International Journal of Automation and Computing 17(5), October 2020, 691-700
DOI: 10.1007/s11633-020-1237-0

Optimization of Grasping Efficiency of a Robot Used for Sorting Construction and Demolition Waste

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Abstract: The recycling of construction and demolition waste (CDW) remains an urgent problem to be solved. In the industry, raw CDW needs to be manually sorted. To achieve high efficiency and avoid the risks of manual sorting, a sorting robot can be designed to grasp and sort CDW on a conveyor belt. But dynamic grasping on the conveyor belt is a challenge. We collected location information with a three-dimensional camera and then evaluated the method of dynamic robotic grasping. This paper discusses the grasping strategy of rough processed CDW on the conveyor belt, and implements the function of grasping and sorting on the recycling line. Furthermore, two new mathematical models for a robotic locating system are established, the accuracy of the model is tested with Matlab, and the selected model is applied to actual working conditions to verify the sorting accuracy. Finally, the robot kinematics parameters are optimized to improve the sorting efficiency through experiments in a real system, and it was concluded that when the conveyor speed was kept at around 0.25 m/s, better sorting results could be achieved. Increasing the speed and shortening the acceleration/deceleration time would reach the maximum efficiency when the load would allow it. Currently, the sorting efficiency reached approximately 2000 pieces per hour, showing a high accuracy.

Keywords: Construction and demolition waste, sorting robot, grasping strategy, mathematical models, robot kinematics parameters.

1 Introduction

1.1 Recycling of CDW

Construction and demolition waste (CDW) usually results from the construction and demolition of buildings, roads, bridges, and other infrastructure. Currently, the European construction industry produces 820 million tons of CDW each year, accounting for 46% of the total waste generated, according to Eurostat[1, 2]. Equivalently, in China, because of the implementation of policy, a large number of housing developments, and heavy infrastructure construction, a large amount of CDW is generated, accounting for 30%–40% of the total waste[3], the amount of CDW is the highest in the world, but the utilization rate is less than 5%. To achieve sustainability, the government has begun to encourage enterprises to recycle CDW.

The traditional method of recycling CDW essentially requires manual sorting of, for example, blocks, bricks, concrete, wood chips, and other residue, such as scrap tires[4] or unrecovered objects. However, because of the long-term exposure to toxic and pathogenic work environments, manual sorting has many risk factors, high labor costs, and low sorting efficiency.

Some indirect sorting includes optical sorting, X-ray transmission (XRT), and hyperspectral imaging-based sorting[5–8]. These technologies involve some end-effectors such as robots or compressed air jets for fine sorting, so it is not possible to process large amounts of complex waste. However, they are superior to the traditional method in terms of recognition efficiency and refinement. Therefore, to process a large amount of CDW, indirect sorting combined with traditional direct sorting can improve the recycling purity of CDW while ensuring efficiency. So, in this paper, we use a three-dimensional (3D) camera combined with robotic sorting.

1.2 Robotic sorting

The grasping problem for a class of dexterous robotic hands is investigated based on the novel concept of constrained region in environment[9]. There are mainly anthropomorphic joint arms that are often used to work in 3D space, selective compliance assembly robot arm (SCARA) is generally used for assembly working in plane positioning, and the delta parallel robot has the characteristics of high speed operation, suitable for small light load conditions, while CDW sorting is a heavy-duty, medium-speed sorting condition. For more flexible grasping, we use a coordinate robot of four-degrees-of-freedom.

On the actual recycling line, dynamic robotic grasping needs high accuracy, and it is necessary to accurately predict the grasping point on the conveyor belt. A method for visual robot guidance in tracking objects moving

Research Article
Manuscript received February 23, 2020; accepted May 19, 2020; published online June 16, 2020
Recommended by Associate Editor Qing-Long Han
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on conveyor belts is proposed, the instantaneous location of the moving objects is evaluated by a vision system[10]. The system uses encoder counting to update the object position in real time. Simultaneously, approaches to 3D perception and manipulator motion planning that enable a general purpose robotic platform to recognize and manipulate a variety of objects at a rate of one pick-and-place operation every 6.7 s, and work with a conveyor belt carrying objects at a speed of 33 cm/s[11]. The visual perception method can improve the location accuracy while avoid designing complex algorithms to perform dynamic grasping, but the control of multi-sensors is an urgent problem for the robustness and real-time performance of the system. To compensate the position error observed by the sensor, there is also a method to select the observation position in visual servoing with an eye-in-vehicle configuration for the manipulator[12].

