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Using machine vision for flexible automatic assembly system

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Abstract

Flexible automatic assembly systems become the useful automation system for high mixed production lines of manufacturing processes. This research was aimed to design the primary prototype of the flexible automatic pick and place assembly system. We integrated the machine vision system with the robotic system to conduct a pick and place process. The product models consisted of a main part and an assembly part. The main parts were transferred to the mechanical system through a conveyor belt. When the main parts were held at the specific location, the images of the main parts were captured. Using the image processing of LabVIEW NI vision software and NI vision builder and image calibration method, we could obtain the shape, and orientation of assemble space in the main part which were used to control selective compliance articulated robot arm (SCARA). The SCARA was used to pick the assembly parts from the storage station and place them into the assembly spaces on the main parts. As the results of the prototyping, we evaluated the coordinate conversion factors from the image calibration and used them to control the movement of the SCARA. We finally obtained the reliable flexible automatic assembly system that could detect and identify the shape, and orientation of the assembly space correctly. The SCARA could also pick the correct assembly parts and place them into the assembly space perfectly.

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Keywords: flexible manufacturing system; machine vision systems; pick and place process; LabVIEW

1. Introduction

Nowadays, customer wishes push demands on variety of individual product features, and shorter delivery time in manufacturing industry[1]. With a high degree of complexity of manufacturing processes, the automation systems have been applied to production and final assembly systems. In the high mix production, product models may have various sizes, shapes, and orientations which require a higher flexibility of the automatic assembly process. When the product models are changed in the conventional assembly process, the production line needs to be stopped and then new configuration and commands of the automatic assembly system need to be set up. This conventional assembly process can increase the production lead time, whereas it can decrease the systems efficiency. Consequently, the production costs are raised by investing in labor cost, machine and equipment cost. To improve the conventional automatic assembly system, the flexible automatic systems have been utilized in the high mix assembly process. This flexible automatic system can modify its working pattern and automatically responds to the new models. In this case, the production line does not need to be stopped remarkably improving the assembly process performance.

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One way to accomplish the flexible automatic system is to integrate machine vision systems with the automation systems. The computer vision techniques have been used to provide product data which assists decision-making of the production systems[2]. In cutting tool process using CNC machine, the vision sensor have been used to monitor cutting tool conditions, including tool wear, and surface texture. In this case, the information on tool wear state obtained from the vision sensor was used to estimate wear parameters which were used as feedback control for CNC controllers[3]. An automated vision system has also been used to inspect defects on printed circuit boards using reference comparison approach. This automated visual inspection system was considered to be efficient for defect detection and defect classification[4]. In the automatic assembly process, the machine vision system is also feasible to inspect the characteristics, size, shape, orientation, and defects of the product models. This inspection assists the automatic assembly system to distinguish the models and respond to those models correctly. The vision system basically based on image classification. First, the object image is captured using camera. Next, the search area of the image is specified to set the environment for image processing. In the image processing step, the classification is identified by comparing the significant features of the captured image to those of the standard image. Two major classifiers are generally used for the image processing: object classifier, and color classifier. The object classifier identifies the object based on its shape while the color classifier distinguishes the object based on its color[5].

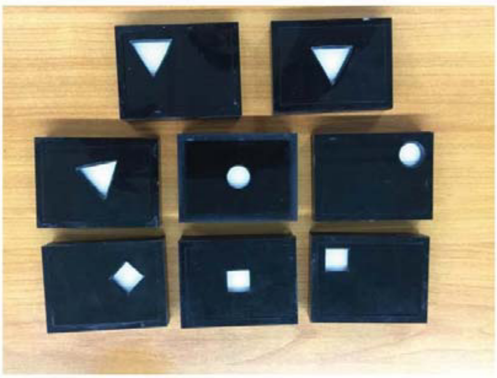
Meanwhile, industrial robots have been also implemented in the automatic assembly process to reduce human errors, lead time, and labor cost. The robots can achieve better performance using novel control methods. Chen and Liu have remarkably succeeded in implementing the robust impedance control algorithm with a selective compliance articulated robot arm (SCARA) to perform a printed circuit board (PCB) assembly[6].

This research paper focuses on the pick and place process, a sub process of assembly process which requires a precise configuration and position to assemble parts of products. The integration system of machine vision system and SCARA robot has been designed to assemble the parts with various shapes, configurations, and orientation in a single production line.

