Smart Grasping of a Soft Robotic Gripper Using NI Vision Builder Automated Inspection Based on LabVIEW Program

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***Abstract*— Grasping an unstructured object and setting the required air pressure is a significant problem for a soft robotic gripper. However, most extant Soft Robotic Grippers struggle to create this function automatically and efficiently. This article develops a new approach to an automated control method for a gripper using the NI Vision Builder Automated Inspection (VBAI) to create an intelligent robotic gripper based on the LabVIEW program. Machine vision and object classification methods were used in this experiment to get information about each object to be gripped. This system has collaborated between measurement and gripping tasks in real-time. Using the state diagram design, detecting and classifying objects at the point of placement found that the state diagram can detect and categorize all measured things precisely according to their actual size with an accuracy of ±0.5 millimeters. Furthermore, from the data obtained by utilizing the NI Distributed system manager feature to transmit data in real-time into the gripper control program, it was found that the gripper can grip perfectly with the automation system that has been built.**

***Index Terms*— autonomous assembly, machine vision, soft robotic gripper, object detection, automated inspection**

I. Introduction

A thing that is the most concern of a gripper is grasping. Grasping is becoming one of the Robot's most essential tasks, enabling many applications ranging from industries to residences [1]–[4]. Despite tremendous advances in robotic grasping development over the last few decades [5]–[8], Grasping objects with complex shapes and adjusting the ability of the gripper remains challenging and requires a different gripper [9]–[11]. However, it is theoretically significant and practical in solving the abovementioned problems. On the one hand, an adaptive grip is necessary [12]–[15]. While holding conventional things in a controlled environment is not difficult, achieving an adaptive grip for the most typical scenarios in everyday life, such as dealing with free-form objects in an unstructured environment, is well worth the effort. Controlling the contact force between the gripper and the object, on the other hand, is critical [4], [11], [16]–[19]. This is due to the fact that excessive force can damage objects, particularly those that are brittle or soft. Insufficient strength, on the other hand, might weaken stability and lead to mission failure. Grip strength estimation and control can increase grasping performance dramatically.

Robot behavior in industrial robot gripper systems will necessitate high speed, precision, and accuracy [20]. These three things are dependent on various factors, including the Robot's programming, the sequence of work, the Robot's firm grip, and sensors that can detect what the Robot needs to act with precision [21], [22] . However, in the soft robotic gripper industry, the operation of robots for specific task needs is still being developed in the process of use. Therefore, the challenge in this paper is to make a soft robotic gripper capable of different gripping objects and controlling the appropriate pressure. Automatic control is one of the challenges because there are systems that work with each other in the robotics system and are expected to have a fast response [23].

This paper proposes a new system to regulate a soft robotic gripper to perform tasks automatically. The main task performed on this gripper is to grip different objects with a camera for vision tasks mounted on a workbench [24], [25]. It must be compensated for the position between the robot grip, the center point on the point calibration plate, the image marker point, and the center of the detected and classified objects. The program settings used are National Instruments Vision Builder Automated Inspection (NI VBAI), Vision Builder AI Vision Builder AI is an application software that rapidly develop and deploy machine vision inspection systems. This system is configured with the LabVIEW program for the control system so that the gripper can work in real-time, precisely, and quickly.

II. Overview System in Machine Vision

Machine vision is one of the fast-growing branches of Artificial Intelligence. With machine vision, machines can have the ability to see like humans, capture and identify images, and make decisions. Thanks to technologies such as Fuzzy Logic, Neural Networks, and Deep Learning, the gap between human vision and machine vision is getting smaller [26], [27]. Based on such research conducted to measure the soft pneumatic

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ability, an image sensor was combined with a computer vision algorithm to evaluate the angle results in soft pneumatics correctly.

Angle shooting and calculation are the two main aspects of an angle detection program. The term "shooting" refers to the process of using a camera to capture the current image. After the image is preprocessed, the nanosatellites angle calculation algorithm is used to calculate the current angle. Instead of running on the Raspberry Pi, the program runs on the computer to speed up the process. The demonstration by Xiran Zhang [28] shows a visible result of soft pneumatics angle.