1.3 Remaining challenges

The challenge in picking up moving objects is the locating method. In many robot applications, it is desirable to reduce the location error of the end-effector relative to the target object. One possible approach to achieve better accuracy is to employ end-effector based sensors[11, 13]. The method mainly relies on image sensors for dynamic locating, which may have higher accuracy, but the real-time requirements for image information transmission are very high, otherwise it will produce inefficient grasping. However, there also exists the problem of incomplete image information, which brings difficulties to pose detection and dynamic grasping[14].

There are many uncertainties in the grasping based on sensors. Then others present a quantitative method for analyzing the effect of sensor resolution on grasp stability prediction[15]. The proposed method is dedicated to improving the accuracy of sensor detection, it has a high success rate on objects of different shapes, but lacks the efficiency when processing a large number of objects. So end-effector based sensors still work inefficiently especially in the occasions with bad working conditions.

A solution approach for the time optimal path following of two robots performing cooperative grasping tasks is recently presented[16]. The dynamic model is established to ensure the reliability of the grasping, the method effectively solves the time optimal path following problem, but it is not suitable for high-speed sorting. The algorithm at literature [10] shows high real-time performance but the experimental results show that there is still a maximum of 10% location error. Other approaches, like [17] and [18], use predefined grasping points or simple control strategies to determine the grasping. These proposed methods track and grasp moving objects in 3D space through visual servoing with strong adaptability and robustness. If the efficiency optimization model is combined with the methods, it will be a significant attempt.

An interesting approach to achieve grasping of unknown rotationally symmetrical objects is presented in [19]. In order to achieve dynamic grasping, these works are dedicated to the realization of complex trajectories and control, and the trajectory estimation is a challenge in path planning. The idea of our model is to directly generate trajectories through single-point prediction, so the model is relatively simple to implement in trajectory generation.

In this paper, robotic sorting is applied to the traditional method of recycling CDW and to improve the recycling purity while ensuring efficiency. We evaluate existing dynamic grasping methods and propose a new method of geometric analysis on the grasping work space, use robot kinematics parameters and conveyor speed to construct a mathematical model for solving the grasping point. In the process of solving the mathematical model, we propose two algorithms for solving the accurate grasping points.

Subsequently, the mathematical models were tested and compared using Matlab. And the real system was built, and the sorting efficiency and success rate are experimentally verified.

To summarize, our main theoretical contributions are:

An efficient robotic dynamic locating method based single grasping point, including grasping strategy and mathematical model. The method avoids the error of image acquisition caused by using end-effector based sensors and does not require complex trajectories and control while guaranteeing high accuracy and real-time performance.

Two algorithms based on iterative theory are used in the process of solving the mathematical model. The algorithms based on Newton–Raphson and dichotomy theories could effectively improve the efficiency and accuracy of the model, greatly reducing unnecessary calculations.

2 Materials and method

2.1 Platforms for experiment

The main instruments used in this experiment are detection module and Cartesian robots. The detection module includes a 3D camera and laser beam. As a light source of invisible infrared laser of a specific wavelength, the laser illuminates the object on the conveyor belt, and tilts the 3D camera to stereoscopically planar the object to achieve stereoscopic imaging. The Cartesian robot acts as the end-effector to grasp the objects on the conveyor belt. The sorting system is shown in Fig. 1. For ease of illustration, the robot is simplified to a grasping module, which includes air bags and fixing rib.