2. Experiment

In this experiment, model components were consisted of main parts and assembly parts. We had three assembly models which were square, triangle, and circle to be placed into the corresponding main parts in various positions. The main parts and assembly parts are presented in Fig. 1(a), and Fig. 1(b), respectively. The main parts were moved along the conveyor belt, while the assemble parts had been stored on the storage station. The assembly process must be done by putting the right assembly part into correct position on the main part. To complete the task, vision system was integrated to identify the geometry and the orientation of the assembly space.

a



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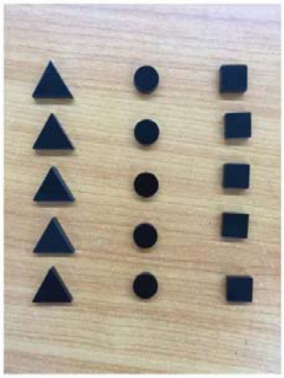

Fig.1. (a) Main parts; (b) Assembly parts.

This chapter is divided into two sections which are hardware design, and software design. The hardware system composed of camera, robot, and end effecter of robot. We also used SCARA model IX-NNC6020-5L-T1-SP to receive processing information. The end effecter of the robot, a 10 mm diameter vacuum suction head, was used to hold the assembly part in the assembly step. Then the SCARA was programmed to move to the desired location in pick and place process.

For the vision module, we used the USB CCD camera with the resolution of 640 X 840 pixels to capture the image of the main part on the conveyor belt. The brightness of the backlight at 700 Lux makes it was easier to create image processing software of LabVIEW. The system used the LabVIEW NI vision software and NI vision builder to develop computer programs for image processing. The program was designed for identifying the position and orientation of the parts. LabVIEW was also used to communicate to the robot controllers by sending the location of the assembly part and the location of the assembly space to the SCARA. NI Vision Builder program was brought in to define the characteristics of the parts such as the configuration of the main part that needed to be searched, color, brightness, searching area, etc. This vision builder helped the program work easily.

2.1. Device Positioning

The SCARA was placed at the center of the base. A camera was mounted on the tip of the robot. The main parts moved along the tracks conveyer. When the main part moved to the specified location, the system held the main part and took an image, as shown in Fig. 2. The image was sent to LabVIEW NI vision software to identify the coordinate of placing position.

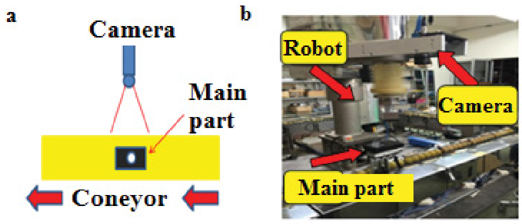

Fig. 2. (a) Schematic layout; (b) True positioning of devices.

2.2. Algorithm for positioning

The captured images of the main part from the camera were sent to LabVIEW program to locate the position and the orientation of assembly space on the main parts where the assembly parts needed to be placed correctly. The captured images were analyzed through the processes as shown in Fig. 3.

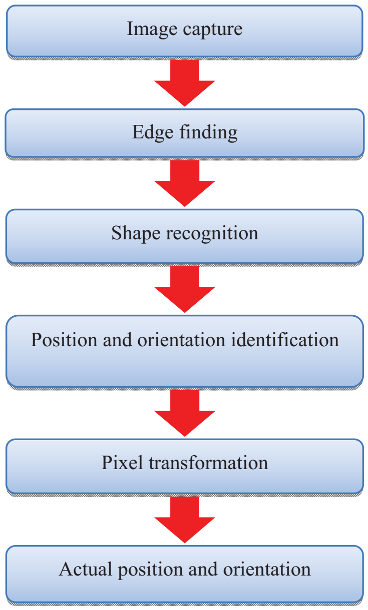

Fig. 3. Flow chart of positioning algorithm.

After taking the image of the main part as shown in Fig. 4, the resolution size of the image was 640 X 480 pixels, the edge of assembly space on the main part was found by specifying the searching area using NI vision builder as presented in Fig. 5. Next, the edge of the assembly space was detected using NI vision builder and LabVIEW, resulting in shape recognition of the program. After that, the center point and the orientation of the space were located in term of pixel position as shown in Fig. 6. The program informed the pixel position along the X axis and Y axis of the captured image.

