Automatic Soft Gripper Implementation on Foods Using Machine Vision

Suharyadi Pancono, Wahyu Adhie Candra and Andi Muhammad Aqil
Department of Automation and Mechatronics Engineering, Bandung Polytechnic of Manufacturing, Bandung, Indonesia

Keywords: Deformable Food Handling, Soft Gripper, Pick and Place, Object Identification.

Abstract: The rigid frame of conventional robots makes the food industry still need a lot of human involvement. Soft gripper is created as one of the solutions for food handling automation system. Various studies have developed a variety of soft grippers in food pick-and-place process. The gripper with 2 finger configurations showing better performance compared to the gripper with single finger configuration because it can handle more diverse object, but the configuration of the fingers is still selected and changed manually. This study proposed a method to automatically selecting and changing the finger configuration. This study developed 4-finger soft gripper with a conversion mechanism for 2 finger configurations. The finger configuration is selected based on the object's length-to-width ratio that calculated using machine vision. Canny edge detection method is used to detect edge contours from the object's image. The results obtained in this study show that the finger configuration conversion mechanism on the soft gripper made has good repeatability performance, the length-to-width ratio measurement using machine vision has accuracy up to 97,81% compared to manual measurement, and food pick-and-place experiment with 100% success rate.

1 INTRODUCTION

Traditional rigid end-effectors are used widely on automatic production lines, which can perform lots of repetitive lifting operations. However, it is difficult for them to handle small, fragile, and deformable objects due to its bulky and rigid body (Zhong et al., 2019). Therefore, handling deformable objects such as foods still need a lot of human involvement. To reduce labor cost, food handling automation systems are highly demanded by food industry (Zhongkui Wang et al., 2016).

Soft grippers replaced rigid body on conventional robots with a structure made of elastic materials that deform continuously in response to the interaction with the objects. Soft grippers are able to continuously vary their shape without requiring complex multi-joint mechanisms, have the potential to provide greater adaptability while presenting lower costs, simpler structures, and simpler control algorithms than hard end-effectors. Soft grippers can be categorized into three groups based on grasping principle: gripping by actuation, gripping by controlled stiffness, and gripping by controlled adhesion. The most suitable group for fruit handling are the first group because of large lifting capabilities, good response time, and have the highest techonology readiness level compared to the other groups (Navas et al., 2021; Shintake et al., 2018).

Various studies have developed a variety of soft grippers. The results show that 3 and 4-finger soft grippers with static finger configuration only capable to lift up spherical objects (Minh Dang et al., 2021; Zhangkui Wang et al., 2018; Zhongkui Wang et al., 2016; Zhongkui Wang, Zhu, et al., 2017). To handle more diverse object, several studies developed 4-finger soft gripper with 2 finger configurations (Zhongkui Wang et al., 2020; Zhongkui Wang, Torigoe, et al., 2017). Compared to grippers with static finger configuration, soft gripper with 2 finger configurations successfully handle spherical and elongated objects, but the finger configuration on the mentioned study is still selected and changed manually.

This study proposed a method to automatically selecting and changing the finger configuration. This study developed a 4-finger soft gripper with conversion mechanism for 2 finger configurations. The object's shape tendency is affected by its elongation factor. Elongation factor (EF) is defined as the ratio of the longest segment within an object to the mean length of the perpendicular segment (Patel et

Pancono, S., Candra, W. and Aqil, A.
Automatic Soft Gripper Implementation on Foods Using Machine Vision.
DOI: 10.5220/0011973700003575
In *Proceedings of the 5th International Conference on Applied Science and Technology on Engineering Science (iCAST-ES 2022)*, pages 971-975
ISBN: 978-989-758-619-4; ISSN: 2975-8246

al., 2021). The finger configuration is selected based on the object's EF that calculated using machine vision. Before calculating the EF, the edge contours from the object's image is traced using Canny edge detection method.

2 SYSTEM OVERVIEW

Image from the object is captured using webcam. The webcam send the data to the laptop for digital image processing to estimate the object's EF and selecting the suitable finger configuration. Then the laptop send the command to the controller based on the selected finger configuration via serial communication. Next, the controller sends PWM signal to the servos and trigger signal to arm robot's I/O port. Servo's shaft rotation will physically determine finger configuration and actuate the fingers on the soft gripper. Soft gripper attached to arm robot and will perform pick-and-place sequence together.

