep gratitude to my research advisor, Asst. Prof. Alongkorn Pimpin, Ph.D., for allowing me to be part of this program and providing invaluable guidance throughout this research. He has taught me the methodology to carry out the thesis and to present it as clearly as possible. I also want to extend my gratitude to my co-advisor, Prof. Hayashi Eiji, Ph.D., Head of Eiji Hayashi Laboratory and Deputy Executive Director for Regional Academia-Industry Revitalization, Kyushu Institute of Technology (KIT), Japan, for allowing me to research in his laboratory during January - September 2020. I am also filled with gratitude for Sakmongkon Chumkamon, Ph.D., Postdoctoral researcher in the Eiji Hayashi laboratory, for his guidance throughout my time at KIT.

I would like to acknowledge the Department of Mechanical Engineering, Chulalongkorn University and Prof. Hayashi Eiji for providing me the financial support throughout this research both domestic and internationally.

I am incredibly grateful to my parents for their love, prayers, caring, and continuing support to complete this research work and prepare me for my future. I am very much thankful to my sister for their support and valuable encouragement.

I want to say thanks to my friends in the CPS program and members of the Eiji Hayashi laboratory, especially Mr. Noboru Takegami, for taking care of me as a tutor, and Mr. Tomofumi Tsuji, for lending me both hands in experiments.

Wiwat Tulapornpipat

TABLE OF CONTENTS

Page

ABSTRACT (THAI) iii

ABSTRACT (ENGLISH) iv

ACKNOWLEDGEMENTS v

TABLE OF CONTENTS vi

LIST OF TABLES ix

LIST OF FIGURES x

Chapter 1 Introduction 1

1.1 Background and motivation 1

1.2 Image processing 4

1.2.1 Image classification with localization VS. object detection 4

1.2.2 Semantic VS. instance semantic segmentation 5

1.2.3 Cascade Mask R-CNN [6] 6

1.3 End-effectors of robot 6

1.3.1 Air-based techniques 7

1.3.2 Contact-based techniques 7

1.3.2.1 Gripper 7

1.3.2.2 Multi-body mechanism 9

1.4 Using multiple end-effectors on a single industrial robot arm 11

1.5 Objectives of research 12

1.6 Scopes of research 12

1.7 Expected benefit gain 12

1.8 Research plan ... 13
Chapter 2 Methodology of research ... 14
2.1 Hardware Design ... 15
2.2 Software Design ... 20
2.2.1 Robot Operating System (ROS) [30] ... 20
2.2.2 MoveIt! [33, 34] ... 21
2.2.3 Rviz [39] ... 22
2.2.4 Instance semantic segmentation for Japanese food ... 23
2.2.5 Image processing to determine the centroid of an object ... 23
Chapter 3 Experiments and results ... 26
3.1 Explanation of pick and place motion ... 26
3.2 Pick and place of a singular object ... 29
3.2.1 Experiment conditions ... 29
3.2.1.1 Karaage ... 29
3.2.1.2 Onigiri ... 30
3.2.1.3 Bologna ... 31
3.2.1.4 Lunchbox ... 31
3.2.2 Experiment results ... 31
3.2.2.1 Karaage ... 31
3.2.2.2 Onigiri ... 32
3.2.2.3 Bologna ... 32
3.2.2.4 Lunchbox ... 32
3.3 Assembly of a singular object ... 33
3.3.1 Experiment conditions ... 33

3.3.2 Experiment results 34

3.4 Assembly of multiple objects 35

3.4.1 Experiment conditions 35

3.4.2 Experiment results 35

Chapter 4 Conclusion and discussion 37

4.1 Conclusion 37

4.2 Discussion 38

REFERENCES 40

VITA 45

LIST OF TABLES

Page

Table 1 Characteristics of Robotiq FT300 18

Table 2 Stiffness of Robotiq FT300 18

Table 3 Instance segmentation on COCO test-dev 23

Table 4 Area of images and annotation in the dataset 23

Table 5 Dimension and weight of karaages 30

Table 6 Dimensions and weight of onigiri 30

Table 7 Dimensions and weight of bologna 31

Table 8 Summary of pick and place of single karaage 31

Table 9 Summary of pick and place of single onigiri in three different orientations . 32

Table 10 Duration of grasping (row "G") and releasing (row "R") of soft gripper 34

LIST OF FIGURES

Page

Figure 1 Evolution of food manufacturing through industry 1.0 to 4.0 [1]...................... 1

Figure 2 Traceability proposal of industry 4.0 (modified from [2]) 2

Figure 3 Estimates of the crude birth rate in Thailand [3].. 3

Figure 4 Different applications of image processing [5]... 5

Figure 5 Comparison between low and high IoU [6].. 6

Figure 6 Architecture of Cascade Mask R-CNN [6].. 6

Figure 7 Parallel jaw gripper (left)[10], specialized jaw gripper (middle)[11], and robot hand (right)[12] 8

Figure 8 Grasping principles of granular jamming gripper [13] 8

Figure 9 Holding force of granular jamming gripper variance with geometry (left) and variation of holding force with the different surface condition (right) [13] 9

Figure 10 Range of geometric motion of Hybrid soft robotic gripper [15].................... 10

Figure 11 Unactuated (left) and actuated (right) of monolithic compliant finger [16]10

Figure 12 Operation process of soft pneumatic grippers with origami pump[17] 11

Figure 13 SetupRobotics quickchange dual toolbase... 12

Figure 14 Conceptual of components in the system 14

Figure 15 Theoretical suction force [19]... 15

Figure 16 Difference opening width of Soft Robotics finger 15

Figure 17 Pose of the robot when using a different tool (top) [21] and vector diagram for weight measurement of both approaches (bottom)... 16

Figure 18 Proposed design (left), and Components of the tool base (right).................. 17

Figure 19 Components of CKD VSXP-T666 [26]... 18

Figure 20 Computer-Aided Design of the modular end effector 19

Figure 21 Hardware diagram of the modular end effector 20

Figure 22 Simulation environment in Gazebo and OctoMap visualization in RViz. [36] 21

Figure 23 Comparison between dataflow and interface model 22

Figure 24 3D centroid extraction process 24

Figure 25 Dataflow model from RGB-D image to ROS markers 24

Figure 26 Ready to pick pose (left) and a workspace of experiments (right) 26

Figure 27 Camera setup in every experiment 27

Figure 28 Graphical representation of experiments scenarios 28

Figure 29 Measurement of karaage dimensions 29

Figure 30 Different orientation of onigiri 30

Figure 31 3D reconstructed from failed trials of picking onigiri by the corner 32

Figure 32 Trajectory of failure of pick and place single lunchbox 33

Figure 33 Conditions for assembly of a singular object assembly 33

Figure 34 Grasping and releasing motion of soft gripper 34

Figure 35 Conditions for assembly of multiple object assembly 35

Figure 36 Viable grasping pose proposals from GPE[42] (left) and 3D model of onigiri in the upright orientation (right) 39

Chapter 1

Introduction

1.1 Background and motivation

Food industry 1.0 utilized human labor from harvest crops/meat to process the products. For example, farmers use sickle or scythe to reap rice from the field then use millstones to grinding it. In the food industry 2.0, electrical-powered appliances have been introduced to cope with people's demands by mass production. For example, a butcher uses an electric meat slicer instead of a butchering knife, or a baker uses an electric oven instead of a gas or firewood oven. Automation processes came in the food industry 3.0 to further accelerate mass production. For example, automated filling/canning, labeling, and palletizing process in various beverages, as shown in Figure 1. Since industry 1.0 to 3.0, humans have tried to make products by mass production faster and faster to fulfill people's demands. Nevertheless, recently, the mass production trend is declining.

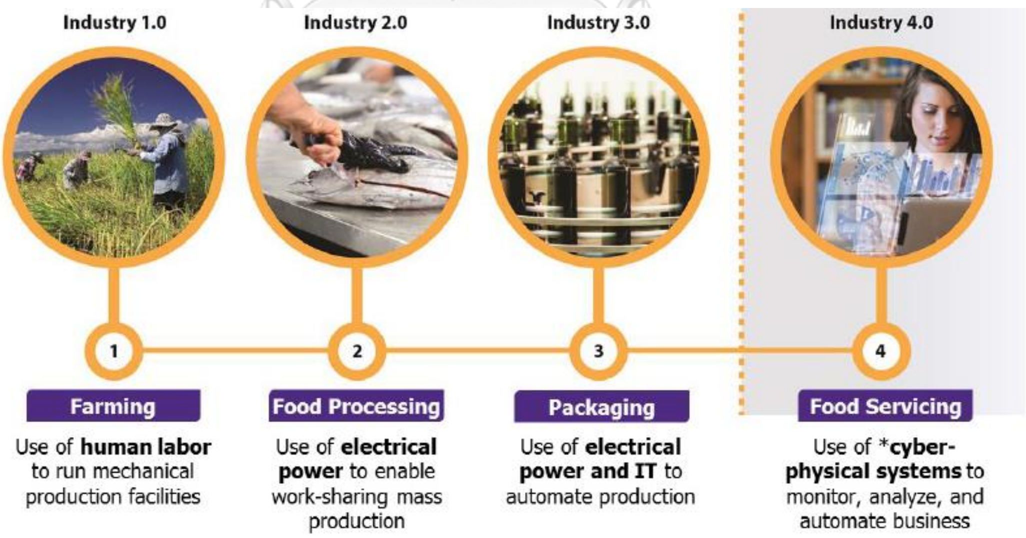


Figure 1 Evolution of food manufacturing through industry 1.0 to 4.0 [1]

Industry 4.0 utilizes connectivity to enhance industry automation further and create the cyber-physical system, which is the system that both cyber and physical are closely intertwined together. Artificial Intelligence (AI) is undoubtedly one of the most famous modules in industry 4.0 because it can make decisions based on big data in any form: images, point clouds, coordinate inputs, cost and retail price of products, the trend of demand-supply. Other famous modules are high-speed connectivity such as 5G or WiFi 6 because they bring monitoring capability and traceability closer to real-time.

The food industry will be benefited from industry 4.0 right from the ingredients tracing[2] to market insight. For example, the identification platform in Figure 2reads and fills the origin of ingredients to the cloud database. Then, the system will measure each ingredient's weight while the robot prepares them for cooking in the manufacturing process of Figure 2. Finally, the system generates a unique nutrition label for each packed meal from the measured values. Consumers can check the specific nutrition from the cloud database, such as the packed meal's exact calories. Every purchase that occurs will be recorded to the cloud for further analysis by the marketing department to adjust the highly flexible production line in the manufacturing plant to minimize food waste and maximized the cost-price margin. Another benefit of the food automation process is reducing food contamination, which can cause foodborne illness, from humans. Even if someone got infected, we could trace it back through processes after processes back to the origin of ingredients because we already have big data about the food, such as where the patient bought that food and how the logistic process handled food containers.

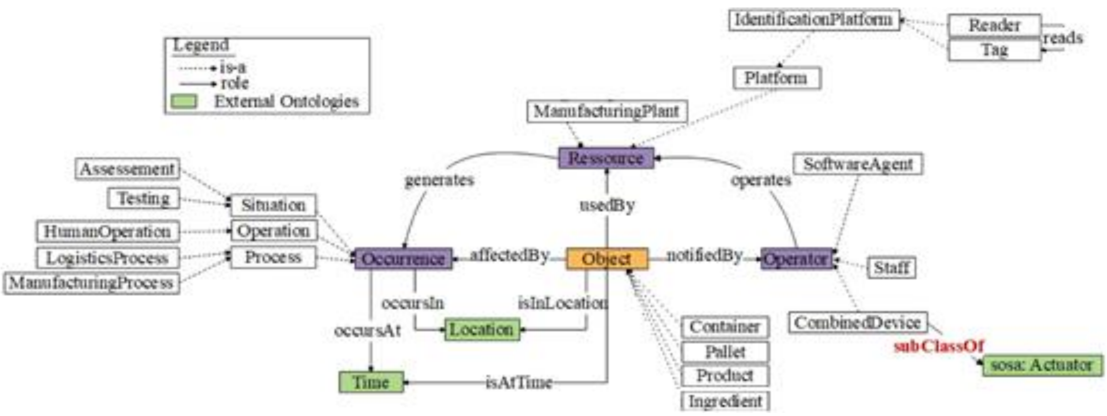


Figure 2 Traceability proposal of industry 4.0 (modified from [2])

Thailand's birth rate declined from 20.2 births per thousand of the population in 1988 to 10.2 in 2019[3], as shown in Figure 3. In addition to the declined birth rate, people over 60 years old will be 20% of Thailand's population by 2021[4]. Furthermore, people over 60 years old will require personalized or reformulated food. For example, older people might need sodium reduction or sugar substitution. Both indicators (birth rate and elder to population ratio) show that Thailand will have less population of workable age.