The main application scope of the robot in this experiment is the sorting of solid waste (such as CDW), and it

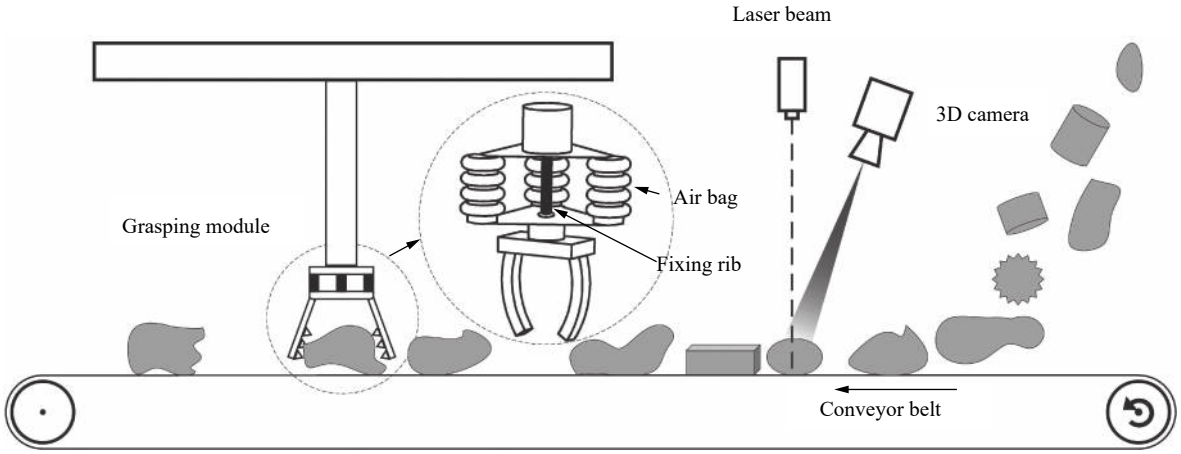

Fig. 1 Structure of the sorting system

requires a high sorting efficiency. Under the operating conditions of high speed and large load, the structure of the grasping module has further requirements. A flexible cushioning device is required to meet the conditions that allow for a particular eccentric load, which prevents the grasping module from performing normal lowering and grasping when located incorrectly, and also prevents the wear and tear of the z-axis under large acceleration forces. The sketch in Fig. 1 shows the structure of the grasping module. The stiffness of the grasping module can be adjusted by moderating the pressure of the airbags. Moreover, to prevent the fixing rib from breaking, the maximum limited pressure cannot be exceeded.

The collected material information is mainly 3D contours of the object, and the exposure time and acquisition rate are set to 2 ms and 200 frames per second (fps), respectively.

The grasping object of the research of this paper is the differentiation of several objects with various sizes and shapes in Fig. 2, and such objects were at different target positions to be grasped in the experiment.

2.2 Methods for experiment

In response to the requirements of high efficiency in the process of CDW, we optimize the robot kinematics parameters to improve the sorting efficiency E. As shown in (1), an optimization model based on parameters such as the interpolation speed v of the robot, acceleration/deceleration time t, and the conveyor speed v_b is proposed. And the optimal solution is obtained through experimental methods.

$$E = f(v, t, v_b). \tag{1}$$

After obtaining the optimal robot kinematics parameters, the efficiency is directly improved, but if the grasping success rate is low, the sorting efficiency will be limited. Subsequently, a method to optimize the dynamic locating accuracy is proposed to improve accuracy in locating, which indirectly improves sorting efficiency.

Fig. 2 Examples of objects to be sorted

The locating mathematical models are firstly tested on Matlab. By comparing the efficiency, solution error, and reliability of different mathematical models, the feasibility of each mathematical model is verified, and an appropriate mathematical model is selected to implement the algorithm in code. As a result of the experiment on grasping success rate, the speed of conveyor belt is initially set to 0.25 m/s. The real system is shown in Fig. 3. Different distances between the objects need to be set for different experimental purposes. The designed sorting efficiency is 1.8 s per piece while the speed of conveyor belt was 0.25 m/s, the conveyed distance of next object was 0.45 m. So we set the threshold of distance to be 0.45 m. To verify the sorting efficiency of the robot, objects were placed close to each other (< 0.45 m) to allow the robot to perform a full-load grasp without waiting. Differently sized and shaped objects were randomly placed on the conveyor belt, then the time of the grasping process and number of success-grasped were used as the evaluation criteria.