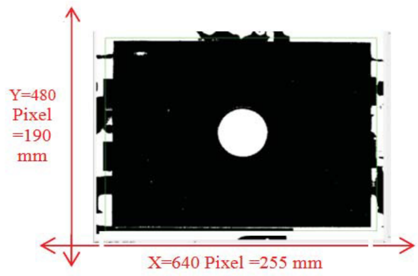

Fig. 4. Example of capture image.

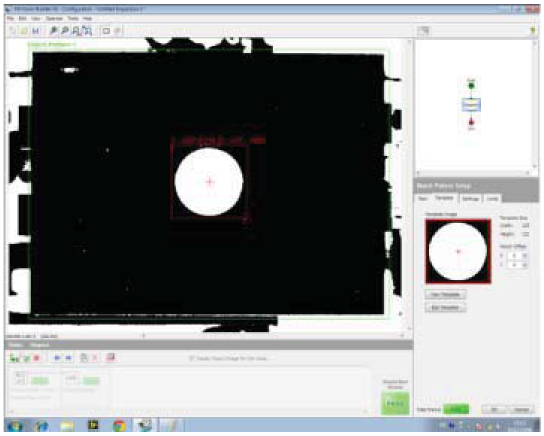

Fig. 5. Searching area determination.

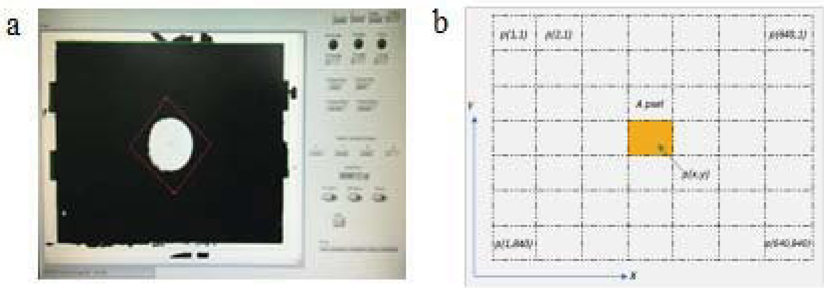

Fig. 6. (a) Searching area of assembly space in the captured image; (b) Specific pixel for the center of assembly space.

When we had the pixel coordinates from the previous step, we needed to convert the pixel coordinates into the coordinates in millimeter using conversion factor of 0.138425 mm/pixel in x-direction and 0.1351095 mm/pixel in y-direction.

Then we had to convert the coordinates in millimeter into series of commands of IAI Protocol B which were in the form of hexadecimal number. The commands of IAI Protocol B were used to control the robot movement in the pick and place process.

2.3. Image calibration

For the specification of assembly space orientation obtained from the captured image, we found that the specified coordinates induced misoriented movement and misoriented destination of the SCARA which deviated from the true position of the object[7, 8]. When the camera was used to capture the image of the main part, it might not be at the center of the main object and might not be perpendicular to the main object, resulting in image distortion and wrong orientation of the specified coordinates. Therefore, it was necessary to calibrate the captured image before specifying the assembly space orientation for the robot.

2.3.1. Calibration object

The size of standard object was equal to the true object size. Forty-eight circles (6x8 rows) with 10 mm diameter were created on the standard object. The distance between each center of the circle was 10 mm. The number and true physical coordinates of the circles were specified as shown in Fig. 7. For example, the center coordinates of the number one circle, number two circle, and number 10 circle were (5,10) mm, (15,10) mm, and (15,20) mm, respectively.

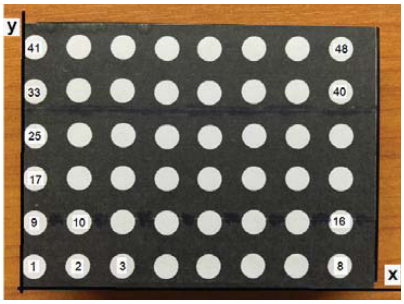

Fig. 7. A standard object with specific oriented circles.

