Research on Control System of Delta Robot Based on Visual Tracking Technology

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Abstract. Delta parallel robot has the advantages of fast motion speed, accurate positioning, low cost and high efficiency. In this paper, OMRON Adapt Hornet 565 3 axis parallel robot is taken as the research object and the control system of Delta robot based on visual tracking technology is studied. The control flow such as camera configuration, model configuration, and process configuration is described in detail, the control system was tested finally. Through the tests, The parallel robot can grasp different shapes of models accurately and quickly under the action of visual tracking.

1. Introduction
Robots have gradually changed the production form of society since they came out in the 20th century. They have played an indispensable role in various fields of industrial production[1], they save the labor cost of the enterprise and greatly improve the production efficiency of the enterprise[2]. With the maturity of technology, robot has become the core of intelligent manufacturing and an important symbol of industrial modernization[3].

Delta parallel robot has the characteristics of light weight, small size, fast movement speed, accurate positioning, low cost and high efficiency, it is suitable for the sorting, handling and grasping of the material on the high-speed production line[4]. It can be used in industries such as food, medicine and electronics.

Visual tracking relies on image sensors to obtain information[5], applying it to the field of industrial robot can improve the robot's perception and adaptability to the external environment, it can make them work more efficiently[6].

In this paper, OMRON Adapt Hornet 565 3 axis parallel robot is taken as the research object and the control system of parallel robot based on visual tracking technology is studied.

2. The structure of parallel robot
This research was based on the parallel robot training platform of our university. The platform consists of robot body and controller, vision system, conveyor belt, computer and control system. Its mechanical structure is shown in Figure 1.
2.1. The robot body and controller
The robot body is OMRON's Adept Hornet 565 Delta parallel robot. The Hornet 565 is a three-axis parallel robot. The three identical axis motors control movement of the robot tool in X, Y, and Z directions. The Hornet 565 uses an eAIB amplifier. The robot is powered and controlled using the eAIB.

2.2. The vision system
The core of the vision system is an AcA 640-90 gm Basler camera. It is used to obtain the image information of the object. The model used in this system is eye-to-hand, the camera is fixed above the conveyor belt and does not move with the manipulator.

2.3. The conveyor belt
It consists of two stepper motors, two incremental encoders and two conveyor belts in the positive and negative directions.

2.4. The control system
The control system is composed of controller, operating software and operating panel. The controller is smart Controller EX motion controller, operating software is adept ACE (Adept Automation Control Environment) 3.6, which is a PC-based software, it can control and simulate OMRON's industrial robots in real time.

3. Control flow of parallel robot
All the control of parallel robot is performed by operating software Adept ACE 3.6. After opening the ACE software, we must connect the robot and the controller firstly, then follow the following steps to operate.

3.1. Add camera and adjust camera parameters
After adding the Basler camera settings, we need to calibrate the camera. The camera parameters can be calibrated by two methods: fixed pixel calibration and grid calibration. First of all, we need to calibrate the camera using the method of grid calibration, which uses the dot map with the standard spacing of 4, 6, 8, 10mm, it is shown in Figure 2. In this step, we need to adjust the green box, select the grid area, input the lattice distance, click Calibration button, and record the pixel value in the XY direction finally.
Secondly, we use fixed pixel calibration to calibrate. In this step, we need to input the pixel values of the grid calibration just recorded. The calibration is completed after image distortion is removed.

3.2. Add Locator Model and Locator
After adding the locator, we need to adjust the search area so that it can be associated with the corresponding locator model. Parameters such as image similarity can be adjusted through the property option. Each locator can be associated with multiple locator models. The locator models
selected for this test are circles and squares with different sizes, shapes and thicknesses. They are shown in figure 3.

![Locator model 1 to 4.](image)

### 3.3. Add and configure conveyor belts
According to the guide, we need to complete the steps of conveyor belt size setting, conveyor belt positioning, controller and encoder selection and so on in order. Then we need to configure the conveyor belts latch signal, the encoder channel needs to be matched with its associated latch. Finally, we can test the correctness of the latch signal configuration by the test latch signal button.

### 3.4. Add and configure part & part target
We need to add the part and the part target to the process and configure them separately, the part property select the belt option, and the property of the belt is associated with the conveyor belt created previously. Select the mode as Vision, and then associate the visual tool to the locator. The part target’s property is set to "Static: Fixed position, no pallet".

### 3.5. Configure process manager
After the process manager is added, parts are added to the single-pick interface and single-place interface. Finally, the calibration is carried out in a sequence of conveyor belts, sensors and robot processes.