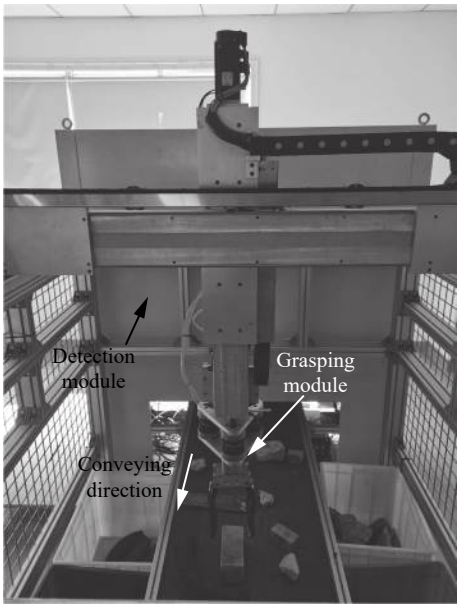

Fig. 3 Real system

2.3 Methods for robotic locating

The sorting system used in this experiment requires the locating and grasping of the objects on the conveyor belt. This paper considers the implementation of the dynamic grasping method. Firstly, the locating mathematical model based on geometric analysis is constructed, and the encounter (grasping point) between the robot and the object is calculated. Secondly, the motion trajectory is generated according to the points. A situation in which the robot locates the target object is shown in Fig. 4.

2.3.1 Grasping strategy in locating

As shown in Fig. 4, the square area is the grasping range, where $O'X'Y'$ is the grasping coordinate, t represents the current system time, periodically updated. The target object is at point B. Let the time when the object (point B in Fig. 4) reaches the position of the grasping area be t_B. Compare t with t_B and analyze the two grasping strategies:

1) $t < t_B$, at this time, the object has not entered the grasping range. For this condition, to shorten the travel path and improve the efficiency, the robot needs to move in advance to the position close to the object, waiting for the material to enter. The waiting position of the grasping module is at point A.

2) $t \geq t_B$, at this moment, the object has entered the grasping range, and the robot starts to dynamically grasp the object. After the object enters the grasping area, t, t_B, the coordinates in the x and y axis direction, and the conveyor speed ν, are all known. Combining the above variables and, according to the calibration result, the coordinates of the object in the robot grasping coordinate system can be obtained and set to (x_b, y_b, z_b). The waiting position (point A in Fig. 4) is artificially set to (x_a, y_a, z_a). Let point C be the predicted robot grasping position, and the grasping time be t_C. At such time, the locating problem is simplified to find the coordinates of

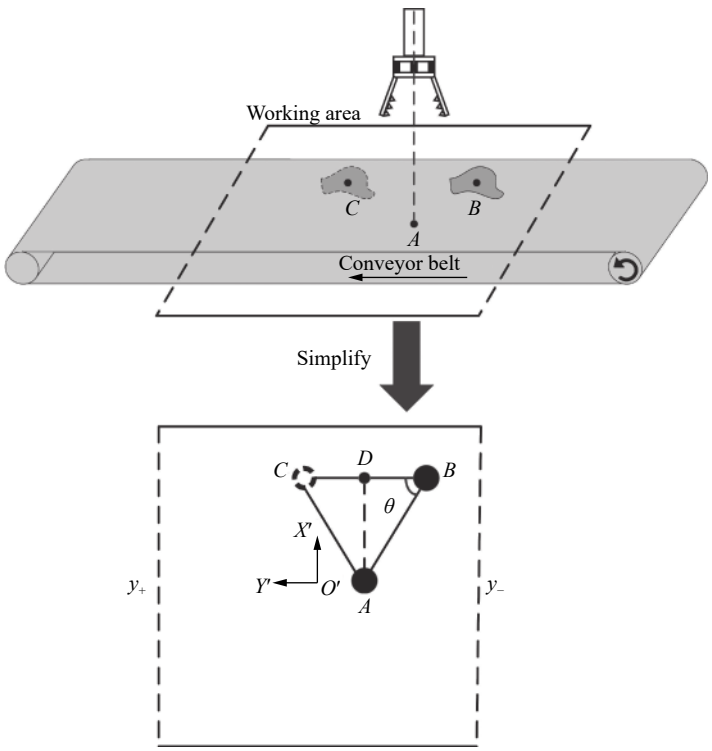

Fig. 4 Geometric schematic for grasping (Point A represents the location of the robot, B represents the actual location of the object, and D represents the predicted location of the object.)

point C. Since the y coordinate of point C differs from that of point B by the value of $\nu \cdot |t_C - t_B|$, the x coordinate is the same as point B, so only t_C needs to be calculated.