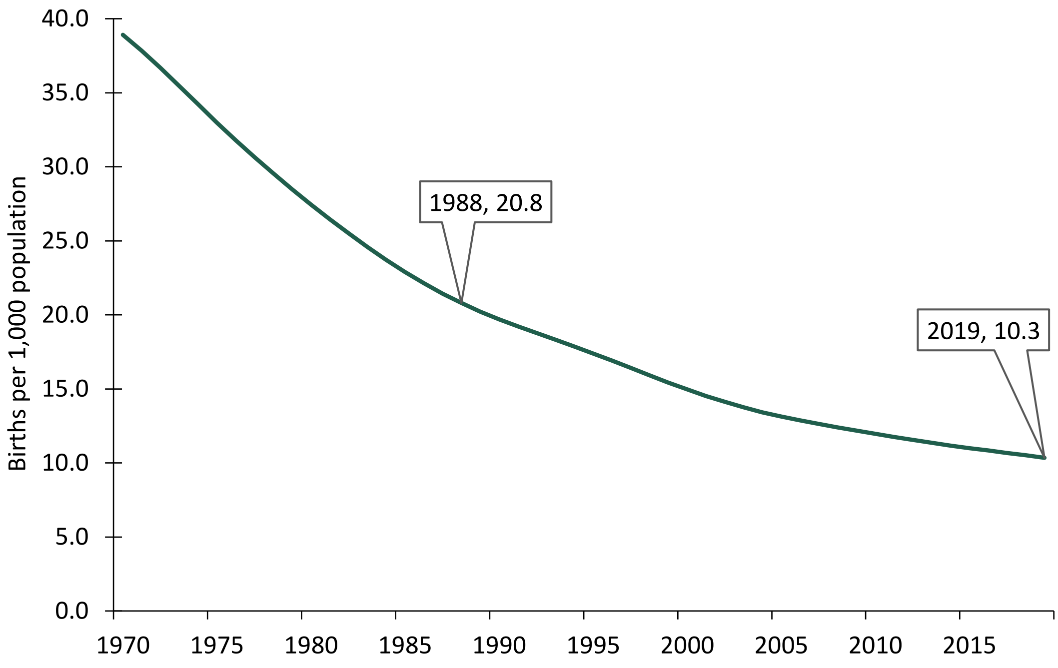


Figure 3 Estimates of the crude birth rate in Thailand [3]

Thailand's food industry should evolve from automated to highly flexible food production lines as soon as possible to produce a specialized or customized meal for people who need or want it with less labor force in the industry. The ideal of highly flexible food production should be the assembly station to complete the packed meal by only one station. It could be multiple robots with different end-effectors for various ingredients to complete the packed meal together or a standalone unit robot with interchangeable end-effectors to handle various ingredients. For example, an industrial robot arm equipped with a wrist camera and modular end-effectors could potentially be that standalone unit. The industrial robot arm is highly flexible for object handling tasks. The wrist camera does not have a blind spot because it is fixed to a robot arm's wrist. Moreover, carefully selected end-effectors can pick a broad range of objects.

In this research, a modular end-effector for the food assembling process with an industrial robot arm has been prototyped and evaluated for pick and place performance in cycle time and success rate. Additionally, this research also experimented with Japanese food because Hayashi robotics laboratory in Kyushu Institute of Technology in Japan already set up a working environment. Furthermore, some of the Japanese food is almost identical to Thai food.

1.2 Image processing

In the early day, image processing came into the industry as a barcode reader or product rejection system based on physical appearance. With the help of AI, image processing could do a lot more than those mentioned applications.

Pick and place systems must have image processing for object localization, shape detection, or pose estimation. Some systems might have object tracking to enable object manipulation while the object moves along the conveyor.

1.2.1 *Image classification with localization VS. object detection*

The most basic applications of image processing are image classification with localization. The image classifier can tell what the object is, and the image localizer will predict the bounding box around the object. Hence, image classification with localization assumes that there is only one object in the given image. The output would be a single vast bounding box that includes every instance if the image has multiple instances of an object, as illustrated in Figure 4(a). However, an image of a single object is hardly found in food manufacturing, so object detection is more suitable than image classification with localization. The object detection can determine each object's bounding box and gives that segment in the bounding box to an image classifier, which labels each bounding box, as illustrated in Figure 4(b).

1.2.2 *Semantic VS. instance semantic segmentation*

It is good to know each object's location in the given image, but we need to know each object's shape if we want to grasp it optimally.

Semantic segmentation can label every single pixel of a given image. So, the output from semantic segmentation could determine the shape of an object for optimally grasping pose. Like object classification and localization, semantic segmentation does not separate an object's instances within the same class. For example, the semantic segmentation algorithm's output will tell us which region of the image is sheep or grass. However, it does not separate each sheep's region in the given image, as illustrated in Figure 4(c). Like object detection, instance segmentation can differentiate each object's region as instances, so we can determine each object's shape, as illustrated in Figure 4(d).

In conclusion, we need the instance segmentation for image processing if we want to grasp the object optimally. The image classification with localization works on a single instance in the given image assumption. Object detection works with multiple instances but does not capable of shape determination. Semantic segmentation can determine the shape of objects. Similar to image classification with localization, it also works with a single instance in a given image assumption.

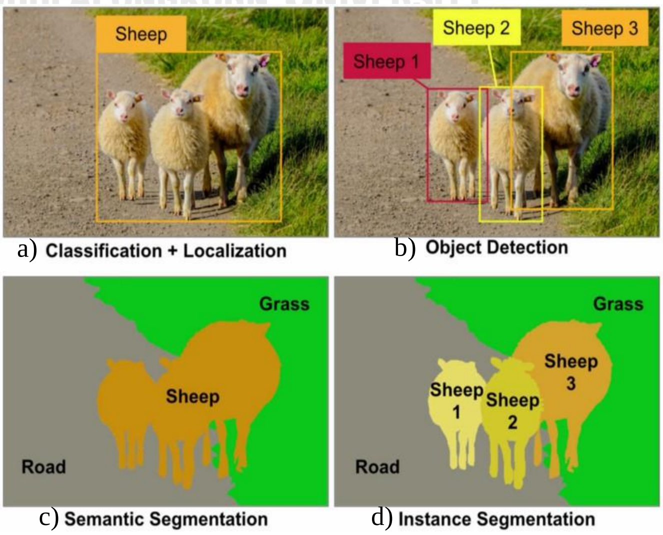


Figure 4 Different applications of image processing [5]

1.2.3 *Cascade Mask R-CNN [6]*

Intersection over Union (IoU) is the threshold in range zero to one, which defines the quality of detection sub-network or detector. High IoU leads to a high-quality detector that produces less noisy bounding boxes, as illustrated in Figure 5. However, detectors trained with high IoU have two problems, which are overfitting: high threshold detector ignores positive samples and quality mismatch between detectors and available hypotheses at inference test.

Cascade Mask R-CNN is a multi-layer architecture composed of sequences of detectors, as illustrated in Figure 6. One layer consists of I: input image, conv: backbone convolution, B0: proposal, pool: region-wise feature extractor, H: region-of-interest (ROI) detector, C: classification, S: mask prediction, and B: bounding box generator. Those detection heads are sequentially trained using the previous detector's output with gradually increasing IoU to mitigate those two problems.

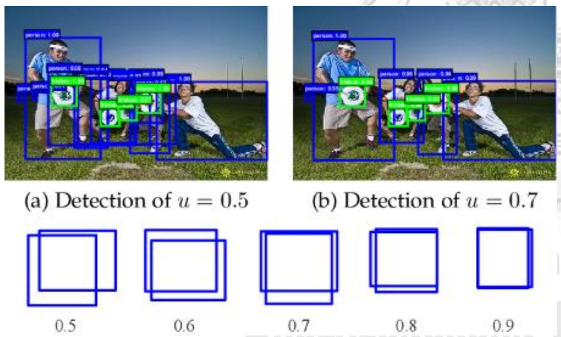


Figure 5 Comparison between low and high IoU [6]

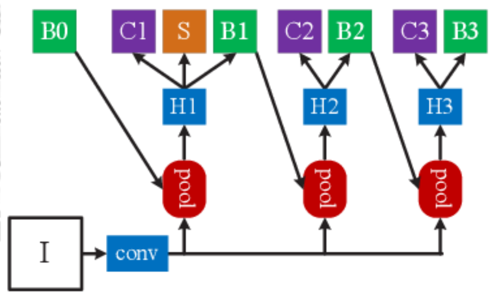


Figure 6 Architecture of Cascade Mask R-CNN [6]

1.3 End-effectors of robot

Robots with proper end-effector can grasp and orientate products up to six degrees of freedom[7]. However, the food industry's equipment must meet hygienic design (ANSI DIN EN 1672-2) for food contacted equipment, ingress protection (IP) at least 65, and corrosion resistance for thorough cleaning.

Air-based and contact-based are two conventional object manipulation techniques. The air-based technique is further separate into vacuum and pressure. Contact-based also separates into gripper and multi-body mechanism.

1.3.1 *Air-based techniques*

Vacuum pads or suction cups transmit force to the product with negative pressure difference, so the product should have as low porosity as possible. Suction cups developed for food handling have few features in common: increased contact area with the inner surface pattern or ribs, prevent clocked airway, distribute suction force on the product, and decreased suction mark.

Positive-pressure pneumatic grippers work by Bernoulli's principle, which utilizes a high flow rate of gas between the surface of the gripper and flat, light, and rigid objects to generate lift force with zero contact. In 2010, Petterson et al.[8] and Sam and Nefti[9] researched Bernoulli gripper for a 3D shape such as grapes, cherries, tomatoes, strawberries.

1.3.2 *Contact-based techniques*

1.3.2.1 Gripper

- There are three types of grippers in the food automation industry: jaw gripper, a robot hand, and granular vacuum jamming gripper.
- Jaw grippers use a pneumatic or electric actuator to actuate rigid fingers. Jaws could be simple as parallel jaws or customized to match the shape of an object. The speed of actuation or gripping force of a jaw gripper could be adjusted with the right actuator. However, the rigid gripper cannot adapt to the non-rigid shape of food.
- The robot hand has more DoFs than the jaw gripper to simulate the human hand, so they can adapt to the non-geometric shape of food, as shown in Figure 7 (right). However, it is too expensive to deploy on a factory scale.

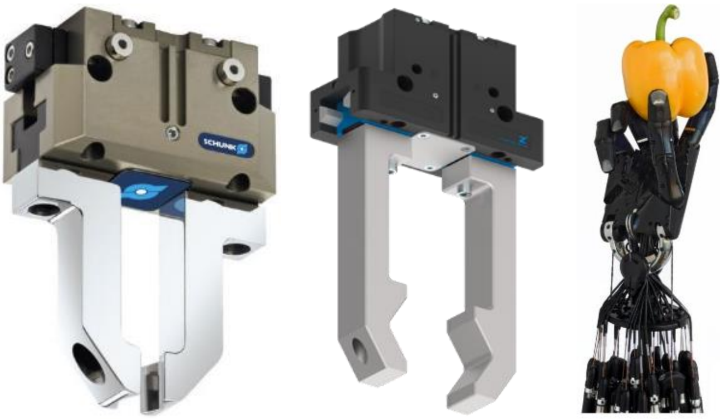


Figure 7 Parallel jaw gripper (left)[10], specialized jaw gripper (middle)[11], and robot hand (right)[12]

- Brown et al. developed a granular jamming gripper, which uses friction, suction, and interlocking mechanisms to build the gripping force for the object's various shapes, as illustrated in Figure 8 [13]. Experiment with different objects' shapes shows a success rate at 100% in 10 trials of any objects, which can sufficiently wrap the side. However, it cannot grip objects without proper geometric conditions, such as thin objects, as illustrated in Figure 9(left). The holding force also drops drastically from 40 N to 4 N because of poor surface conditions (non-porous surface powdered with cornstarch), as illustrated in Figure 9(right).