2.3.2. Image calibration methodology

After that, we imported the standard object to the machine for checking the center coordinates of each circle which was prescribed as (x_m, y_m) . Then the machine coordinates (x_m, y_m) were compared with the true physical coordinates (x_r, y_r). Position errors in x-direction (ε_x), and y-direction (ε_y) were derived from the comparison between (x_m, y_m) and (x_r, y_r) as expressed in Eq. (1) and Eq. (2), respectively.

$$\varepsilon_x = \frac{x_r - x_m}{x_r} \times 100 \tag{1}$$

$$\varepsilon_y = \frac{y_r - y_m}{y_r} \times 100 \tag{2}$$

Thus, we can express the total errors as in Eq. (3).

$$\varepsilon_T = \sqrt{\varepsilon_x^2 + \varepsilon_y^2} \tag{3}$$

3. Results and Discussion

3.1. Calibration Results

As the results of calibration, the maximum error in x-direction (ε_x) was 10.59 % for the number 41 circle, and the maximum error in y-direction (ε_y) was 7.41 % for the number two circle, whereas the total error computed from the Eq. (3) was 10.621 % for the number 41 circle. Meanwhile, the ten descending rank of total errors are illustrated in Table 1.

Table 1. Ten descending rank of total errors

Number	X error $(\varepsilon_x \%)$%	Y error $(\varepsilon_y \%)$	Total error $(\varepsilon_T \%)$
41	10.59912	0.771277	10.6271424
1	4.164234	6.672929	7.86567417
2	1.295119	7.142118	7.25859347
3	0.759795	6.907524	6.94918494
9	5.676706	2.829725	6.34289689
33	6.061699	0.863274	6.12286227
25	5.374212	1.491159	5.57724909
6	0.566799	5.141168	5.1723173
10	1.643446	4.347688	4.64793517
4	0.42823	4.478784	4.49920983

From Table 1, the error increased in the boundary region of the image because the image distortion induced the perspective image instead of orthogonal image[8].

This calibration data provided parameters for coordinate conversion of the captured image. The conversion factors were 0.138425 mm/pixel in x-direction and 0.1351095 mm/pixel in y-direction Thus, the machine coordinates (x_m, y_m) could be adjusted and were close to the true physical coordinates (x_r, y_r). After we calibrated the program using those parameters, we obtained the adjusted coordinates (x, y) which were used to identify the assembly position on the main part and also control the robot movement. Fig. 8 shows the coordinates adjustment of each type of the models in different orientation. The percentage differences of the coordinates of the assembly space center compared between before the image calibration and after the image calibration are also presented in Fig. 9. The percentage differences of the coordinates in y-direction (0.26 – 1.40%) were significantly high compared with the percentage differences of the coordinates in x-direction (0.008 – 0.141%). Meanwhile, percentage differences of the coordinates in y-direction at the center and on the left side of the main parts were higher than those on the right side. The results demonstrates that the significantly large adjustment was necessary for all types of assembly spaces where were located at the center of the main parts and on the left side of the main parts, especially the coordinates in y-direction. These results corresponded to the results of calibration in Table 1 that the maximum error was found on the left side region of the standard objects.

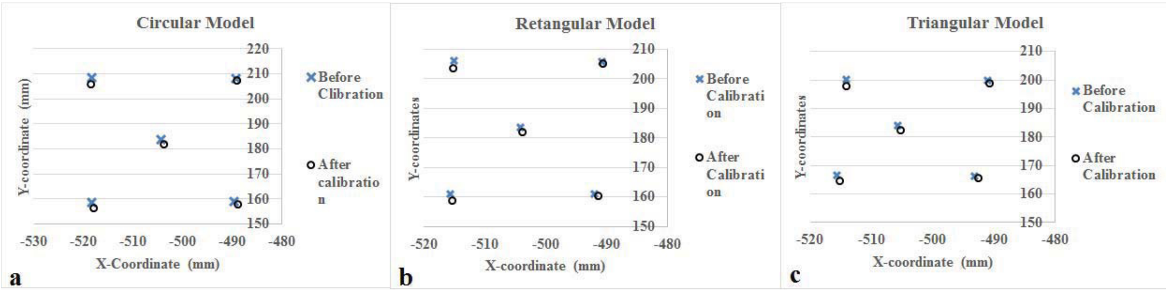

Fig. 8. Comparison of the coordinates of the assembly space center between before image calibration and after image calibration: (a) circular model; (b) Rectangular model; (c) Triangular model.