2.3.2 Mathematical model

A. Newton–Raphson method

When $AD \perp BC$ is found in $\triangle ABC$, it can be seen that the coordinates of point D are (x_b, y_a). In $\triangle ABC$, the length AB of the Pythagorean relationship is

$$l_{AB} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}. \tag{2}$$

From this, the angle θ in Fig. 4 can be obtained as

$$\cos\theta = \frac{y_b - y_a}{l_{AB}}. \tag{3}$$

The length BC is

$$l_{BC} = v\,(t_C - t) = v\Delta t. \tag{4}$$

In (4), v is the conveyor speed, Δt is the total motion time of the robot moving from point A to point C. The tracking, locating, and grasping process uses xy-axis linear interpolation; the z-axis performs separately and does not affect the total time of the two-dimensional locating, so only the motion time of the A to C segment is calculated. Since the linear interpolation uses the trapezoidal acceleration/deceleration control algorithm, the interpolation maximum vector speed is $v_{\max}$, the acceleration/deceleration time is $t_{\min}$, and the maximum acceleration is $a_{\max}$. Because of the limitation of the shortest acceleration distance $l_{\min}$, there may not be a uniform velocity section. Therefore, according to the length of AC and $l_{\min}$, the analysis of the two working conditions is performed.

1) $l_{AC} < l_{\min}$

At this time, it is impossible to accelerate to the maximum speed. The acceleration/deceleration control is used without uniform speed, and the maximum acceleration remains $a_{\max}$:

$$l_{AC} = 2 \times \frac{1}{2} a_{\max} \left(\frac{\Delta t}{2}\right)^2 = \frac{1}{4} a_{\max} \Delta t^2. \tag{5}$$

Use the cosine theorem in $\triangle ABC$:

$$\cos\theta = \frac{{l_{AB}}^2 + {l_{BC}}^2 - {l_{AC}}^2}{2 l_{AB} l_{BC}}. \tag{6}$$

Simultaneously (3)–(6) obtain the unary quadratic equation of Δt:

$$f_1(\Delta t) = \frac{1}{16} {a_{\max}}^2 \Delta t^4 + 2v\Delta t\,(y_b - y_a) - v^2 \Delta t^2 - {l_{AB}}^2 = 0. \tag{7}$$

Equation (7) is a mathematical model for locating and tracking objects according to trapezoidal acceleration/deceleration control. It is difficult to directly solve the nonlinear equation. Therefore, the Newton–Raphson iterative method in Algorithm 1 is used to solve the equation.

Algorithm 1. Newton–Raphson algorithm

Initialize parameters: Δt_0 the time it takes for the end-effector to reach point D, and the number of iterations k.

Input: mathematical model for locating $f_1(\Delta t) = \frac{1}{16} {a_{\max}}^2 \Delta t^4 + 2v\Delta t\,(y_b - y_a) - v^2 \Delta t^2 - {l_{AB}}^2 = 0$.

The iteration tolerance ε. Maximum number of iterations M.

Output: the total motion time of the robot moving from point A to point C, Δt.

$\Delta t_0 = \sqrt{\frac{4|x_b - x_a|}{a_{max}}}$, k=0;

For k in M {

$\Delta t_{k+1} = \Delta t_k - \frac{f_1(\Delta t_k)}{f'_1(\Delta t_k)}$;

If $|\Delta t_{k+1} - \Delta t_k| \le$ **Then**

$\Delta t = \Delta t_{k+1}$;

break;

else

k++;}

After obtaining Δt, the position of point C can be determined. If the position of point C is not within the grasping area, or the number of iterations exceeds the maximum value, the grasp is discarded, and the missed object will be recorded; and if the position of point C is within the area, the size of l_{AC} needs to be reversed to verify whether the condition $l_{AC} < l_{\min}$ is satisfied. If it is satisfied, the grasping motion will continue according to the planned trajectory. Otherwise, the grasp will be discarded, and the missed object will be recorded.