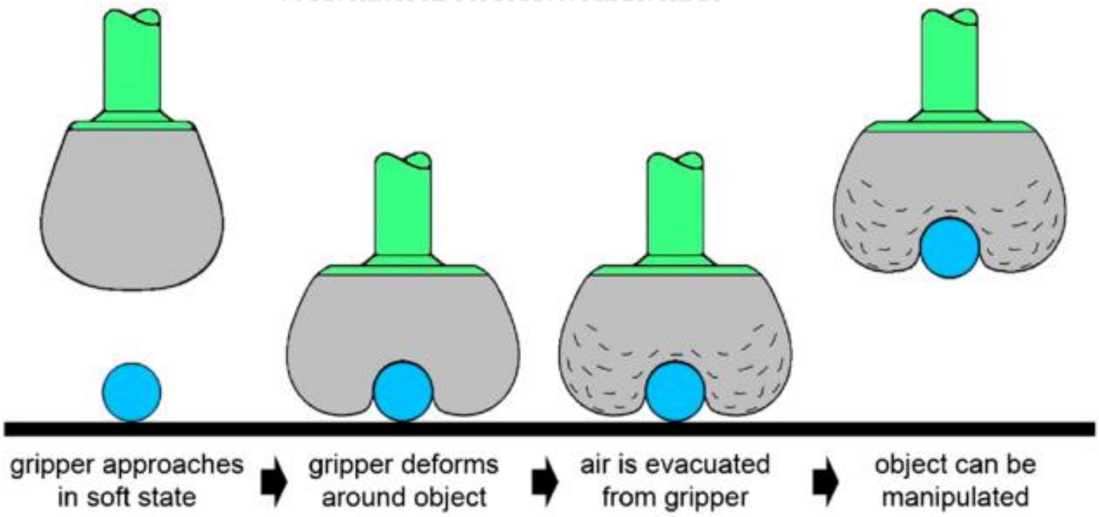


Figure 8 Grasping principles of granular jamming gripper [13]

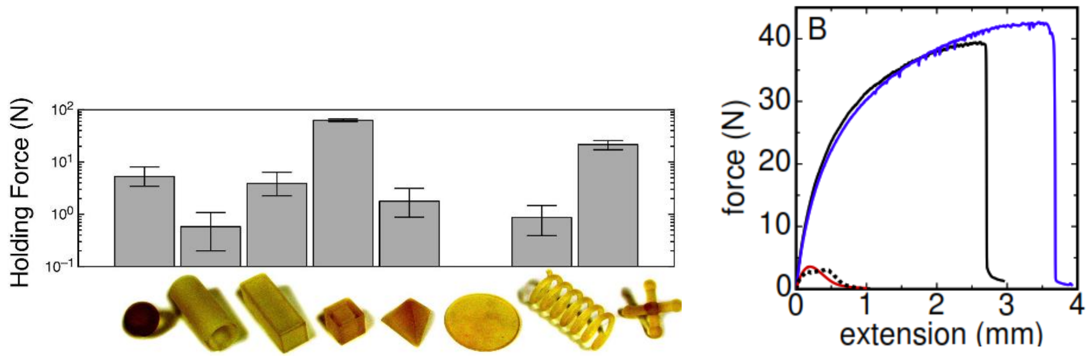


Figure 9 Holding force of granular jamming gripper variance with geometry (left) and variation of holding force with the different surface condition (right) [13]

1.3.2.2 Multi-body mechanism

With the expansion of automation, especially in sorting and bin packaging for delivery, many newly developed grippers can handle various objects. The multi-body mechanism has more output DoFs than the number of actuators to reduce the end-effector's cost while maintaining the universality of object handling. Hence, the generic name of this gripper is an underactuated mechanism. On the contrary, an underactuated mechanism is challenging to control trajectory if they are too flexible.

The significance of soft robotics for industrial is soft grippers, manipulators, and sensors because automation processes and robotics applications grow toward unstructured tasks with not well-defined environments [14]. Continuum body manipulators made from soft materials have large deformation, which means they have high DoFs, but the precise control for real-world application is challenging. As DoFs increased, soft grippers/manipulators can grasp objects with more universality. However, high DoFs decreased the ease of manipulator control in actuator control or behavior simulation, if not both.

Jiawei Meng et al. researched a hybrid tendon-driven, pneumatically actuated soft robotic gripper[15] with a wide range of geometric motion. This finger exploits the stiffness difference between silicone's inner and outer layers, as shown in Figure 10.

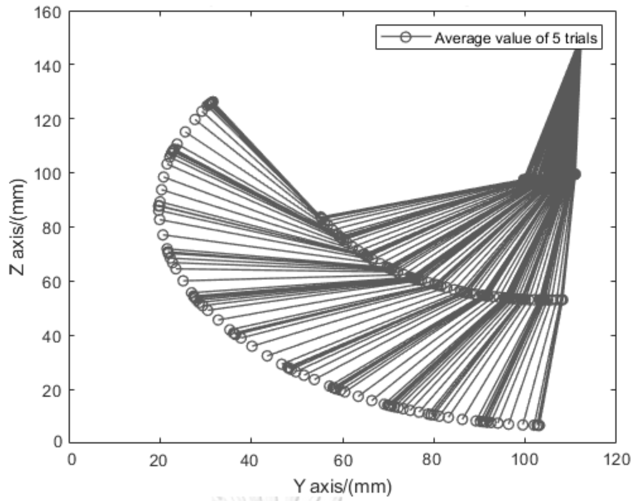


Figure 10 Range of geometric motion of Hybrid soft robotic gripper [15]

Chih-Hsing Liu et al. used the topology optimization method to synthesize the monolithic compliant finger with a high mechanical and geometric advantage (MA and GA, respectively) [16] to develop a soft gripper to solve the issue with fragile and irregular object automation processes. Their experiments show a high MA characteristic with no damage to the surface of fruits and a high GA characteristic with two-dimensional output motion from linear input, as shown in Figure 11.

Yeunhee Kim and Youngsu Cha developed a soft pneumatic gripper made from silicone with a pneumatic chamber and soft air compressor made from “Kresling” origami-patterned polypropylene film[17]. This soft gripper exploits geometric differences from unequal material extension between the finger's flat and wavy side to create two-dimensional finger motion, as illustrated in Figure 12.

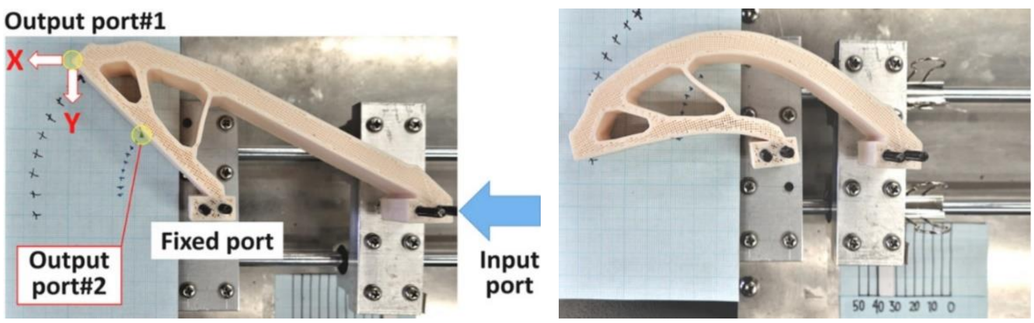


Figure 11 Unactuated (left) and actuated (right) of monolithic compliant finger [16]

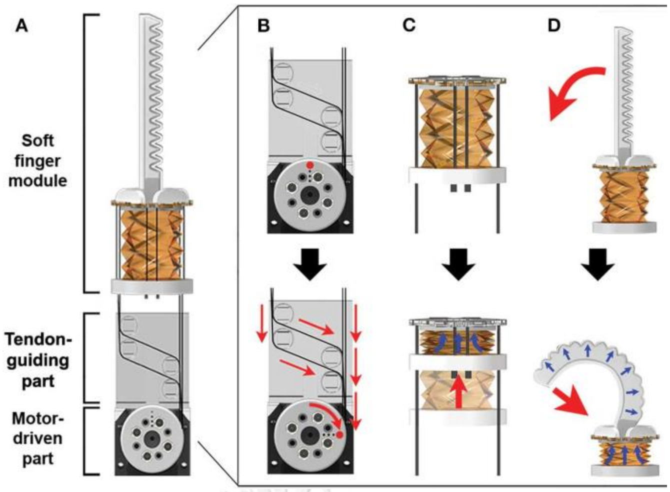


Figure 12 Operation process of soft pneumatic grippers with origami pump[17]

To summarize, the granular jamming gripper is the gripper with the most universality. Supposed that we use this gripper with food, it could contaminate the food. Because the bag of granular material must be air permeable, so the liquid from food such as oil or seasoning may get trap in the fabric of the bag or the granular material itself. Tentacle-like hybrid gripper would be too difficult to simulate gripper's behavior when actuated because it is actuated by both tendon and pneumatic pressure, not to mention that the material is heterogeneous. Monolithic compliant finger looks promising, but flexure joints from topology optimization prone to suffer from fatigue. The soft pneumatic gripper is the all-around performer in terms of good geometric advantage and ease of both behavior simulation and actuator control.

1.4 Using multiple end-effectors on a single industrial robot arm

In order to realized a standalone food assembly unit, the industrial robot arm should be able to use multiple end-effectors. There are several practical approaches to enable a single industrial robot arm to use multiple end-effectors. Most of those approaches are tool swapping techniques inspired by CNC machines. Another approach installed two end-effectors on a single unit, as shown in Figure 13[18]. However, this approach chooses end-effectors with the industrial robot arm's degree of freedom, so each tool's axis is not aligned with the industrial robot arm's axis.

Misalignment of each tool leads to difficulty in computing both trajectory and object's weight.

Figure 13 SetupRobotics quickchange dual toolbase

1.5 Objectives of research

This research aims to prototype and evaluate modular end-effector for non-rigid food. This modular end-effector solves a misalignment problem by maintaining each of both end-effectors' axis as if it is installed directly to the robot arm.

1.6 Scopes of research

The following topics are included in this thesis.

- A prototype of modular end-effector made from additive manufacturing.
- An instance segmentation model for karaage, onigiri, bologna, and meal box.
- Experiment to evaluate modular end-effector in these criteria
  - The success rate of pick and place process.
  - Actuation duration of the soft gripper's grasping and releasing
  - Actuation duration of end-effector switching

The following topic is excluded from this thesis.

- Modification of instance segmentation algorithm

1.7 Expected benefit gain

An operational pick and place system for non-rigid food with low cycle time is expected from this research.

1.8 Research plan

Steps	(Month and year the thesis research starts...January 2020...)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Design and fabricate twin tool																		
2	Hardware installation																		
3	Label dataset and train instance segmentation model																		
4	Create a digital twin of the system																		
5	Create image processing python script																		
6	Experiment																		
7	Conclude the work to thesis																		

Chapter 2

Methodology of research

There are several types of grippers for the food industry, such as vacuum pads, which are good at pick flat and light objects, and soft grippers that are good at picking non-geometric objects. However, the highly flexible food production cannot rely only on either end-effector because it will expose the food too long. Therefore, a modular end-effector with both a vacuum pad and soft gripper in a single unit was proposed to open a possibility for highly flexible food manufacturing. A vacuum pad could pick the thin and light object, such as leaves vegetable, meal box and lid, sliced meat, and a bag of seasoning. Soft gripper could grasp a solid object, such as fried food, fruits, a chunk of meat, et cetera. Furthermore, a 6-axis force-torque sensor, IMU, and RGB-D camera are added, as illustrated in Figure 14, to add weight measurement and instance segmentation capabilities to the system.

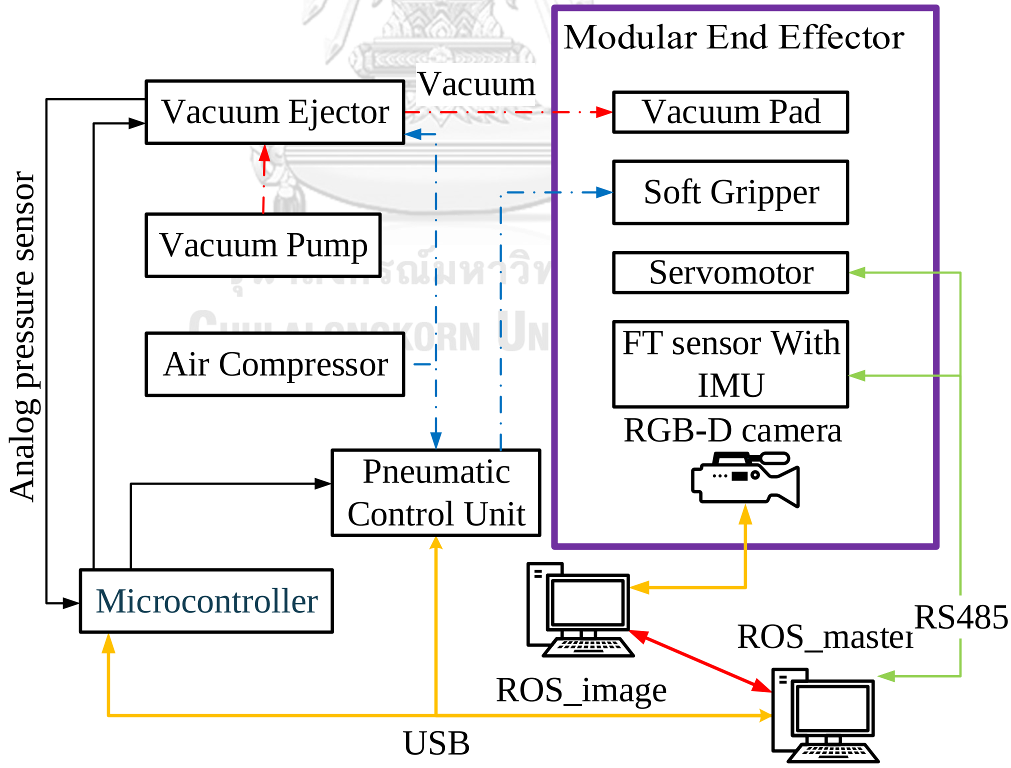


Figure 14 Conceptual of components in the system

2.1 Hardware Design

There are many shapes of vacuum pads: standard for flat objects, deep for round shape, sponge, and multi-bellow for uneven surface objects. Nevertheless, multi-bellow also capable of handling fragile objects, which is suitable for bologna and meal boxes. We used a multi bellow vacuum pad with ten millimeters diameter, four millimeters bellows stroke, and eight Newton of theoretical suction force at -100 kPa vacuum[19], as shown in Figure 15.