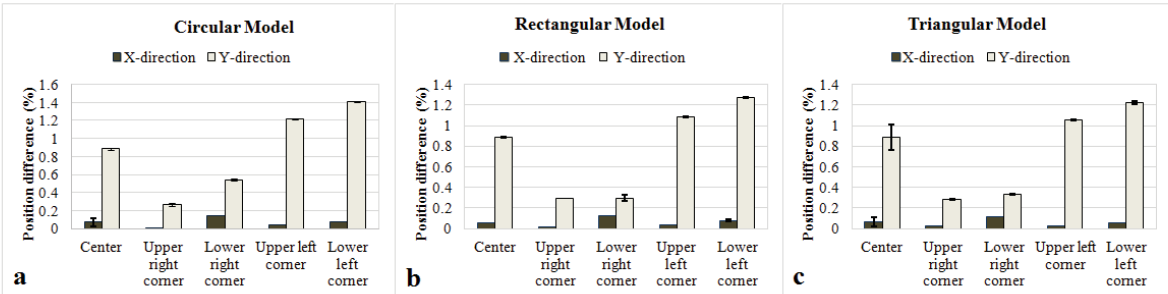

Fig. 9. Percentage difference of the coordinates of the assembly space center compared between before image calibration and after image calibration: (a) circular model; (b) Rectangular model; (c) Triangular model.

3.2. Operating Results

Using LabVIEW, we obtained friendly user interface program that helped users to track the status of assembly process. The program displayed the captured image, assembly space, the adjusted coordinates (x, y), the orientation of the assembly space, and the commands of IAI protocol B as shown in Fig. 10 and Fig. 11.

With the image processor, the system could recognize and distinguish the shape and orientation of the assembly space correctly. The robot could pick up the correct assembly part that corresponds to the assembly space. After we calibrated the program using the conversion factors, we found that the robot could move to the correct assembly position. Fig. 12 shows that the robot could place the assembly part into the main part correctly (100%), resulting in efficiency improvement of this assembly process.

This automatic assembly system needs to be improved the system's flexibility. Now this system can be perfectly applied with the black color parts which are easy for the image processor to detect the assembly space, shape, and orientation of the assembly space. However, this system may not be compatible with luminous parts which may reflect vivid light to the camera. In this case, it may cause some errors of the image processor to detect the shape and correct orientation of the assembly space. This further improvement is considered to be the future work of the team.

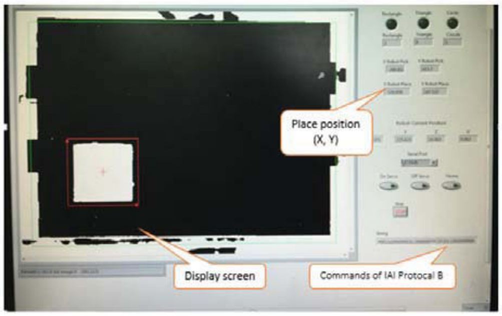

Fig. 10. User interface of LabVIEW for flexible automatic assembly system.

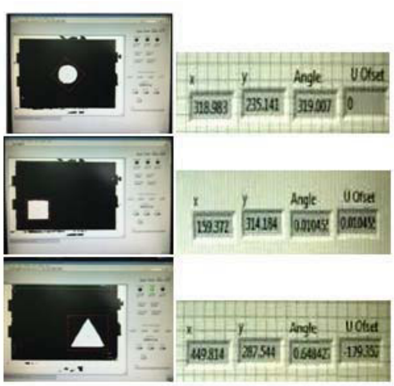

Fig. 11. Captured images format (left) and the coordinates X, Y at the center of the assembly space (right).

Fig. 12. Samples of placing the assembly parts into the assembly space on the main part.

4. Conclusion

This paper has proposed the primary prototype of flexible automatic assembly system combined with the machine vision system. For the image processing of the machine vision system, the perspective captured image was the major concern in specifying the correct target position of placing the assembly part. We needed to conduct the image calibration for obtaining the correct coordinates of assembly space used for robotic pick and place process. The large adjustment was necessary for all types of assembly spaces where were located at the center of the main parts and on the left side of the main parts, especially the coordinates in y-direction. We finally obtained the reliable flexible automatic assembly system that could detect and identify the shape, and orientation of the assembly space correctly, resulting in the perfect pick and place process of the SCARA. This prototype is expected to be developed for use with a complex product model, and complicated production line which will be our challenging work in the future.

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