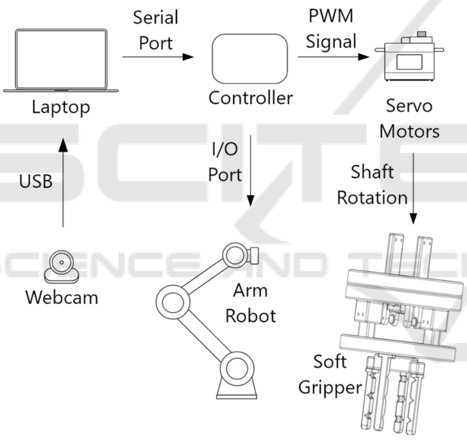


Figure 1: System overview.

3 IMPLEMENTATION

3.1 Soft Gripper with Conversion Mechanism

Soft gripper in this study is created using 3D Print method. The body parts are created using PLA filament with 25% infill and 1,2mm wall thickness. The finger parts are created using TPU filament with 10% infill and 0,8mm wall thickness. The mechanical construction of the soft gripper is refer to reference (Mishra et al., 2017) with modifications.

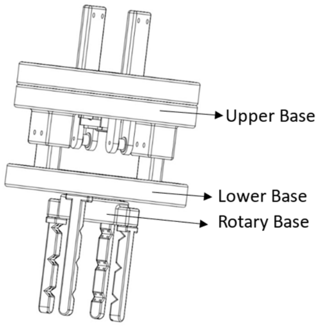
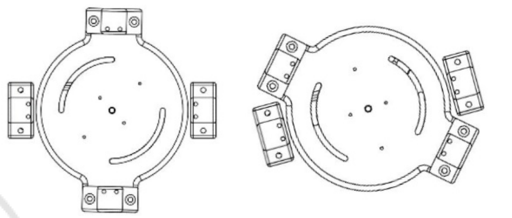


Figure 2: Soft grippers CAD Model

<Rotary base is rotatable to provide 2 finger configurations as illustrated on figure 3.



(a) (b)

Figure 3: (a) Perpendicular and (b) Parallel finger configurations on the gripper.

Perpendicular configuration used for spherical objects while parallel configuration used for elongated objects. Commonly used finger model for "gripping by actuation" soft grippers are pneumatics (Minh Dang et al., 2021; Zhangkui Wang et al., 2018; Zhongkui Wang et al., 2016; Zhongkui Wang, Zhu, et al., 2017; Zhong et al., 2019) and tendon-driven (Gafer et al., 2020; Hussain et al., 2021; Mishra et al., 2017). Tendon-driven actuation model is used on the gripper in this study because it needs less component and easier to produce than the pneumatics model, also the pneumatics model is susceptible for leakage in the air chamber (N. Tan et al., 2018; Zaidi et al., 2021).

Two servo motors set on the gripper. The first one is TowerPro MG90S located on the lower base and used to rotate the rotary base. Another servo is TowerPro MG995 located on the upper base and used to pull the wire for finger actuation.

3.2 Elongation Factor Estimation

Machine vision is used to estimate the elongation factor (EF) of the object. Spherical object's EF is approximately 1 (one). Before the EF calculation, the edges contour of the object is traced using Canny Edge Detection method. Canny is used because canny is the best edge detection method compared to

Prewitt, Roberts, Sobel, and Laplacian of Gaussian (LOG) edge detection method (Ansari et al., 2017; Kumar Shah et al., 2020) and reference (Devi et al., 2017; Luo et al., 2021; Phate et al., 2019; S. H. Tan et al., 2021) used canny edge detection to detect the edge contours of the food which is the object in this study. The program is created on pycharm software using OpenCV and NumPy library. Below are the steps of EF estimation in this study.

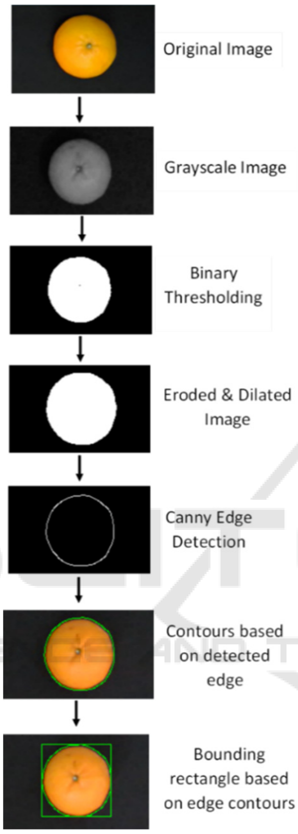


Figure 4: Steps of EF estimation using machine vision.

The length-to-width ratio of the bounding rectangle is the EF estimation of the object.

4 RESULTS

4.1 Conversion Mechanism Repeatability Test

The conversion mechanism of the gripper is tested with repeatability test. The test is executed by changing the finger configuration 20 times. The distance between fingers is measured before and after the test. The expected result from this test is the distance difference between fingers before and after the test is as small as possible that show the conversion mechanism has good repeatability performance. Each finger is given number as illustrated on figure 5.