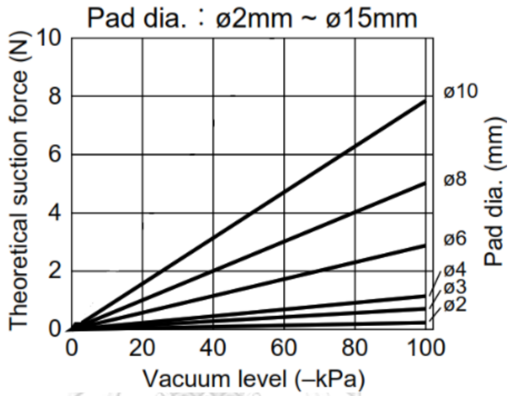


Figure 15 Theoretical suction force *[19]*

There are several types of soft grippers, such as contact-driven compliant fingers[16], tendon-driven[15], fluidic elastomer actuators[17]. Soft Robotics mGrip[20] was chosen because it is a commercial fluidic elastomer soft gripper system, as shown in Figure 16. The mGrip's maximum pressure of compressed air is 14psi, controlled by an electronic pressure controller, so users can vary the control loop response to match their applications. There are eight on-the-fly selectable profiles, which can pre-defined pressure and opening width for different objects' weight and dimensions.

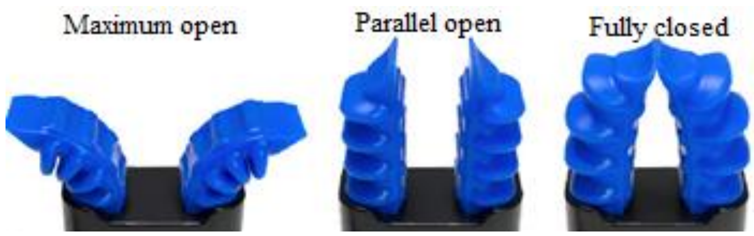


Figure 16 Difference opening width of Soft Robotics finger

The branching point in hardware design is how to install both vacuum pad and soft gripper in a single unit. The first approach attaches both end-effector to a rigid structure and uses the industrial robot arm's degrees of freedom to select the end-effector[18], as illustrated in Figure 17 (top). This approach has the advantage of low manufacturing and maintenance costs because it does not require actuators. On the contrary, this approach leads to complications in motion planning because it needs to specify additional goals as to which end-effector will be used to pick objects. Moreover, suppose we need to measure the weight of objects with a force-torque sensor installed at the wrist just before the end effector. In that case, it will be challenging to vectorize gravity to calculate the actual weight, as shown in Figure 17 (bottom). The second approach, which is our design, uses another actuator to select the end-effector by rotation about the auxiliary axis, axis 2, which is inclined 45 degrees but in-plane with axis 1 in Figure 18(left). This approach eliminates every previously mentioned complication because both grippers' axis was maintained as if it directly attached to the industrial robot arm.

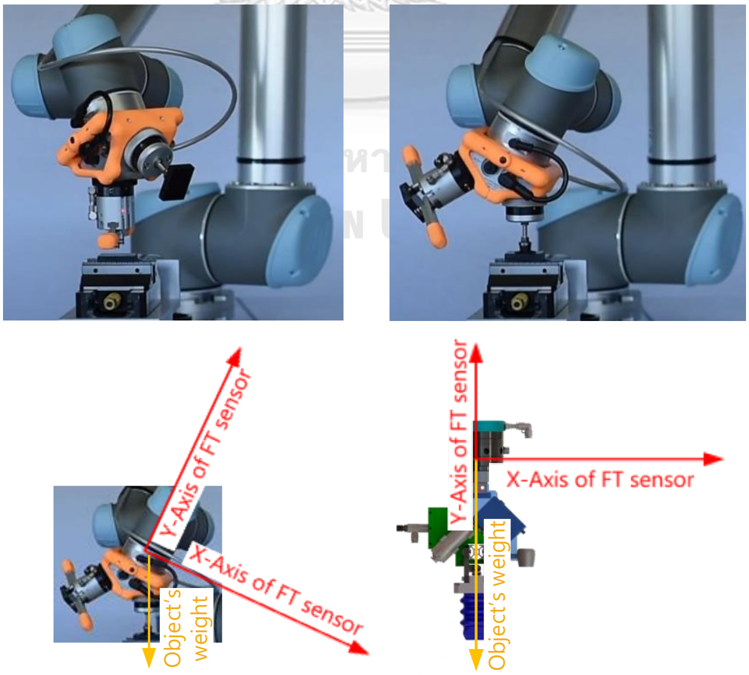


Figure 17 Pose of the robot when using a different tool (top) [21] and vector diagram for weight measurement of both approaches (bottom)

Dynamixel MX-106R servomotor was chosen because of twenty Newton of allowable axial load in a compact size and weighs only 153 grams[22]. Additionally, this servomotor's angular position could be commanded at a 12-bit resolution and visualized with ROS and RViz via a 12V RS485-USB converter.

This thesis's modular end-effector has been designed with a modular principle for ease of manufacturing and maintenance. Both grippers are attached to individual tool plate, assembled to side plates and tool base, then attached to the servo motor, as illustrated in Figure 18(right). This design also allows for a fast tool change, which is crucial for industrial.

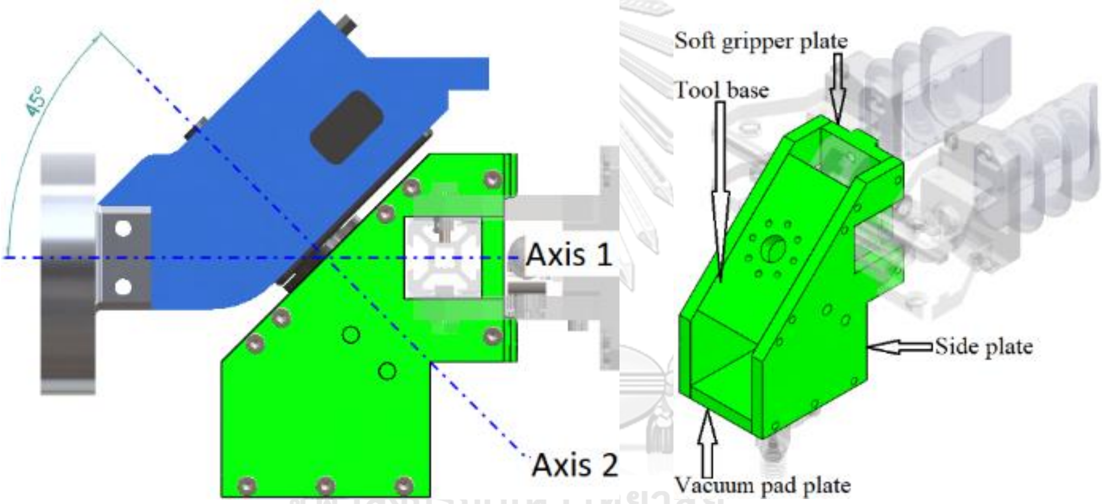


Figure 18 Proposed design (left), and Components of the tool base (right)

Since this research cooperates with Yaskawa Japan, Motoman SIA5F 7-axis industrial robot arm has been used because its best-in-class wrist performance delivered freedom of reachable space with repeatability ±0.05mm[23].

Robotiq FT300 6-axis force-torque sensor was installed for an object's weight measurement. This sensor has little signal noise compared to a full-scale value of three hundred Newton resultant force in three axes and the minimum threshold for the static state (the smallest variation that sensor can detect reliably) as shown in Table 1. Additionally, this sensor also provides a ROS package to communicate via a 24V RS485-USB converter up to 100 Hz. The stiffness of this sensor is high enough to allow the attached tool to perform precision tasks, as shown in Table 2[24].

Table 1 Characteristics of Robotiq FT300

	Signal noise	Minimum threshold
Force in X, Y, Z [N]	0.1	1
Moment in X, Y [Nm]	0.005	0.02
Moment in Z [Nm]	0.003	0.01

Table 2 Stiffness of Robotiq FT300

	Axis X, Y	Axis Z
Force [N/m]	3.2×10^6	3.9×10^6
Moment [Nm/rad]	4.7×10^3	4.6×10^3

9-axis IMU (LPMS-B2) with Bluetooth Low Energy (BLE) 4.1 from LP-Research was used to calibrate the force-torque sensor. This sensor can transmit data up to 400 Hz in quaternion format (ROS native format). It could be powered by connected to a 5V DC source or an internal battery which lasts six hours, with a power consumption of 132mW at 3.3 V[25].

A three-way vacuum ejector (CKD VSXP-T666) was chosen because it significantly reduces the vacuum release time. Two-way valves use only vacuum break air to equalized from vacuum to atmospheric pressure, but three-way valve also let atmospheric pressure from another airway into the vacuum volume to equalized the vacuum pressure[26]. It also has an in-line vacuum filter and an analog pressure sensor for feedback, as shown in Figure 19.

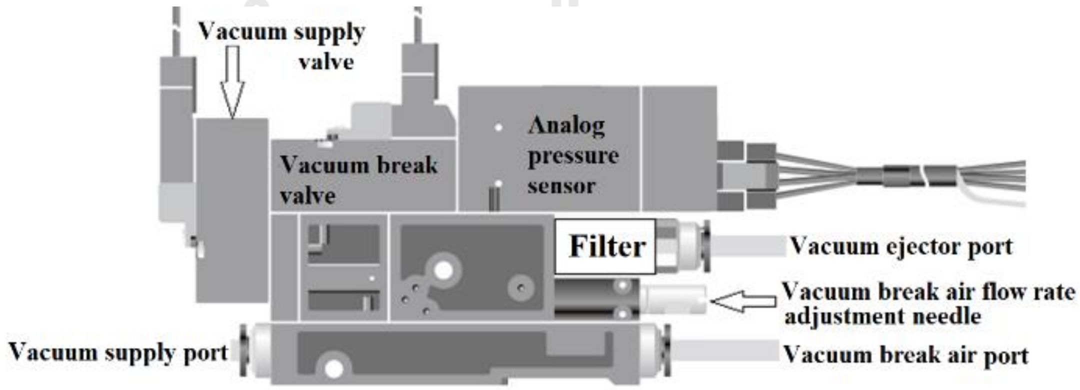


Figure 19 Components of CKD VSXP-T666 [26]

RGB-D cameras, which is Intel Realsense D435i, was installed on the modular end-effector as a wrist camera, as shown in Figure 20. Intel Realsense D435i has IMU, active IR stereo depth sensor, and RGB sensor[27]. RGB-D stream will be sent to the "ROS_image" node, as illustrated in Figure 21, for instance segmentation and image processing to determine each instance of the object's centroid.

Computer-Aided-Design of the modular end effector with pneumatic manifold (the leftmost component in teal-colored), which internal pneumatic hoses came off the wrist of the industrial robot arm, 6 DoFs force-torque sensor (the second left component in black-colored) and RGB-D camera (greyish component on the top) is shown in Figure 20.

A six-liter oil-less air compressor capable of 0.7 MPa with an automatic pressure switch at 0.49 MPa was chosen to supply soft gripper and vacuum break air. A two-stage oil-less vacuum pump capable of -100 kPa vacuum without reservoir was chosen for a vacuum pad[28, 29].

Arduino UNO was used as a microcontroller between ROS and both Soft Robotics's control unit for soft gripper and vacuum ejector for vacuum pad, as illustrated in Figure 21. Arduino subscribes to ROS topic for actuation message of end-effector. When actuation message came into ROS topic, the microcontroller can actuate the vacuum pump and vacuum ejector (both vacuum ejector and break valve) or actuate the soft gripper through NPN transistors. Furthermore, Arduino also selects profiles of the soft gripper with three digital bits signal.