2) $l_{AC} \ge l_{\min}$

At this time, according to the trapezoidal acceleration/deceleration control:

$$l_{AC} = 2 \times \frac{1}{2} a_{\max} (t_{\min})^2 + v_{\max}\,(\Delta t - 2t_{\min}) = v_{\max}\,(\Delta t - t_{\min}). \tag{8}$$

Similarly, according to the motion conditions of the trapezoidal acceleration/deceleration control, connecting (3), (4), (6) and (8) can obtain a quadratic equation for Δt:

$$\begin{aligned} f_2(\Delta t) = {v_{\max}}^2 (\Delta t - t_{\min})^2 + 2v\Delta t\,(y_b - y_a) - \\ v^2 \Delta t^2 - {l_{AB}}^2 = \left({v_{\max}}^2 - v^2\right) \Delta t^2 + \\ \left[2v\,(y_b - y_a) - 2t_{\min} {v_{\max}}^2\right] \Delta t + \\ {v_{\max}}^2 {t_{\min}}^2 - {l_{AB}}^2 = 0. \end{aligned} \tag{9}$$

Equation (9) is a mathematical model for locating and tracking objects according to the trapezoidal accelera-

tion/deceleration control, and the roots of any quadratic equation is given by

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}.$$

So the result is

$$\Delta t = \frac{2t_{\min} {v_{\max}}^2 - 2v\left(y_b - y_a\right) \pm Q}{2\left({v_{\max}}^2 - v^2\right)}. \tag{10}$$

In (10),

$$Q = \left(\left[2v\left(y_b - y_a\right) - 2t_{\min} {v_{\max}}^2\right]^2 - 4({v_{\max}}^2 - v^2)({v_{\max}}^2 {t_{\min}}^2 - {l_{AB}}^2)\right)^{1/2}. \tag{11}$$

For the two solutions of Δt, the l_{AC} is found by (8), and it is verified thereafter whether the condition $l_{AC} \geq l_{\min}$ is satisfied, and solutions that do not satisfy the condition are discarded. If both solutions satisfy the condition, the larger value is discarded, and the solution with the shorter movement time is maintained. The coordinates of the position C of the grasping target point are then calculated, and the grasping motion is performed according to the planned trajectory.

B. Dichotomy

The dichotomy in Algorithm 2 mainly uses an iterative method to apply the zero-point principle to solve the mathematical model.

Algorithm 2. Dichotomy algorithm

Initialize parameters: converting the coordinates of the object at the capture time to the coordinates (x, y, z) of the robot grasping coordinate system, which represents the real-time location of the object in the robotic system. The number of iterations $k = 0$.

Input: the robotic motion time according to the acceleration/deceleration control model,

$$T\left(l_{AC}\right) = \begin{cases} \sqrt{4l_{AC}/a_{\max}}, \text{if } l_{AC} < l_{\min} \\ l_{AC}/v_{\max} + t_{\min}, \text{if } l_{AC} \geq l_{\min} \end{cases}.$$

Using the range (y_-, y_+) to represent the size of the area in the y-direction. The capture time t_{cap} of the object and the current time t of the system.

The iteration tolerance ε. Maximum number of iterations M.

Output: the total motion time of the robot moving from point A to point C, Δt.

For k in M {

$t_{\text{in}} = t_{\text{cap}} - (y - y_-)/v$;

$t_{\text{out}} = t_{\text{cap}} - (y - y_+)/v$;

$t_{\text{temp}} = (t_{\text{in}} + t_{\text{out}})/2$;

$y_{\text{temp}} = y + v\left(t_{\text{temp}} - t_{\text{cap}}\right)$;

If $y_{\text{temp}} \in (y_-, y_+)$ **Then**

$y_c = y_{\text{temp}}$;

$l_{AC} = \sqrt{(x_a - x_c)^2 + (y_a - y_c)^2}$;

$\Delta t' = T\left(l_{AC}\right)$;