The angular recognition program is written in Python 3 with the Open Source Computer Vision (OpenCV) library. The current method separates the three circles above, middle, and bottom of the finger to aid identification. When the algorithm detects the boundary of three circles, it calculates the circle's center of gravity and calculates three points. The current angle is determined using the finite circle of three-point fixation and the central angle corresponding to the arc produced by the three points.

Convert to Grayscale, Image Smoothing, Image Thresholding, Canny Edge Detection, Contour Detection, and Calculation are six critical phases in image processing. To continue the process, the algorithm must convert the color image to grayscale after capturing it from the camera. After smoothing and thresholding the image, the algorithm will detect edges using the Canny Edge Detection function. Finally, the angle will be calculated using the boundary points stored by the reverse detection algorithm. Camera resolution and edge detection accuracy are the essential factors in determining the accuracy of a limited angle reading. Angle detection can be affected by the environment and lighting during the experiment, so filters are included in the algorithm to limit this effect.

In order to measure in this study, an approach using machine vision based on the Laboratory Virtual Instrumentation Engineering Workbench (LabVIEW) program available in the NI Vision Builder Automated Inspection has been proposed. Object measurement can be done more quickly and precisely using this system. In addition, it is possible to configure the camera using menu-based development tools, customize image processing of hundreds of algorithms and inspection steps, interface with automation hardware, and generate inspection results.

III. Block Diagram

Fig. 1 shows that the whole system process starts from the camera hardware and is continued by several other software until finally, at the gripper end, the control is automatically controlled by the system. The block diagram presented shows that the system being implemented is linear and loops continuously to achieve the goal of grasping. In addition, the system will automatically update the signal in real-time.

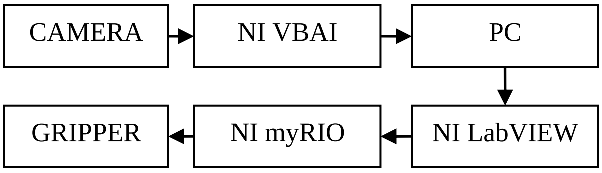


Figure 1. Block diagram of system control on the gripper.

This paper aims to automate the gripper soft robotic gripper process so that the gripper can grip objects of various shapes and sizes. The hardware used in this system are camera, Personal Computer (PC), NI myRIO, and gripper. Figure 1 shows a camera connected to a PC that will be used as an image capture process for initial processing in the NI Vision builder automatic inspection (NI VBAI) application. In this application, real-time image processing will be carried out by utilizing this automatic capability. The resulting image is converted into data with shapes and sizes, then sent through the NI Distributed system manager to be distributed to the control system managed by NI myRIO. The following NI myRIO hardware has been integrated with an electro-pneumatic regulator valve that can control the air pressure that is passed so that it can be used as input from the gripper. Eventually the Gripper can grip objects of a calibrated size and shape.

IV. Flow Chart

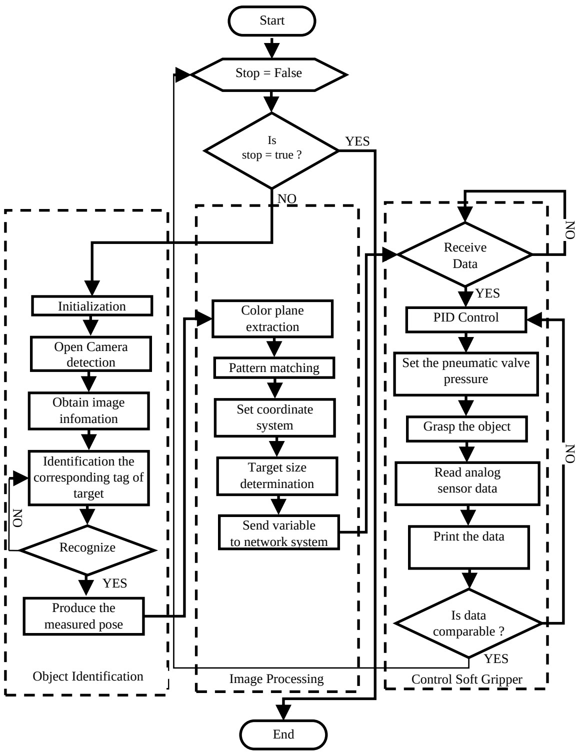


Figure 2. Flow diagram of the soft robotic gripper control.