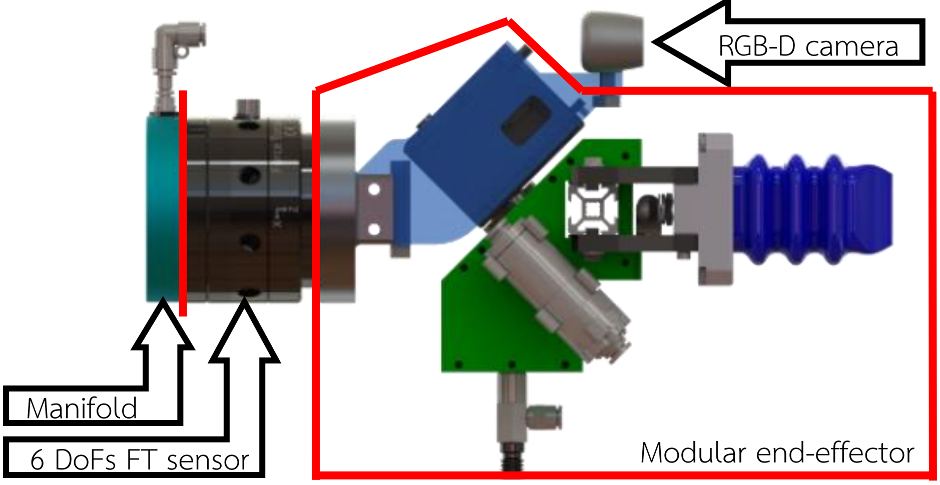


Figure 20 Computer-Aided Design of the modular end effector

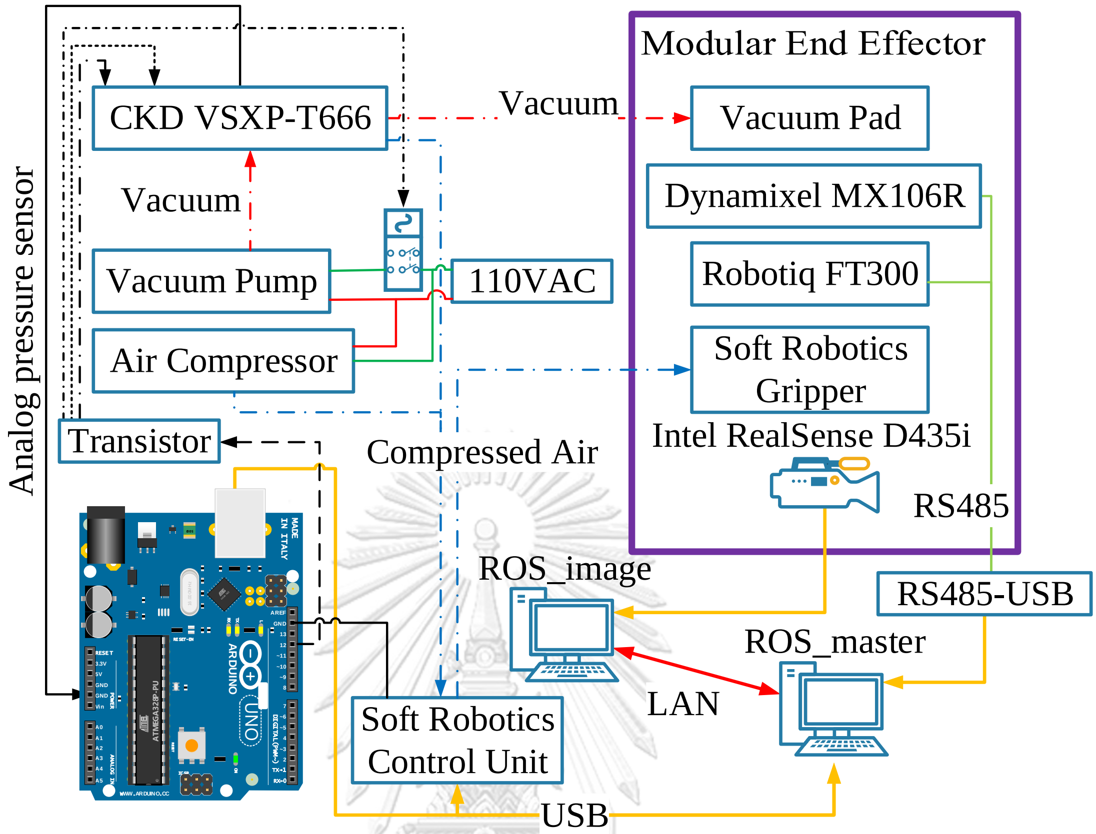


Figure 21 Hardware diagram of the modular end effector

2.2 Software Design

Most of the software in this research is open-source software such as Robot Operating System (ROS), MoveIt! and RViz for communication with robot controller and servomotor, mmdetection, and OpenCV for image processing. However, proprietary instance segmentation for Japanese food was created in this research.

2.2.1 *Robot Operating System (ROS) [30]*

ROS is an open-source robot operating system which piggybacks onto various host operating system such as ROS officially supported: Ubuntu and experimental: Raspbian, Debian, OS X, and Windows. ROS only provides a structured communication layer between heterogeneous computation cluster. ROS has three other philosophical goals since the beginning: peer-to-peer communication topology, multi-programming-lingual, tool-based, and thin.

Peer-to-peer communication topology enables task allocation according to the computation effort requirement, but this requires a process matching mechanism called “rosmaster”.

ROS reuses open-source projects for each major problem, such as OpenRAVE[31] for planning algorithms, OpenCV [32] for computer vision. However, ROS only exposes configuration and provides data routes between each software.

2.2.2 *MoveIt! [33, 34]*

MoveIt! is the open-source robot manipulation platform in ROS capable of 3D perception, manipulation, inverse kinematics, motion planning, collision checking, and joint control. Additionally, MoveIt! is a standard tool for the industrial robot arm. MoveIt! uses OctoMap [35] to convert 3D occupancy map from depth sensor and point clouds to numerous specific resolution cubic for ease of collision checking and memory efficiency, as illustrated in Figure 22.

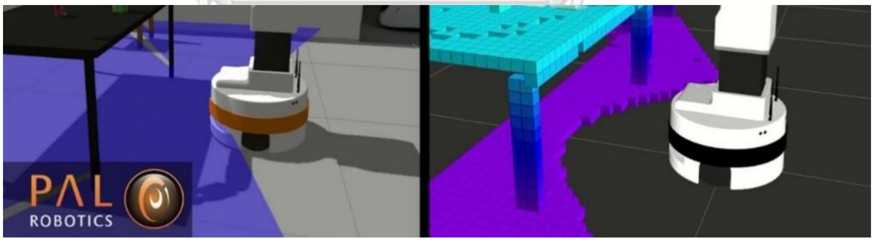


Figure 22 Simulation environment in Gazebo and OctoMap visualization in RViz. [36]

Manipulation of MoveIt! can analyze and interact with the environment, whether it is a representative environment created from 3D perception or the defined environment from the config file. Furthermore, manipulation of MoveIt! can generate grasp solutions for simple objects such as boxes or cylinders. Inverse kinematics (IK) will solve for joint positions from a given specific pose of any link. Typically, the pose of the end-effector is given to IK, and joint positions solution from IK is further given to motion planning as current and goal pose.

There are four motion planning libraries in MoveIt! but there is only one fully supported library, which is OMPL (Open Motion Planning Library)[37]. OMPL collects many state-of-the-art sampling-based motion planners such as RRT* (Optimal Rapidly-exploring Random Trees)[38]. Moreover, OMPL does not specify a collision checker because this makes OMPL easier to integrate other systems.

MoveIt! also provided collision checking from geometric primitives (box, cylinder, sphere, and cone), meshes, or point clouds for OMPL as additional required components. Lastly, MoveIt! executes joint trajectories with respect to time by communicating with low-level hardware controllers of the robot.

2.2.3 *Rviz [39]*

Conventional real domain data visualizer uses the dataflow model. The dataflow model accepts only specific data structures and visualizes algorithms at the invention time of those data visualizer. In the dataflow model, data are kept in specific data structures, converted to transformed data with filter, and send to the renderer as shown in the left of Figure 23. On the contrary, RViz utilizes modular design to separate interfaces from implementations to accelerate the process for researchers who want to use their data structures and algorithms. In the interface model, data implementation of the simple interface such as vector field and decorator implicitly handled the dataflow network, as shown in the right of Figure 23. RViz becomes the main data visualizer in ROS because of the interface model.

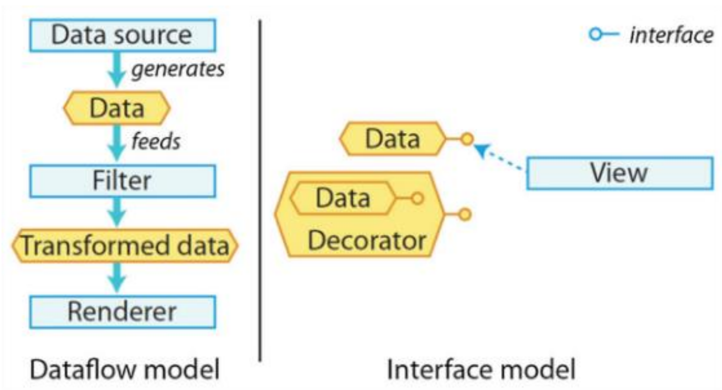


Figure 23 Comparison between dataflow and interface model

2.2.4 *Instance semantic segmentation for Japanese food*

Firstly, the system must know where objects and goals are. Therefore, cascade mask R-CNN was chosen as an instance segmentation algorithm. R-50-FPN backbone with PyTorch style and learning rate of 1x was used to train the model with MMDtection[40]. R-50-FPN has less performance in terms of the mask prediction and bounding box average precision. However, it uses memory more efficiently (the model uses less memory but has faster inference time) than X-101-64x4d-FPN, as shown in Table 3[41]. Model for Japanese food such as piles of karaage, onigiri, box, and bologna was trained for 5,000 epochs with various sizes of images, area of segments, and the number of objects per image as shown in Table 4 with additional 42 images of workspace.

Table 3 Instance segmentation on COCO test-dev

Backbone	Memory (GB)	Inference time (frame per sec)	Mask prediction AP	Bounding box AP
R-50-FPN	6.0	11.2	35.9	41.2
X-101-64x4d-FPN	12.2	6.7	39.2	45.3

Table 4 Area of images and annotation in the dataset

		Quantity	Area [pixel^2]		
			Median	Standard Deviation	Average
Total image		267	330,000	705,578	611,606
Annotation	Karaage	531	4,587	18,840	11,063
	Onigiri	350	10,191	114,722	38,777
	Meal box	105	37,983	31,584	41,957
	Bologna	213	11,214	116,519	42,774

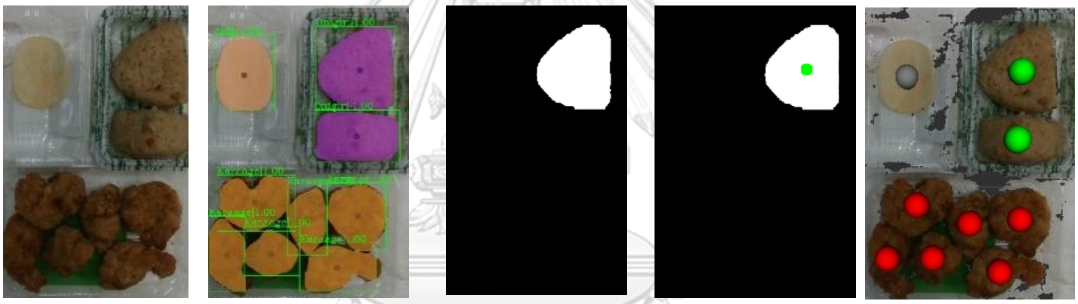
2.2.5 *Image processing to determine the centroid of an object*

3D centroid from each instance segment must be extracted to represent the object's coordinates in ROS, as illustrated in Figure 24. Start with feeding a raw RGB image (as shown in Figure 24(a)) to an instance segmentation model to determine the region of each instance called segments(as shown in Figure 24(b)).

After that, OpenCV was used to extract 2D centroids from segments (illustrated in Figure 24(c)), and deprojection calculation (Equation (1)) was used to deproject pixel coordinates of 2D centroids (shown in Figure 24(d)) to 3D distance coordinates with respect to RGB-D camera. Then, 3D coordinates were sorted by depth and distance. We represent 3D coordinates with ROS markers, as shown in the rightmost picture of Figure 24(e).

$$
\begin{aligned}
x &= (U - ppx)/fx * D * depth\_scale, \\
y &= (V - ppy)/fy * D * depth\_scale, \\
z &= D * depth\_scale
\end{aligned}
\tag{1}
$$

Where U, V, and D are horizontal, vertical and depth pixel values, ppx and ppy are the pixel value of the center of projection, fx and fy are the focal lengths of the image depth_scale is distance per depth pixel value.



a)RGB image b)Superimposed masks prediction c) Binary image of onigiri d)Superimposed 2D centroid e)Superimposed ROS markers

Figure 24 3D centroid extraction process

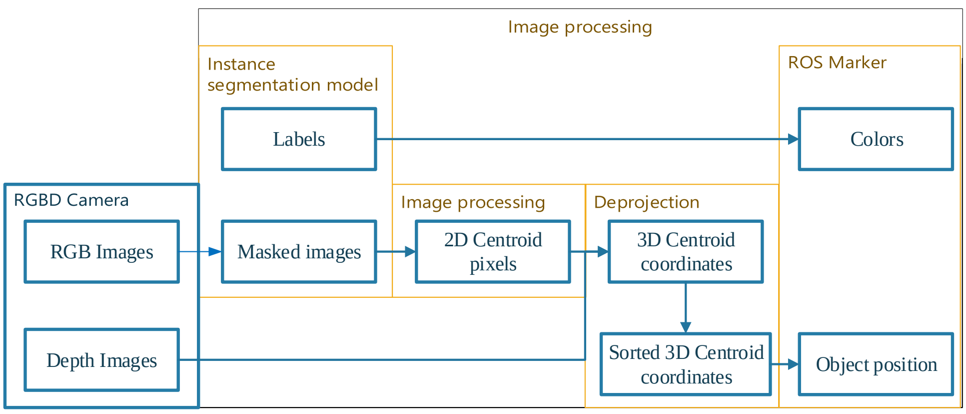


Figure 25 Dataflow model from RGB-D image to ROS markers

Graph search algorithms assume the deterministic system, so most graph search found an optimal path because of exhaustive search, which is considerably computational expensive. On the contrary, sampling-based rapidly-exploring random trees (RRT*) was used to generate the pick-and-place motion from object to the goal location with no prior knowledge about the environment.