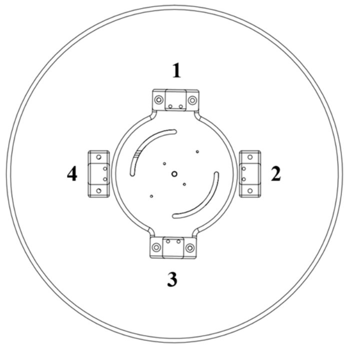


Figure 5: Gripper's finger numbering.

The distance between finger 1-4 and 2-3 is measured before and after the test. The results provided on table 1.

Table 1: Distance between fingers.

Condition		**Finger 1–4 Distance**	**Finger 2-3 Distance**
Before	Parallel	21 mm	21 mm
	Perpendicular	49 mm	49 mm
After	Parallel	21 mm	21 mm
	Perpendicular	49 mm	49 mm

The results show no difference before and after the test.

4.2 Machine Vision Accuracy Test

The test is excecuted by comparing the object's EF estimation by machine vision and manual measurement. The results provided on table 2.

Table 2: EF estimation using manual measurement and machine vision comparation.

Test	**Elongation Factor**		**Error (%)**
	Manual	**Machine Vision**	
1	1,04	1,04	0,00
2	1,01	1,01	0,00
3	1,03	1,01	1,94
4	1,04	1,05	0,96

Table 2: EF estimation using manual measurement and machine vision comparation. (cont.)

5	1,01	1,01	0,00
6	1,34	1,3	2,99
7	1,00	1,03	3,00
8	1,82	1,86	2,20
9	1,39	1,32	5,04
10	1,44	1,43	0,69
11	1,00	1,02	2,00
12	1,49	1,47	1,34
13	1,00	1,02	2,00
14	3,49	3,62	3,72
15	1,33	1,3	2,26
16	1,31	1,25	4,58
17	1,01	1,05	3,96
18	1,06	1,04	1,89
19	1,32	1,25	5,30
20	1,28	1,28	0,00
Average Error Rate			**2,19**

Based on the results, the machine vision has 97,81% accuracy compared to manual measurement.

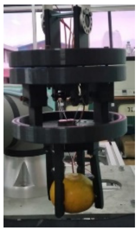
4.3 Pick-and-Place Test

This test is executed by pick-and-place experiment using bananas, oranges, round buns, and hot dog buns 5 times for each objects. The gripper attached to UR5e arm robot.

Figure 6: Work Area.

If the object's EF estimation is below 1.2, perpendicular finger configuration will be used. If the object's EF is ≥ 1.2, parallel finger configuration will be used. The representative result for each objects provided on table 3.

Table 3: Pick-and-place results.

Documentation	Status	Documentation	Status
	Success		Success
	Success		Success

The results show 100% success rate at pick-and-place test. Experiments using round buns showing some damaged part at the top of the buns. Based on observation during experiments, it is caused by the size of the buns is bigger than the opening size of the gripper's finger.

5 CONCLUSION

The results obtained in this study show that the conversion mechanism of the finger configurations on the soft gripper made has good repeatability performance, the elongation factor estimation using machine vision has accuracy up to 97,81% compared to manual measurement, and food pick-and-place experiment with 100% success rate. For upcoming research, the opening size of the fingers suggested to be bigger than the size of the objects to prevent damage on the upper parts of the object.

ACKNOWLEDGEMENTS

This research is conducted in Automation and Mechatronics Department's sensor laboratory at Bandung Polytechnic of Manufacturing. Thank you for being allowed to use the laboratory.

REFERENCES

Ansari, Mohd. A., Kurchaniya, D., & Dixit, M. (2017). A Comprehensive Analysis of Image Edge Detection Techniques. International Journal of Multimedia and Ubiquitous Engineering, 12(11), 1–12. doi: 10.14257/ijmue.2017.12.11.01

Devi, T. G., Neelamegam, DR. P., & Sudha, S. (2017). Image Processing System for Automatic Segmentation and Yield Prediction of Fruits using OpenCV. International Conference on Current Trends in Computer, Electrical, Electronics and Communication.