The experiment was divided into three central systems, which were processed by two different software. As shown in Fig. 2, the processes conducted are object identification, Image Processing, and Control Soft

Gripper. In this first process, the NI VBAI software is used for the inspection process of the object to be identified. From the identification results, the shape of the object will be found which will then lead from each pattern (case) to the measurement process that occurs in the second process. This process is image processing because this process will perform precise data processing to get the actual size. In the end, after the data is obtained, the data will be sent to the NI myRIO which takes the PID data on the sensor and provides an electrical signal to the valve. Fig. 3 shows the entire system that has been integrated in this research.

This experiment uses several hardware components which are the main points in the experiment. Each piece of hardware has its function to control the gripper.

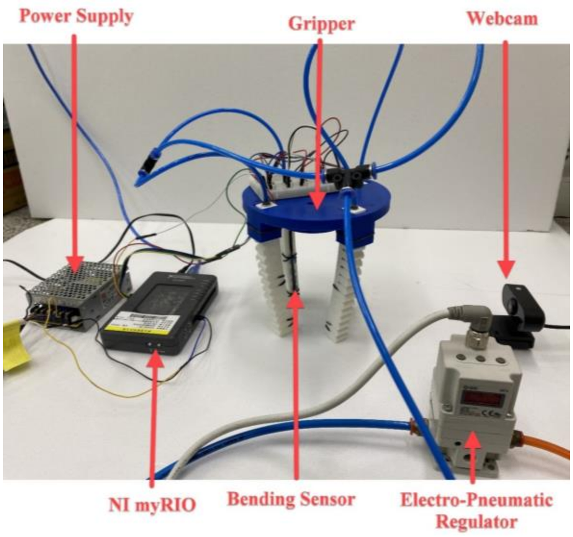


Figure 3. Distribution of devices in the experiment.

This experiment uses two object shapes as experiments with different sizes so that it has four paths in the gripping task shown in Figure 4. The object being held is placed on the workbench next to it so that when the system is running, the program can detect the object's shape and size.

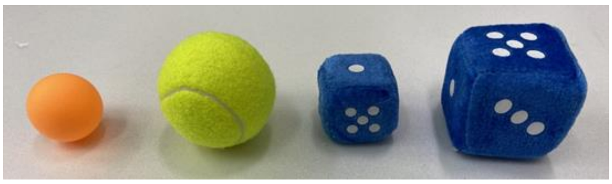


Figure 4. Different objects and sizes for grasping task.

V. Code Implementated in the System

A. Object Detection Using NI VBAI

Image processing is responsible for capturing the areas that need to detect objects. Then analyze and classify objects and find the location of objects in that area. When processing is complete, the object location information will be sent via the NI Distributed system manager to the control gripper system. The image processing flow chart is shown in the figure. 5.

The first stage is to measure the object using the NI VBAI program run on a PC. The speed expected in the measurement is as fast as possible cause the processing was running on a PC. So, running NI VBAI programs that require large memory cannot run properly if placed on NI myRIO.

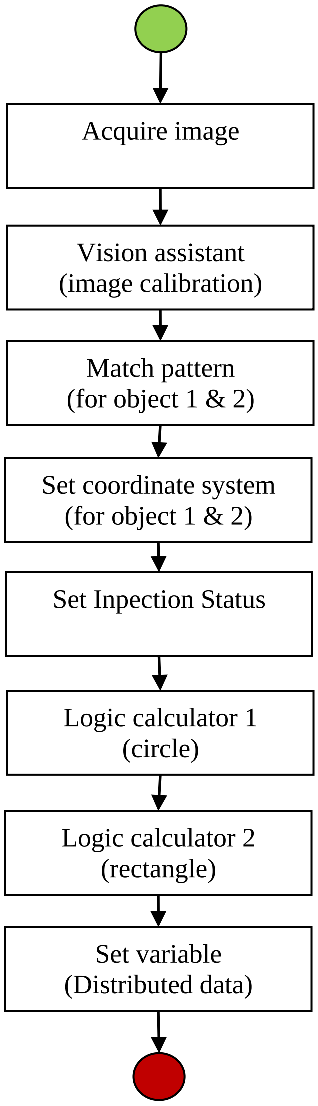


Figure 5. Distribution of devices in the experiment

In Fig. 5, the object in this experiment uses two shapes: a circle and a rectangle. Each object must be classified individually in its stages, which are called states one and two. From the initial inspection results, when looking for patterns to determine the shape of objects, determine the coordinates and size of each object. After determining the classified objects, the system will automatically use the logic that has been built to determine which stage the program will run next.