#### 3.5.1. Belt-to-robot calibrate.
According to the guide, choose the fixture at first, then test the encoder, the accurate information of speed and position must be returned by the encoder. Thirdly, use the target object to determine the upstream limit, downstream limit, and downstream pick limit, the aim is to determine the effective grasping range of the robot. In this process, we need to move the fixture to aim at the target object at the upstream limit, downstream limit, and downstream pick limit respectively. Click here to complete the teach. It is shown in Figure 4. Finally, the test calibration is carried out. Click start tracking, open the conveyor belt, the robot will move synchronously with the conveyor belt, and the belt-to-robot calibrate is completed. It is shown in Figure 5.

#### 3.5.2. Camera-to-robot calibrate.
According to the guide for visual calibration, after selecting the fixture, the target model in the field of vision is editted and tested to ensure that all targets can be located in the monitoring area. The sequence of the locate object needs to be recorded. Move the target to the grasp range of the robot, aim the fixture at the target in turn, and carry out point calibration in accordance with the order just recorded. After calibration, the calibration data will be displayed. The calibration is successful when the proportional coefficient is close to 1, and the effective proportional coefficient ranges from 0.92 to 1.08.

![The upstream limit, downstream limit and downstream pick limit calibration.](image)
3.5.3. Teach Process. After the above two calibrations are completed, the robot teach process begins. In this process, the coordinates of the stopping position, pick-up position and placing positions of the robot need to be specified and recorded into the system.

- Stopping position teaching. After entering the teaching interface, the stopping position should be taught firstly. The spatial position of the parallel robot can be moved through the control box on the right side of the teaching page. Move the robot to the desired position, and then click Here to store the teaching position.

- Pick-up position teaching. First of all, it is need to locate the target object. We can place a target object in the camera's field of vision, move the conveyor belt, and push the product into the grasping range of the robot, and move the robot until the end-effector touches the target object, and then click the Here button to store the pick-up position. It is shown in Figure 6.

- Placing position teaching. When the pick-up position is finished, click “Move” to move the robot to the free position, and then teach the placing position with the same method as the teaching of pick-up position.

After the placement teaching is completed, click “Start” to verify the visual tracking effect. The robot can accurately pick up and place objects on the conveyor belt. Teach process is complete.

4. System test and analysis
Two groups of models were selected for this test. One group of models contained unrecorded locator model, and the other group of models were all recorded locator models. The models contained unrecorded locator model are shown in Figure 7, the triangle models are added to the models.
Under the same conditions (transmission speed and external lighting), five sets of data were taken for each group of models and the number of parts was increased from 20 to 80 by 15 at a time. Finally, we record the grasping situation of the robot and analyze the data. The test results of the two groups are shown in Table 1 and Table 2.

Table 1. Test data of the group of models contained unrecorded locator model.

| Total Number of triangles | Number of triangular models caught | Number of non-triangular models caught | Number of false catches | number of missing catches | Catching success rate |
|---------------------------|-----------------------------------|----------------------------------------|-------------------------|--------------------------|----------------------|
| 20                        | 2                                 | 18                                     | 0                       | 0                        | 100%                 |
| 35                        | 5                                 | 30                                     | 0                       | 0                        | 100%                 |
| 50                        | 8                                 | 41                                     | 0                       | 1                        | 97.62%               |
| 65                        | 12                                | 51                                     | 0                       | 2                        | 96.23%               |
| 80                        | 15                                | 62                                     | 0                       | 3                        | 95.38%               |

Table 2. Test data of the group of models were all recorded locator models.

| Total Number of models caught | number of missing catches | Catching success rate |
|-------------------------------|---------------------------|----------------------|
| 20                            | 20                        | 0                    | 100%                 |
| 35                            | 35                        | 0                    | 100%                 |
| 50                            | 48                        | 2                    | 96%                  |
| 65                            | 62                        | 3                    | 95.38%               |
| 80                            | 76                        | 4                    | 95%                  |

From the comparative analysis of experimental data in Table 1 and Table 2, we can see that:

- The parallel robot based on visual tracking can identify the different shapes of the models effectively and accurately, and there is no false catching; The catching success rate did not decrease significantly with the addition of the unrecorded models;
- Because the interval between the models is large, the catching success rate is higher when the number of parts is small. When the number of models increases, the model interval is small and the catching success rate decreases, which can be improved by optimizing the data. And repeated pick up occurs in the process of testing, which is optimized by setting the control source data.

5. Conclusion

In this paper, The OMRON Adapt Hornet 565 3-axis parallel robot is configured and programmed with ACE software, the system realizes the real-time tracking control of Delta robot. Finally, the grasping ability of the robot was tested. The experimental results show that the Delta parallel robot control system based on visual tracking technology can catch different shapes of parts efficiently and accurately.

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