To summarize, this chapter shows this research's methodology from two different aspects: hardware and software. The hardware ranges from end-effector selection to computer-aided design model and complete hardware diagram, including electronics, pneumatic and vacuum schematic, and network diagram of ROS nodes. The software ranges from the robot operating system to image processing with a concluded dataflow model.

Chapter 3

Experiments and results

3.1 Explanation of pick and place motion

The motion started with an industrial robot arm in a "ready to pick" pose, where the wrist camera sees as much area of the workspace from the top as possible), as shown in Figure 26 (left). Food (karaage, onigiri, or bologna), an object to be picked, is located in the elliptical area. A meal box, which is a goal, locates in the rectangular area, as shown in Figure 26(right). First, Intel Realsense D435i (wrist camera installed on the robot, as shown in Figure 27) feeds RGB-D stream of images to ROS_image node for 3D centroid extraction process. ROS_Image node is PC with Intel i9-9900k, Nvidia Geforce RTX 2080Ti, and 32GB of DDR4 RAM. Second, ROS_master reads 3D centroids coordinates from the ROS network, solves the trajectory from object's to target's location, and executes the pick and place (P&P) motion. ROS_master is Dell's Inspiron 7590 laptop. All of the experiments were recorded by an observation camera (GoPro Hero 8), located in front of the industrial robot arm, as illustrated in Figure 27.

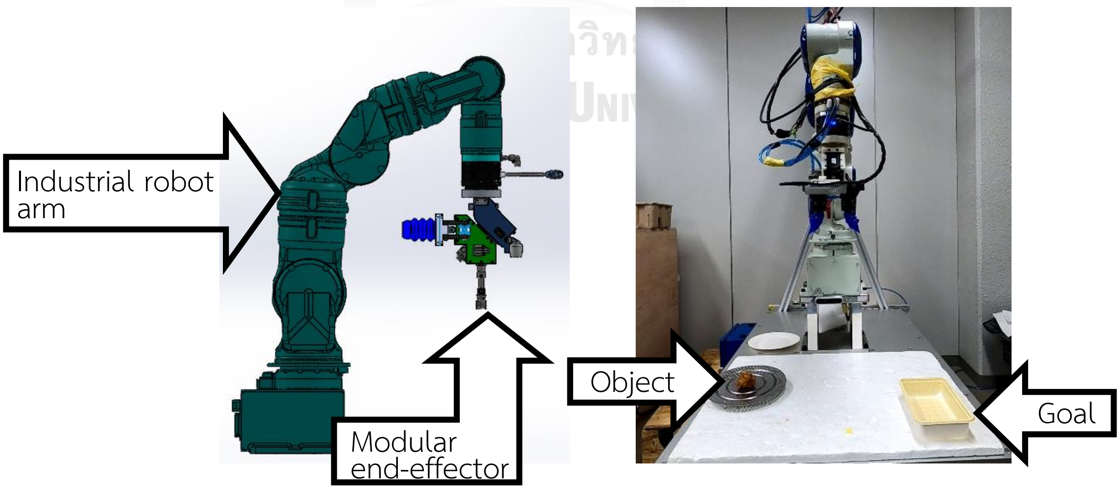


Figure 26 Ready to pick pose (left) and a workspace of experiments (right)

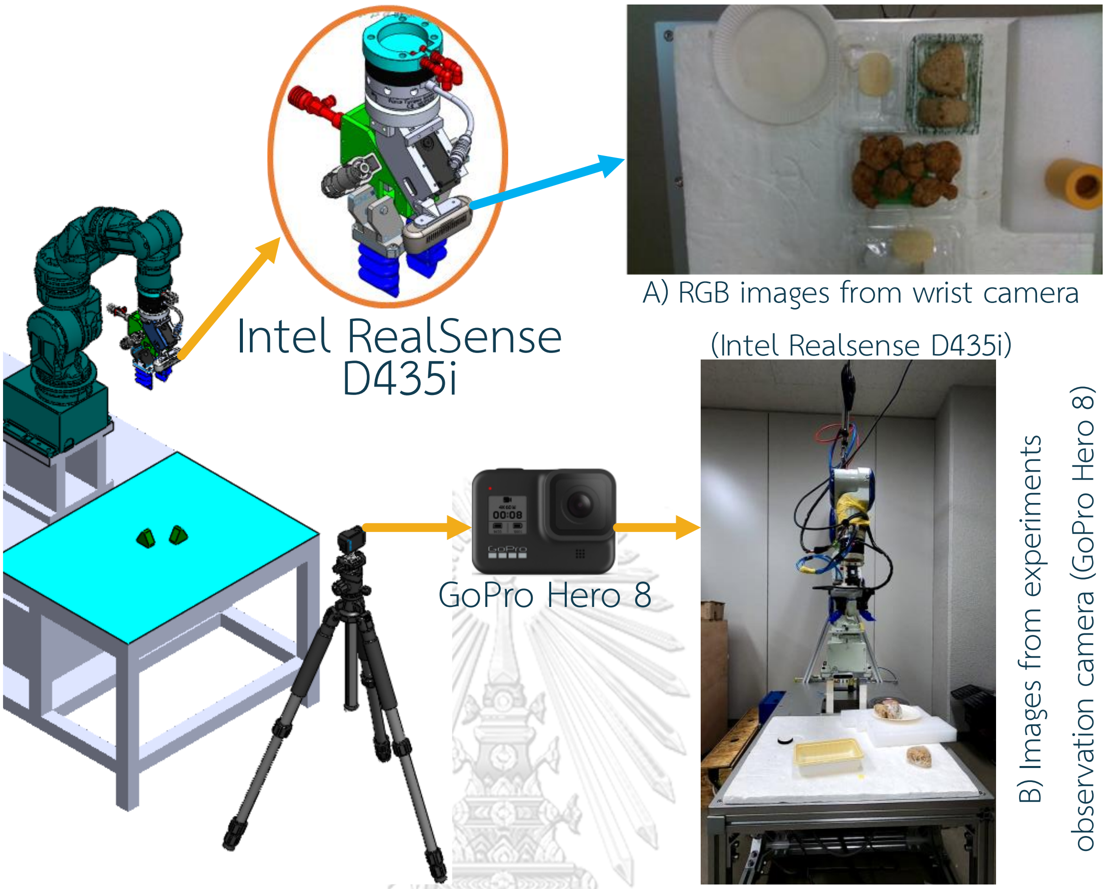


Figure 27 Camera setup in every experiment

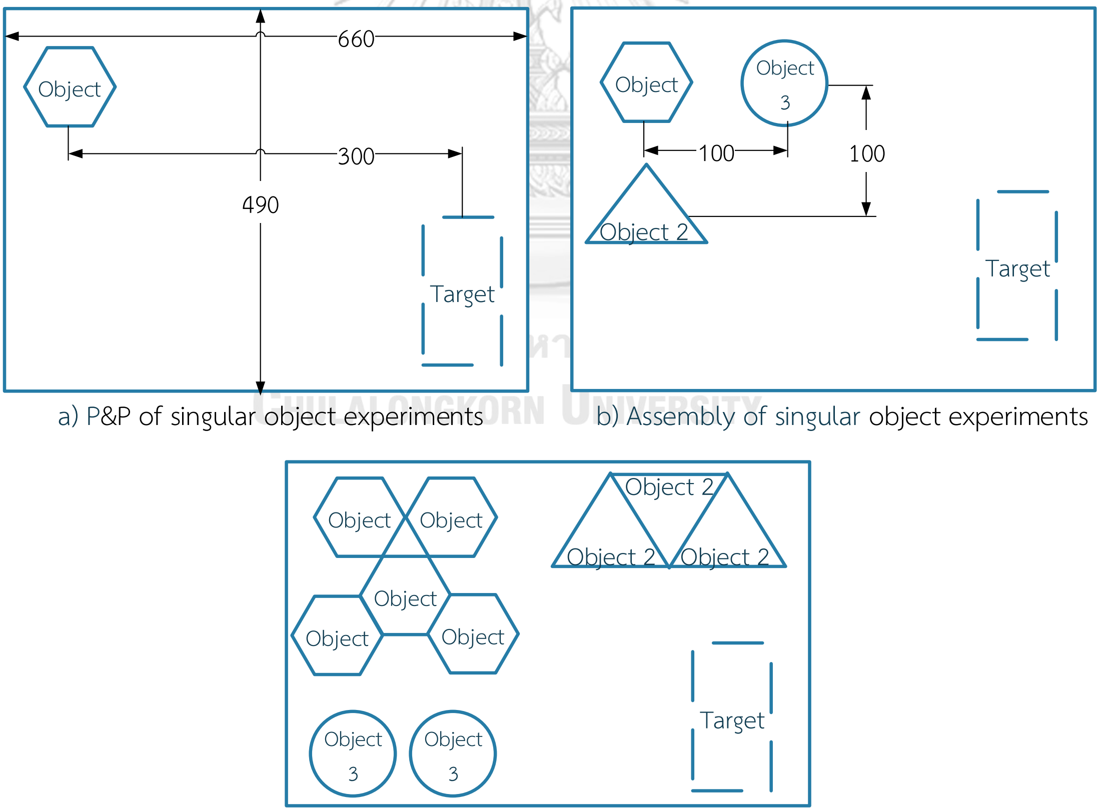
There is no region of interest that the robot will be looking for a particular object. The robot will look at the whole working space from the top view in the “ready to pick” pose. The instance segmentation model will then recognize any object located anywhere in the working space as long as the wrist camera sees it.

For trajectory planner (RRT*) to works, robot pose could begin from any pose and end at any pose. For consistency reasons, every experiment begins in a “ready to pick” pose.

The sequence of which object to be pick and place and which end-effector to be used is hard code in python script.

Modular end-effector has been evaluated by several scenarios as listed down below and illustrated in Figure 28.

- The robot's workspace is 490mm in width by 660mm in length, as shown in Figure 28 (a).
- Pick and place (P&P) of singular object experiments: there is one object in working space, and the robot will pick that object and place it in a designated area.
- Assembly of singular object experiment: A single object from different classes and robots will repeatedly pick and place them one by one.
- Assembly of multiple object experiment: there are multiple objects from different classes, and the robot will repeatedly pick one object per class and place it.



a) P&P of singular object experiments b) Assembly of singular object experiments

c) Assembly of multiple object experiments

Figure 28 Graphical representation of experiments scenarios

3.2 Pick and place of a singular object

3.2.1 *Experiment conditions*

3.2.1.1 Karaage

There are five karaage for all experiments. The robot will pick each of them six times to sum up for 30 experiments of pick and place single karaage to evaluate soft gripper capability against non-rigid food.

A layout grid and straight edge ruler has been used to determine the dimension of karaage because of the complex shape. First, a straight edge ruler was used to set karaage flush with the layout grid ruler's outer edge, as shown in Figure 29 (left). Second, measure the width and length of karage by keep a straight edge ruler parallel to measurement marks of the layout grid ruler while touching the karaage, as shown in Figure 29 (middle, right). Last, set layout grid ruler to be perpendicular with the tabletop and measure the height of karaage by keep straight edge ruler parallel to tabletop while touching the karaage. The uncertainty of measurement in dimensions is ±0.5 mm. MS-2000 electronic scale with 0.1g resolution and ±0.5g accuracy, measured in 0-500 grams range, was used to measure any object's weight in this thesis.