B. System Control Using LabVIEW

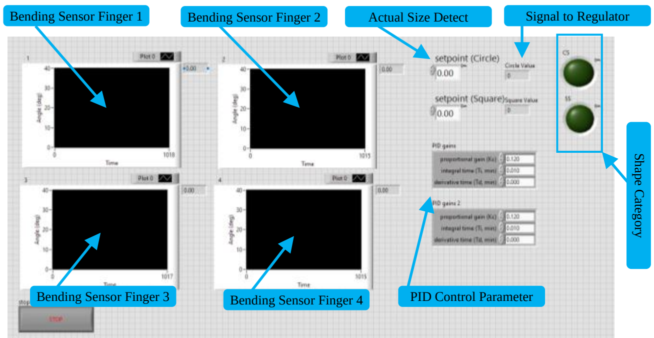


Figure 6. The front panel of the LabVIEW interface.

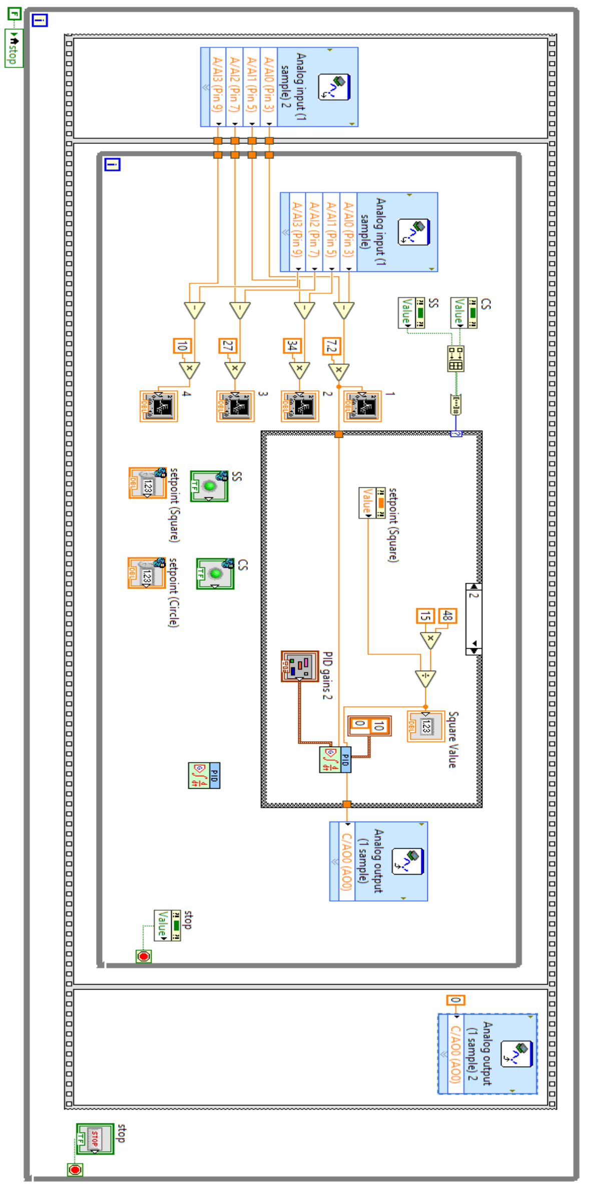


Figure 7. The Block diagram of the LabVIEW program.

The Proportional, Integral, and Derivative (PID) system is used to create a feedback mechanism in the gripper task control system. Fig. 7 shows that the system used in the program is a case structure where each process will run in the same direction and one case. In this system, four bending sensors are used to obtain the released pressure data so that it can control the electro-pneumatic valve continuously as shown in Fig. 6.