Gafer, A., Heymans, D., Prattichizzo, D., & Salvietti, G. (2020). The Quad-Spatula Gripper: A Novel Soft-Rigid Gripper for Food Handling. 2020 3rd IEEE International Conference on Soft Robotics (RoboSoft). doi: 10.1109/RoboSoft48309.2020.9115968

Hussain, I., Malvezzi, M., Gan, D., Iqbal, Z., Seneviratne, L., Prattichizzo, D., & Renda, F. (2021). Compliant gripper design, prototyping, and modeling using screw theory formulation. International Journal of Robotics Research, 40(1), 55–71. doi: 10.1177/0278364 920947818

Kumar Shah, B., Kedia, V., Raut, R., Ansari, S., & Shroff, A. (2020). Evaluation and Comparative Study of Edge Detection Techniques Related papers Evaluation and Comparative Study of Edge Detection Techniques. IOSR Journal of Computer Engineering (IOSR-JCE), 22(5), 6–15. doi: 10.9790/0661-2205030615

Luo, L., Liu, W., Lu, Q., Wang, J., Wen, W., Yan, D., & Tang, Y. (2021). Grape berry detection and size measurement based on edge image processing and geometric morphology. Machines, 9(10). doi: 10.3390/machines9100233

Minh Dang, H., Thanh Vo, C., Tran Trong, N., Duc Nguyen, V., Binh Phung, V., Minh City, C., & Chi Minh City, H. (2021). Design and development of the soft robotic gripper used for the food packaging system. In Journal of Mechanical Engineering Research and Developments (Vol. 44, Issue 3).

Mishra, A. K., del Dottore, E., Sadeghi, A., Mondini, A., & Mazzolai, B. (2017). SIMBA: Tendon-driven modular continuum arm with soft reconfigurable gripper. Frontiers Robotics AI, 4(FEB). doi: 10.3389/ frobt.2017.00004

Navas, E., Fernández, R., Sepúlveda, D., Armada, M., & Gonzalez-De-santos, P. (2021). Soft grippers for automatic crop harvesting: A review. In Sensors (Vol. 21, Issue 8). MDPI AG. doi: 10.3390/s21082689

Patel, K. K., Kar, A., & Khan, M. A. (2021). Rapid Assessment of Some Physical Parameters of Mangoes Using Monochrome Computer Vision. Agricultural Research, 10(3), 468–482. doi: 10.1007/s40003-020-00517-9

Phate, V. R., Malmathanraj, R., & Palanisamy, P. (2019). Classification and weighing of sweet lime (Citrus limetta) for packaging using computer vision system. Journal of Food Measurement and Characterization, 13(2), 1451–1468. doi: 10.1007/s11694-019-00061-3

Shintake, J., Cacucciolo, V., Floreano, D., & Shea, H. (2018). Soft Robotic Grippers. In Advanced Materials (Vol. 30, Issue 29). Wiley-VCH Verlag. doi: 10.1002/adma.201707035

Tan, N., Gu, X., & Ren, H. (2018). Design, characterization and applications of a novel soft actuator driven by flexible shafts. Mechanism and Machine Theory, 122, 197–218. doi: 10.1016/j.mechmachtheory.2017.12.021

Tan, S. H., Lam, C. K., Kamarudin, K., Ismail, A. H., Rahim, N. A., Azmi, M. S. M., Yahya, W. M. N. W., Sneah, G. K., Seng, M. L., Hai, T. P., & Lye, O. T. (2021). Vision-Based Edge Detection System for Fruit Recognition. Journal of Physics: Conference Series, 2107(1). doi: 10.1088/1742-6596/2107/1/012066

Wang, Zhangkui, & Hirai, S. (2018). Geometry and Material Optimization of A Soft Pneumatic Gripperfor Handling Deformable Object. International Conference on Robotics and Biomimetics.

Wang, Zhongkui, Chathuranga, D. S., & Hirai, S. (2016). 3D Printed Soft Gripper for Automatic Lunch Box Packing. International Conference on Robotics and Biomimetics, 503–508. doi: 10.1109/ROBIO. 2016.7866372

Wang, Zhongkui, Or, K., & Hirai, S. (2020). A dual-mode soft gripper for food packaging. Robotics and Autonomous Systems, 125. doi: 10.1016/j. robot.2020.103427

Wang, Zhongkui, Torigoe, Y., & Hirai, S. (2017). A Prestressed Soft Gripper: Design, Modeling, Fabrication, and Tests for Food Handling. IEEE Robotics and Automation Letters, 2(4), 1909–1916. doi: 10.1109/LRA.2017.2714141

Wang, Zhongkui, Zhu, M., Kawamura, S., & Hirai, S. (2017). Comparison of different soft grippers for lunch box packaging. Robotics and Biomimetics, 4(1). doi: 10.1186/s40638-017-0067-1

Zaidi, S., Maselli, M., Laschi, C., & Cianchetti, M. (2021). Actuation Technologies for Soft Robot Grippers and Manipulators: A Review. Current Robotics Reports, 2(3), 355–369. doi: 10.1007/s43154-021-00054-5

Zhong, G., Hou, Y., & Dou, W. (2019). A soft pneumatic dexterous gripper with convertible grasping modes. International Journal of Mechanical Sciences, 153–154, 445–456. doi: 10.1016/j.ijmecsci.2019.02.028.