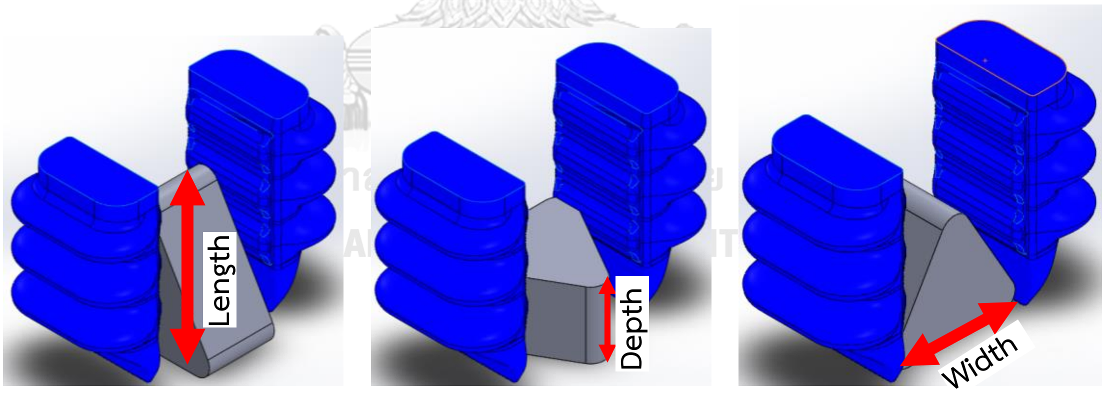
Figure 29 Measurement of karaage dimensions

Table 5 Dimension and weight of karaages

NO.	Width [mm]	Length [mm]	Depth [mm]	Weight [grams]
1	4.5	4.5	4	24
2	4	5	4	24.4
3	4	5.5	3.5	28.4
4	4.2	5	2.8	24.4
5	3.8	5.3	2.7	22.8
Average	**4.1**	**5.06**	**3.4**	**24.8**
Standard deviation	**0.24**	**0.34**	**0.56**	**1.89**

3.2.1.2 Onigiri

There are three onigiris for all experiments. The robot will pick each of three different orientations, as illustrated in Figure 30, of onigiri for ten times to sum up for 30 experiments to evaluate the object's shape adaptation of modular end-effector. Uncertainty of measurements) of dimensions and weight in Table 6 is ±0.5 mm and ±0.5g, respectively.



a) Grasp by parallel side b) Grasp by corner from top c) Grasp by slope side

Figure 30 Different orientation of onigiri

Table 6 Dimensions and weight of onigiri

NO.	Width [mm]	Length [mm]	Depth [mm]	Weight [grams]
1	48.3	38.6	19.8	117
2	50.2	37.4	17.6	122
3	49.6	39.7	18.5	124

3.2.1.3 Bologna

There are two bolognas for all experiments, and the robot will pick any of them 30 times to evaluate the capabilities of the vacuum pad against thin and fragile food. The uncertainty of measurements of dimensions and weight in Table 6 is ±0.5 mm and ±0.5g, respectively.

Table 7 Dimensions and weight of bologna

NO.	Diameter [mm]	Thickness [mm]	Weight [grams]
1	75.2	2	19.3
2	74.9	2	18.7

3.2.1.4 Lunchbox

There is only one meal box, and the robot will pick and place it to evaluate the vacuum pad's capabilities against a solid object. The meal box is 100mm in width, 165mm in length, 45mm in depth, and 15.6g in weight. The uncertainty of measurements of dimensions and weight is ±0.5 mm and ±0.5g, respectively.

3.2.2 *Experiment results*

3.2.2.1 Karaage

As listed in Table 5, soft gripper could grasp non-rigid food, karaage, or fried chicken in this experiment, with a 100% success rate of any listed karaage dimensions in Table 8.

Table 8 Summary of pick and place of single karaage

Configure	Trials	Failed	Success rate
1	6	0	100%
2	6	0	100%
3	6	0	100%
4	6	0	100%
5	6	0	100%

3.2.2.2 Onigiri

From a total of 30 experiments, as listed in Table 9, soft gripper could grasp onigiri in any orientation, whether it is oriented to be grasped by parallel sides, corner, or slope sides. However, it failed twice to grasped onigiri by corners. Because the corner that too close to the gripper’s edge went out of grasp while the gripper was deforming, as illustrated in Figure 31.

Table 9 Summary of pick and place of single onigiri in three different orientations

Objects	Configure	Trials	Failed	Success rate
Onigiri	Parallel	10	0	100%
	Corner	10	2	80%
	Slope	10	0	100%

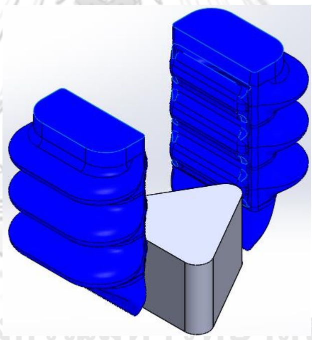


Figure 31 3D reconstructed from failed trials of picking onigiri by the corner

3.2.2.3 Bologna

From a total of 30 experiments as planned, soft gripper could grasp any bologna with a 100% success rate because bologna is thin circular meat with 75 mm in diameter and 2mm thick.

3.2.2.4 Lunchbox

From a total of 30 experiments, only one trial considerably failed to pick the lunchbox because trajectory planners cannot find trajectory in cartesian, which resulted in overwhelming trajectory, as shown in Figure 32.

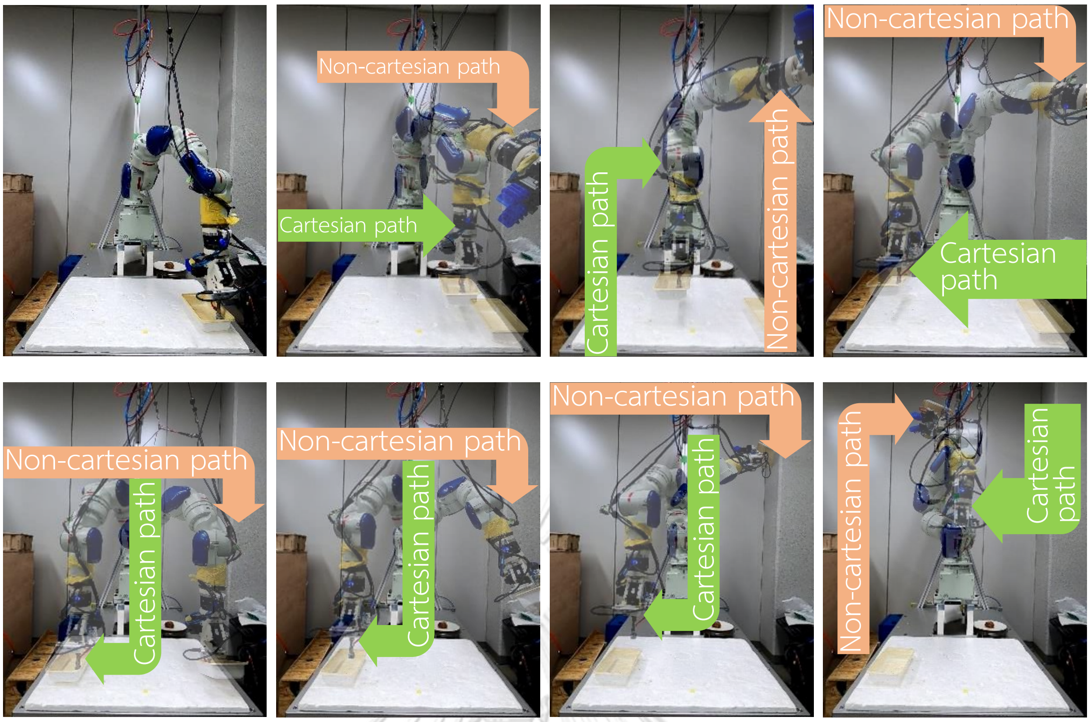


Figure 32 Trajectory of failure of pick and place single lunchbox

3.3 Assembly of a singular object

3.3.1 *Experiment conditions*

The robot picks and place each object one by one from object 1 (karaage), object 2 (onigiri), and object 3 (bologna). The location of each object and goal (meal box) will be slightly randomized within the colored boundary around each object, as illustrated in Figure 33. The duration of the soft gripper when grasping and releasing objects were evaluated in this experiment.

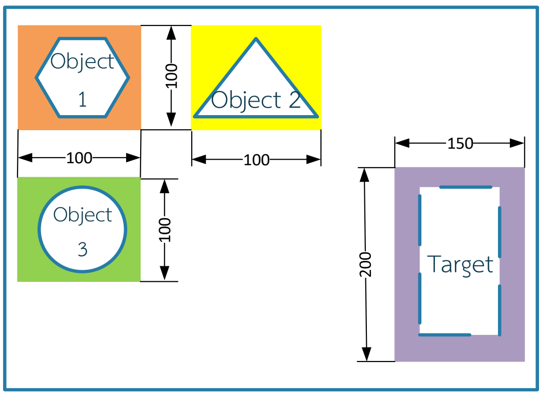


Figure 33 Conditions for assembly of a singular object assembly

3.3.2 *Experiment results*

This experiment is 100% successful, which meant that the robot could pick and place objects without failure during grasping, moving, and releasing motion. Grasping motion of soft gripper starts with the last frame of video that soft gripper is fully open, as shown in Figure 34(a), and ends with the last frame of video that soft gripper is fully inflated or fully grasp the object, as shown in Figure 34(b). Then, the duration of grasping motion is calculated by dividing the amount of frame within grasping motion by 30 frames per second. Calculated durations of grasping motion are listed in row “G” of Table 10. Releasing motion of soft gripper starts with the last frame of video that soft gripper is fully inflated, as shown in Figure 34(c), and ends with the last frame of video that soft gripper is fully open, as shown in Figure 34(d). Then, the duration of releasing motion is calculated the same way as the grasping duration. Calculated durations of releasing motion are listed in row “R” of Table 10.

a) Fully open　　b) Fully grasp　　c) Fully grasp　　d) Fully open

Figure 34 Grasping and releasing motion of soft gripper

Table 10 Duration of grasping (row “G”) and releasing (row “R”) of soft gripper

G[sec]	1.73	1.7	1.63	1.93	2.07	1.87	1.67	1.73	1.6	1.83	2.1	2	2.03	1.67	1.83
R[sec]	0.6	0.63	0.57	0.77	0.63	0.63	0.68	0.63	0.6	0.67	0.63	0.6	0.63	0.67	0.63

Soft robotics’s mGrip has actuation time for grasping is averagely 1.83 seconds (variation between 1.60-2.10 sec.) with a standard deviation of 0.16 second from 15 entries in row G of Table 10. From 15 entries in row R of Table 10, the actuation time for releasing is averagely 0.55 seconds (variation between 0.57-0.77 seconds) with 0.22 seconds standard deviation.

3.4 Assembly of multiple objects

3.4.1 *Experiment conditions*

There are five karaage (object 1), three onigiris (object 2), and two bolognas (object 3) in working space, as shown in Figure 35. The location of objects and goal (meal box) will be slightly randomized within the colored boundary around each object. The duration of tool switching was evaluated in this experiment.

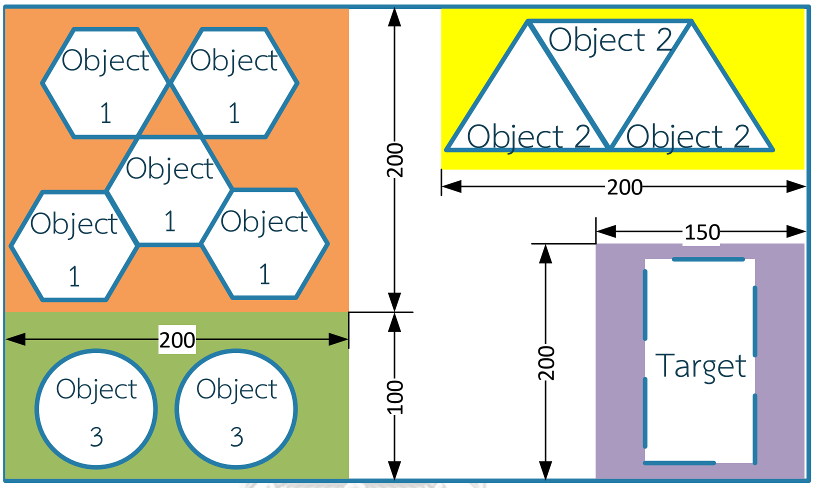


Figure 35 Conditions for assembly of multiple object assembly

3.4.2 *Experiment results*

From a total of 15 trials, the success rate of complete pick and place of every object is 47%. Three trials failed in karaage grasping because the soft gripper was open too wide, so it caught two karaage simultaneously. Three trials failed in onigiri grasping, while onigiri was oriented to be grasped by sloped sides once and by the corner twice. Two trials failed in bologna picking because of load in the ROS network. It took an average of 2.88±0.5 seconds to change from vacuum pad to soft gripper, and it took an average of 2.93±0.2 seconds to change from soft gripper to vacuum pad.

To be a summary, the evaluation conditions, process, and results are explained in this chapter. The performance of the vacuum pad and fluidic elastomer soft gripper has been evaluated with two objects per end-effector. Karaage and onigiri are objects for the evaluation of fluidic elastomer soft gripper. Meal box and bologna are objects for evaluation of multi-bellow vacuum pad. For object picking and placing one by one, as in “Pick and place of a singular object” and “Assembly of a singular object” experiments, the overall success rate is 97% (3 failed in a total of 135 trials). However, the overall success rate drastically drops to 46% in the “Assembly of multiple objects” experiment (7 succeed in a total of 15 trials), in which the robot assembled the meal box from one of the multiple instances of objects. Many failed trials are because of unrealistic object orientation, such as grasping the onigiri by the corner. A few failed trials are due to technical issues like a heavy load in the network. These experiments proved that the pick and place process could be done using centroid as object representation.