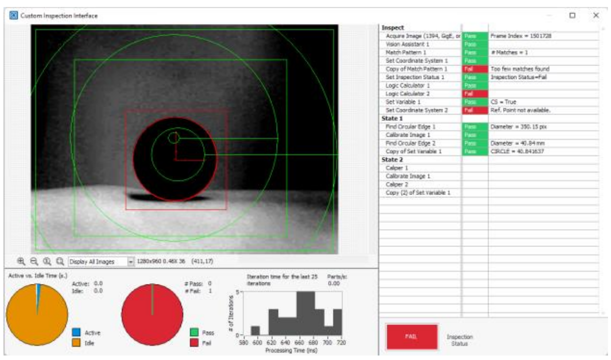
VI. RESULT

In order to verify that the pneumatic soft gripper can be used for the range of object sizes, this paper focuses on A. Case 1: Circle, Size:40mm; B. Case 2: Circle, Size:65 mm; C. Case 3: Rectangle, Size:47 mm; D. Case 4: Rectangle, Size: 69 mm. The size of the object is confirmed by the vision detection system, and then the pneumatic soft gripper is given with the appropriate pneumatic pressure control to achieve the object clamping function.

The gripping process as a result of Case 1 is to measure the diameter of a small circle which in this process uses a ping pong ball with a diameter of 40 mm. The results of the examination from the NI VBAI program showed that the final ball result was 40.841637 mm. The results show that the figure is close to the actual value. Fig. 8 shows the measurement results on a Ping Pong ball in real-time. In the second gripping process, the second circle test was carried out using a tennis ball with a diameter of 65 mm. The program results show a tennis ball with a size of 65.90 mm. Figure 9 shows the results of the measurement process. In the process of holding a ball with a diameter of 65 mm, it undergoes a break time process. This is because the VBAI program identifies image acquisition as a process that sometimes fails. This is identified because the process of converting images for machine vision needs to use bright colors so that the detected object does not look the same as the background or good lighting on the workbench.

After previously measuring the circle object. In this cases 3 and 4, we carried out tests to measure rectangular objects with actual width of 47 mm, as shown in Figure 10. The program's success process shows that the object's size obtained is 47.75 mm. The last step is to measure the square object with a larger size than before. In this process, we use objects with actual width of 69 mm. The NI VBAI program showed a measurement result of 69.28 mm. Fig. 11 shows the real-time measurement results in this process.

A. Case 1: The detection shape is a ball with a diameter of 40mm, and the image measurement size of 40.84mm can be calculated by the contouring process.



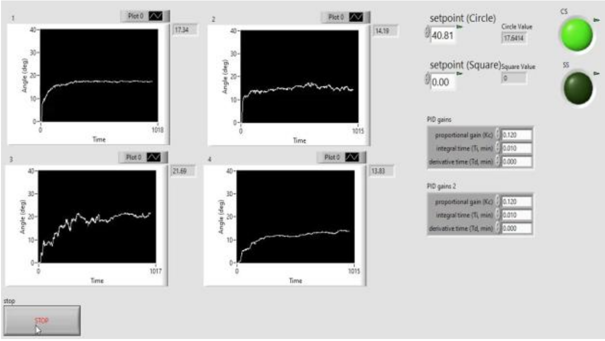


Figure 8. Result Case 1.

B. Case 2: The detection shape is a ball with a diameter of 65 mm, and the image measurement size of 65.90 mm can be calculated by the contour algorithm.

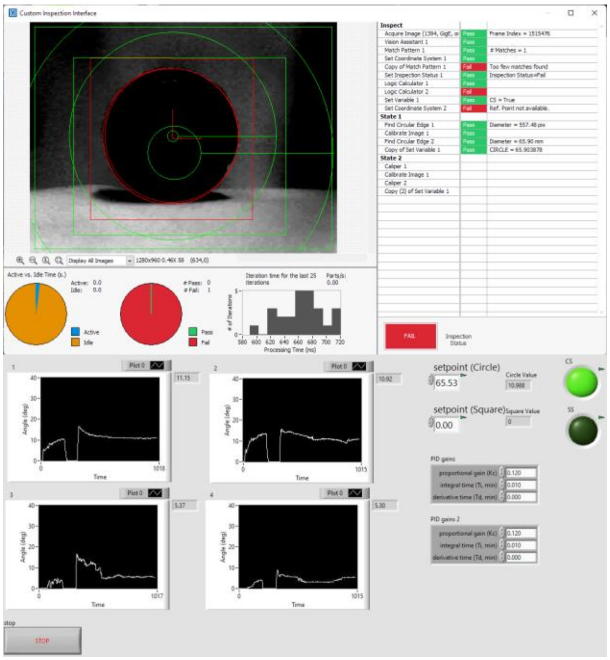
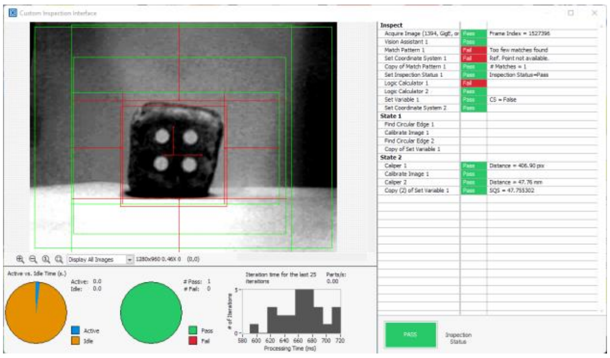


Figure 9. Result Case 2.

C. Case 3: The detection shape is a square body, the body appearance size: 47*47*47mm, through the contour, border size algorithm, can calculate the image measurement size of 47.7*47.6mm.



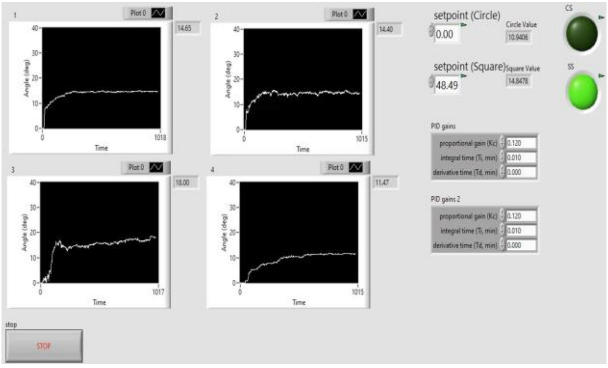


Figure 10. Result Case 3.

D. Case 4: The recognition shape is a square body, the body appearance size: 69*69*69mm, through the contour, border size algorithm, can calculate the image measurement size of 69.3*69.3mm.

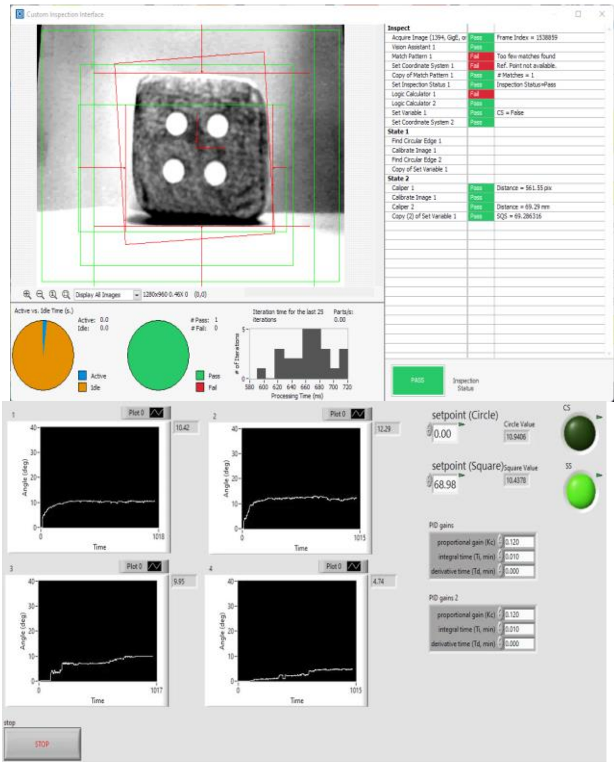


Figure 11. Result Case 4.

The resulting gripper can grip the smallest object with a size of 10 mm and the largest size is 100 mm. This is because the maximum distance between actuator 1 and actuator 2 horizontally is 100 mm. The process of gripping each object is shown in figure 12. Each case shows that the object can be lifted in the gripping process with a force that is accurate enough to be able to grip without damaging the gripped object.