Chapter 4
Conclusion and discussion

4.1 Conclusion

There are two objectives of this research. The first objective is to prototype a modular end-effector for assembling non-rigid food into a meal box. The second objective is to evaluate the performance of this prototype in three scenarios.

The vacuum pad and soft gripper have been chosen to be end-effectors in this thesis because they can adapt to non-rigid food. The multi-bellow vacuum pad has been used in this thesis for fragile objects (bologna) and lightweight objects (meal boxes) because it has enough flexibility. The mGrip from Soft Robotics, which is categorized as a fluidic elastomer soft gripper, has ease of actuator control and sufficient geometric advantage to pick non-rigid food (karaage and onigiri).

There are several approaches to change the end-effectors of the industrial robot arm. However, both the vacuum pad and soft gripper in this thesis have been installed on a single modular end-effector. The modular end-effector utilized the concept of changing the end-effector by 180 degrees rotation in the auxiliary axis. The prototype has been fabricated with ABS filament by the fused deposition modeling (FDM) method. Furthermore, the end-effector in this thesis is a modular design. It is not limited to being equipped with only a vacuum pad or soft gripper. Users can customize the essential tool for their application. Users can even design an attachment for the soft gripper to function like spaghetti tongs or rice ladles.

Apart from a soft gripper and vacuum pad, the modular end-effector is also equipped with an RGB-D camera and instance segmentation model (based on Cascade mask R-CNN) for recognition and localization of karaage, onigiri, bologna, and meal box.

The modular end-effector was evaluated in three scenarios: pick and place of a singular object, assembly of a singular object, and assembly of multiple objects. There are eleven failures from a total of 150 experiments. One grasping cycle is about five seconds from changing the tool to completely grasp the object with either a soft gripper or a vacuum pad. The object's dimension does not affect the soft gripper's performance because it can grasp karaage with an average size of 4.5cm at a 100% success rate and onigiri with an average length of 2cm (if pick by parallel or sloped sides) at a 93% success rate. However, the Object's orientation affects the success rate of grasping. For example, there are five failures when a soft gripper picks onigiri by corners in "Pick and place of a singular object" and "Assembly of multiple objects" experiments. Another factor that affects the success rate is space between instances of an object because it causes three failures out of fifteen trials in the "Assembly of multiple objects" experiment. These remarkable performances were achieved by using only the object's centroid.

The cost of changeover from automated food manufacturing to highly flexible food manufacturing should be lower than ever before because the job can be done with only one robot with a modular end-effector. The highly flexible food manufacturing is the solution for an aging society, such as Thailand, Japan, or any country, because it can make personalized food to match people's exact requirements.

4.2 Discussion

It does not matter how high is the success rate in experiments of this research is because failed experiments lead to improvement. First, the system should be integrated with a grasping pose estimator (GPE) because it can propose the optimal robot arm pose to grasp the object with a two-finger gripper[42], as shown in Figure 36(left). For example, it will not be different for the robot to grasp onigiri in an upright orientation, as illustrated in Figure 36(right). Because GPE always proposed the robot pose to grasp onigiri by slope or parallel side as specified by the user.

The multi-bellow vacuum pad has been proved to be an excellent choice for intended purposes. Unlike a soft gripper that has electronic pressure control, this thesis’s vacuum system has only mechanical vacuum pressure control with an adjustable knob and vacuum pressure gauge. The disadvantage of not having the electronic pressure control is that the system can not adjust vacuum pressure even if it has an algorithm.

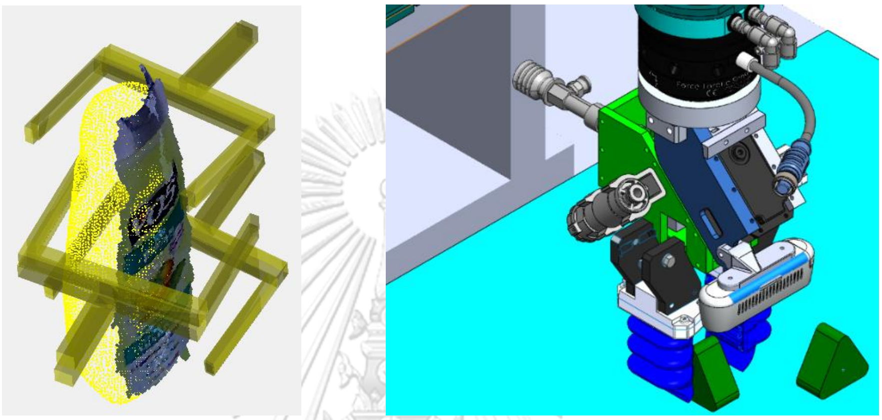


Figure 36 Viable grasping pose proposals from GPE[42] (left) and 3D model of onigiri in the upright orientation (right)

Apart from failure in grasping some object, placing motion also has some concern. Each object in this thesis’s experiments was stacked on top of another object because the system was programmed to place every object at the same coordinate. That coordinate could be the centroid of the meal box or a relative coordinate to the robot arm. Placing the object at the same coordinate does not make a packed meal look delightful. The system should be able to shift the placing location parallel to the axes of the meal box.

REFERENCES

1. Tulaphol, N., *Food Industry* 4.0...*A new era of consumer empowerment*. 2016.
2. Bougdira, A., I. Akharraz, and A. Ahaitouf, *A traceability proposal for industry* 4.0. Journal of Ambient Intelligence and Humanized Computing, 2020. 11(8): p. 3355-3369.
3. *Thailand - Crude birth rate*. Available from: https://knoema.com/atlas/Thailand/Birth-rate.
4. สำนักเลขาธิการสภาผู้แทนราษฎร, ส., สังคมผู้สูงอายุกับการขับเคลื่อนเศรษฐกิจไทย. 2018.
5. Parmar, R. *Detection and Segmentation through ConvNets*. 2018; Available from: https://towardsdatascience.com/detection-and-segmentation-through-convnets-47aa42de27ea.
6. Zhaowei Cai and Nuno Vasconcelos, *Cascade R-CNN: High Quality Object Detection and Instance Segmentation.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 2019: p. 1-1.
7. Blanes, C., et al., *Review. Technologies for robot grippers in pick and place operations for fresh fruits and vegetables.* Spanish Journal of Agricultural Research, 2011. 9(4): p. 1130.
8. Anders Petterson, T.O., Darwin G. Caldwell, Steve Thomas Davis, John O. Gray,Tony J. Dodd, *A Bernoulli principle gripper for handling of planar and 3D (food) products.* Industrial Robot, 2010. 37(6): p. 8.
9. Rosidah Sam, S.N. *Design and feasibility tests of flexible gripper for handling variable shape of food products*. in *WSEAS International Conference on Signal Processing, Robotics and Automation*. 2010. Cambridge, UK.
10. *Parallel gripper*. Available from: https://schunk.com/de_en/gripping-systems/category/gripping-systems/schunk-grippers/parallel-gripper/.
11. ROBOTS, U. *ROBOT GRIPPER SHOWDOWN: AIR GRIPPER VS. ELECTRIC GRIPPER*. 2020; Available from: https://www.universal-robots.com/blog/robot-gripper-showdown-air-gripper-vs-electric-gripper/.
12. Company, S.R., *Shadow Dexterous Hand*.

13. E. Brown, et al., *Universal robotic gripper based on the jamming of granular material.* Proceedings of the National Academy of Sciences, 2010. 107(44): p. 18809-18814.

14. Josie Hughes, et al., *Soft Manipulators and Grippers: A Review.* Frontiers in Robotics and AI, 2016. 3.

15. Meng, J., et al., *A Tendon-Driven, Preloaded, Pneumatically Actuated, Soft Robotic Gripper with a Telescopic Palm.* 2020 3rd IEEE International Conference on Soft Robotics (RoboSoft), 2020: p. 476-481.

16. Liu, C.-H., et al., *A Soft Robotic Gripper Module with 3D Printed Compliant Fingers for Grasping Fruits.* 2018 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2018: p. 736-741.

17. Yeunhee Kim and Youngsu Cha, *Soft Pneumatic Gripper With a Tendon-Driven Soft Origami Pump.* Frontiers in Bioengineering and Biotechnology, 2020. 8.

18. *SetupRobotics Quickchange Dual Toolbase*. Available from: https://www.universal-robots.com/plus/urplus-components/accessories/setuprobotics-quickchange-dual-toolbase-for-all-jobs/.

19. *Vacuum Pad Multi-Bellows Series*. p. 66.

20. *The mGrip Ecosystem*. [cited 2020; Available from: https://www.softroboticsinc.com/products/mgrip/.

21. *Universal Robots+ ToolBase for finger grippers and suction cups by SetupRobotics*. 2018.

22. *Dynamixel MX-106R specifications*. Available from: http://www.robotis.us/dynamixel-mx-106r/

23. *Yaskawa Motoman SIA5F*. Available from: https://www.motoman.com/en-us/products/robots/industrial/assembly-handling/sia-series/sia5f.

24. *Frequently Asked Question: Robotiq FT* 300.

25. *Specification of LPMS-B2* Available from: https://lp-research.com/9-axis-bluetooth-imu-lpmsb2-series/.

26. *CKD VSXP Digital catalog*.

27. *Intel® RealSense™ Depth Camera D435i*. Available from: https://www.intelrealsense.com/depth-camera-d435i/.

28. *KENOH Mini Oilless Compressor KML*-60. Available from: https://item.rakuten.co.jp/daiyu8/4941901026354/?l2-id=pdt_shoplist_title_item_1#10022577.

29. *Ulvac Kiko DOP-40D Piston Vacuum Pump*. Available from: https://ulvac-kiko.com/en/product.php?action=detail&category=1&ID=DOP-40D.

30. Quigley, M., et al. *ROS: an open-source Robot Operating System*. in *ICRA* 2009. 2009.

31. Diankov, R. and J.J. Kuffner. *OpenRAVE: A Planning Architecture for Autonomous Robotics*. 2008.

32. Bradski, G., *The openCV library.* Dr. Dobb's Journal of Software Tools, 2000. 25.

33. Coleman, D., et al., *Reducing the Barrier to Entry of Complex Robotic Software: a MoveIt! Case Study.* Journal of Software Engineering for Robotics 2014. 5(1): p. 14.

34. Sucan, I.A. and S. Chitta. *MoveIt*. Available from: moveit.ros.org.

35. Armin Hornung, et al., *OctoMap: an efficient probabilistic 3D mapping framework based on octrees.* Autonomous Robots, 2013. 34(3): p. 189-206.

36. Fava, A.D. *Planning with Octomap demo*. Available from: http://wiki.ros.org/Robots/TIAGo/Tutorials/MoveIt/Planning_Octomap.

37. A. Sucan, I., Mark Moll, and L. E. Kavraki, *The Open Motion Planning Library.* IEEE Robotics & Automation Magazine, 2012. 19(4): p. 72-82.

38. Sertac Karaman and Emilio Frazzoli, *Sampling-based algorithms for optimal motion planning.* The International Journal of Robotics Research, 2011. 30(7): p. 846-894.

39. Ryeol Kam, H., et al., *RViz: a toolkit for real domain data visualization.* Telecommunication Systems, 2015. 60(2): p. 337-345.

40. Kai Chen, J.W., Jiangmiao Pang, Yuhang Cao, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jiarui Xu, Zheng Zhang, Dazhi Cheng, Chenchen Zhu, Tianheng Cheng, Qijie Zhao, Buyu Li, Xin Lu, Rui Zhu, Yue Wu, Jifeng Dai, Jingdong Wang, Jianping Shi, Wanli Ouyang, Chen Change Loy, Dahua Lin, *MMDetection: Open MMLab Detection Toolbox and Benchmark.* 2019: p. 11.

41. *Instance segmentation ranking on COCO test-dev*. Available from:

https://github.com/open-mmlab/mmdetection/tree/master/configs/cascade_rcnn

42. Andreas ten Pas, M.G., Kate Saenko, Robert Platt, *Grasp Pose Detection in Point Clouds.* 2017.

VITA

NAME	Wiwat Tulapornpipat
DATE OF BIRTH	15 March 1997
PLACE OF BIRTH	Bangkok
INSTITUTIONS ATTENDED	2019 - Present Chulalongkorn University 2015 - 2019 King Mongkut's University of Technology North Bangkok
HOME ADDRESS	135/40 Moo.1 Rd.Rangsit-Pathum Ban Klang, Mueang, Pathum Thani 12000
PUBLICATION	Wiwat Tulapornpipat, Alongkorn Pimpin, Sakmongkon Chumkamon, Eiji Hayashi (2020). Grasping motion for small non-rigid food using instance semantic segmentation. Society of Instrument and Control Engineers (SICE), Thailand.