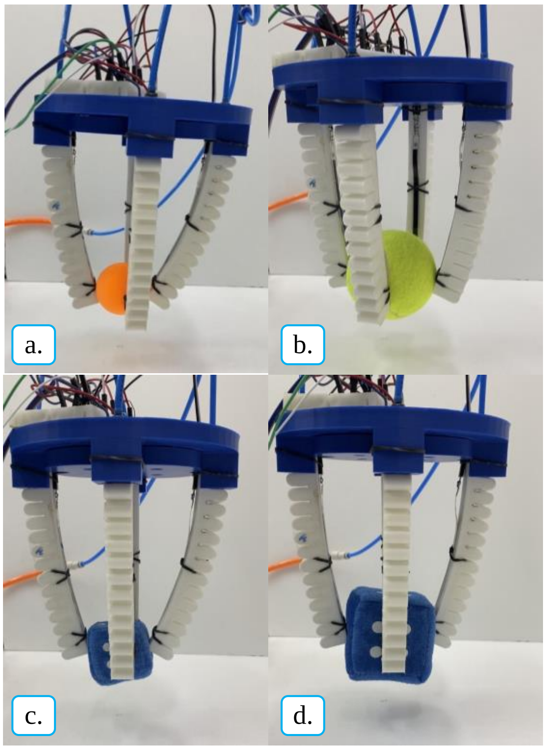


Figure 12. Grasping tasks result. (a) Case 1, (b) Case 2, (c) Case 3, (d) Case 4.

In this section, the process of analyzing the ability of each gripping task to ensure the smart grasping of a soft robotic gripper is carried out. After the application of the NI VBAI based on LabVIEW program has been carried out in the previous process, this stage shows the success rate of the gripping process by utilizing the error rate of the signal and actuator. Because the deformation characteristics of the actuator depend on the type of object to be gripped and the success of each actuator during fabrication. Each gripping task shows a data signal generated by a different bending sensor. The combination of sensor data used as a control variable on the PID led to a significant comparison of the output results in performing the tasks shown in Fig. 12. Next, we compared the degree of deformation of each actuator during the gripping task. The inflation side space will be used for the circular motion, so bending around the x-axis is the most important part of this section.

The grasping task shows that 95% success is achieved from the object being tested. Soft grippers are better at gripping larger objects with a coarser texture. This is because the surface of the soft gripper has a sensor and is flat. This causes an object with a slippery surface to easily slip in the other direction. This is due to the soft robotic fingers' ability to produce different abilities in gripping tasks. Below will be shown the signal generated from each finger during the gripping process.

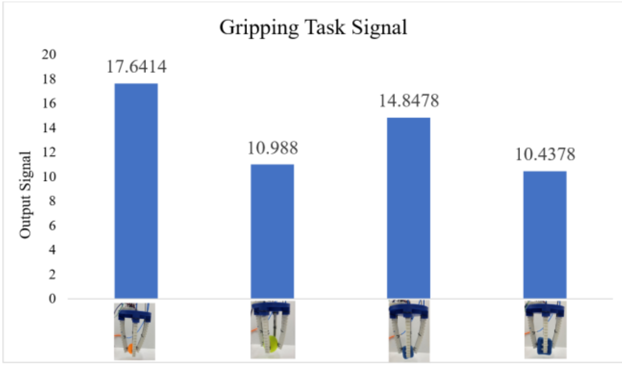


Figure 13. Grasping tasks signal comparison.

In the experiment, we focused on the successful gripping task of the soft gripper for the overall results. The most significant error rate is in Fig. 9, where the graph shows a sudden decline in 2 seconds. This is due to the failure of object recognition performed in the NI VBAI program. Fig. 13 shows the comparison of each output signal generated by the gripping process in an effort to achieve the goal of accurate gripping. However, everything is adjusted accurately, but the difference in each signal generated is due to the characteristics of each sensor and actuator, as shown in Table I.

E. Error Percentage Value of Gripping Task Process

Gripping ability can be performed. However, several things affect the gripper's accuracy level because of the bending sensor's signal. Therefore, we analyze the error value of each task to find out the highest error value obtained from each process. Fig. 14 shows that each gripping task has a different error rate. From the graph, calculate the signal difference error value for each gripping process by finding the average value generated by looking at the final signal performance.

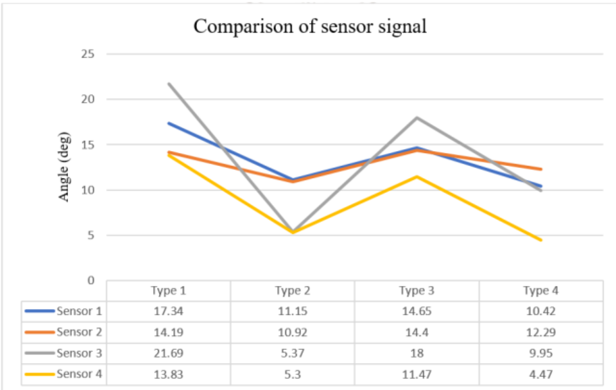


Figure 14. Comparison of bending sensor.

TABLE I. PERFORMANCE SIGNAL PRODUCTION

Description	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Total	Average
Type 1	17.34	14.19	21.69	13.83	67.05	16.7625
Type 2	11.15	10.92	5.37	5.3	32.74	8.185
Type 3	14.65	14.4	18	11.47	58.52	14.63
Type 4	10.42	12.29	9.95	4.47	37.13	9.2825

In this step, compare the average of the final signal issued. The calculation process is also carried out for each gripping task. The error value obtained in this process results from dividing each number by the average value. Table II shows the error value of each sensor for the gripping task performed.

TABLE II. ERROR VALUE OF GRIPPING TASK

Description	Average Signal	Actual Value	Error Value (%)
Type 1	16.7625	17.6414	5.243251
Type 2	8.185	10.988	34.24557
Type 3	14.63	14.8478	1.435407
Type 4	9.2825	10.4378	12.446

From the Table II , it is shown that the largest error rate is generated during object the type 2 gripping process with an error value of 34.24 %. This is due to an incorrect detection in the VBAI program that confused the PID signal, resulting in a variable that is different from the actual value. While the highest level of accuracy was obtained from the object the type 4 gripping task with an error value of 1.43 %. From the result in this analysis, look for the error rate of each sensor in detail by comparing the actual value of each sensor with the average value in the gripping task of each different type of object. Table III shows the error rate of each sensor on each process.

From the result shown in table III, it can be concluded that the biggest error was experienced by actuator number 4 where from the signal data the error value was shown at 52.71 %. After further analysis and research, the biggest on actuator number 4 is caused by the difference in the resulting angle. This difference is due to leakage in the actuator so the ability to accept fluid pressure received by the actuator is also small compared to other actuators. Because the input on the soft gripper only uses a centralized regulator, it makes it difficult to configure different pressures for each actuator.

TABLE III. ERROR VALUE OF ACTUATOR

Description	Sensor 1	Sensor 2	Sensor 3	Sensor 4
Type 1	3.44519	18.12896	29.39597	21.2039
Type 2	36.2248	33.41478	52.42086	54.43396
Type 3	0.136705	1.597222	23.03486	27.55013
Type 4	12.25424	32.39968	7.190951	107.6622
Error Average (%)	13.01523	21.38516	28.01066	52.71255

The following error data is used as a further development to get maximum results to produce a perfect grip. Because an error in 1 actuator will affect the success of the gripping task. From the data generated above, the soft robotic gripper produced can still perform the gripping task proper so that the smart gripper that is carried out automatically can still be conducted.

VII. CONCLUSION

This paper presents a system for automated gripping tasks using the NI vision builder integrated with the LabVIEW program for automated inspection. The designed program has been successfully tested by utilizing the PID controller system on the gripper so that the gripper can continuously grip successfully on different objects and at a speed of 0.5 seconds from the start of the program. The accuracy of the measurement results in the error rate of less than 1 millimeter. In addition to the process of measuring the fabrication process of the actuator, further attention needs to be paid in an effort to minimize the error rate given by the actuator in controlling the PID. Because each actuator receives the same pressure, further actuator printing needs to be done in further research to make the system more robust. But overall, it can be categorized as the development of an intelligent gripping system from a soft robotic gripper that has been carried out. Therefore, this system can later be applied in the industrial sector in automatic gripping tasks.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

All authors contributed to design, implementation and analysis of the research. Ilham Saputra and Chen-En Shi were involved in the implementation of the research. Chin-Yi Cheng and Ilham Saputra did the preparation of the final manuscript. Ilham Saputra completed the research under the supervision of Chin-Yi Cheng and Jhy-Chyang Renn. All authors had approved the final version.

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