$t' = t + \Delta t'$;

If $t' > t_{\text{temp}}$ **Then**

$t_{\text{in}} = t_{\text{temp}}$;

else

$t_{\text{out}} = t_{\text{temp}}$;

break;

If $|t' - t_{\text{temp}}| \leq$ **Then**

$\Delta t = \Delta t'$;

break;

else

$k{+}{+}$;}

During the execution of the algorithm, determine whether y_{temp} is without the grasping range (y_-, y_+). Otherwise, when not in range, continue waiting at the appropriate position. If the target has escaped from the range, begin processing the grasping of the next object, and if k is greater than M, end the iteration, and the missed object will be recorded.

3 Results and discussion

3.1 Locating mathematical model test based on Matlab

The grasping module has strong adaptability and low requirements for locating accuracy; consequently, it is impossible to compare the actual application differences of different mathematical models. Therefore, a Matlab simulation test was carried out on the mathematical models to verify the reliability and accuracy of each solution.

Experimental conditions: CPU (3.40 GHz), RAM (16.00 GB), OS (Windows 7 ultimate)

Parameter setting: Input iteration tolerance ε=0.001 before initialization; the maximum number of iteration steps M is 100.

Experimental results: the object and robot coordinates are input randomly within the specified grasping range, the calculation of the grasping points under ten random conditions is simulated. The calculation results are shown in Tables 1 and 2.

Experimental conclusion: it can be seen from the above that the solution result of the dichotomy is more accurate and the calculation time is shorter, which shows a good real-time performance; but the number of iteration steps is longer, and the actual program may occupy significant memory during the running process. In comparison, the results of the Newton–Raphson method mostly meet the location error requirement (≤1 mm); however, because of the particularity of the mathematical model, some of the grasping conditions do not need to be solved iteratively, whereby the calculation error is almost 0, while the other part of the working condition is iterated with a significantly larger error, but the method has fewer iteration steps and faster convergence.

Table 1 Solution results of dichotomy

Experiment number	Calculating time (ms)	Iteration steps	Locating error (10^{-3} mm)
1	0.005	9	0.636
2	0.015	9	0.302
3	0.005	9	0.826
4	0.005	9	0.753
5	0.005	8	0.926
6	0.005	9	0.940
7	0.005	8	0.361
8	0.005	8	0.461
9	0.006	9	0.025
10	0.005	9	0.002

Considering the reliability of the solution results, robustness and the simple implementation of the algorithm, the dichotomy method is selected to establish the robotic locating mathematical model and the implementation of the robotic grasping program.

3.2 Real system experiment on grasping success rate

An experiment to test the performance of the robotic grasping is carried out. This experiment can test the grasping success rate of the real system. At the same time, the veracity of the calibration result, image recognition, and the tracking and grasping algorithm can be verified. The experimental process is as follows: the conveyor belts are set to different speeds, and 60 different objects are integrated (20 bricks, foam and wood); the bricks are irregular in shape compared with the other two, and the foam is lighter than the other two. Objects are randomly placed on the conveyor belt with a distance greater than 0.45 m between each other (to ensure that the robot can complete the grasping cycle while another coming in the grasping area). In terms of the kinematics parameters of the robot, the maximum vector speed of interpolation is set to $v_{\max} = 1\,500$ mm/s, the acceleration/deceleration time $t_{\min}$ is set to $t_{\min} = 0.3$, and the maximum acceleration is $a_{\max} = 500$ mm/s^2 at this time. The experimental results are shown in Table 3.

As can be seen from Table 3, because of mechanical structural characteristics and high-speed operating conditions, light materials such as foam are more difficult to grasp, and the grasping success rate of them is lower. As the locating model needs to collect the capture time, when the conveyor speed is too fast, the locating error is amplified, resulting in a lower grasping success rate. Nevertheless, the system grasping success rate in the speed range is basically above 90% and shows good robustness.

Table 2 Solution results of Newton–Raphson method

Experiment number	Calculating time (ms)	Iteration steps	Locating error (10^{-3} mm)	Remark
1	59.560	3	0.022	
2	56.866	1	0	
3	56.774	4	0.006	
4	57.166	3	29.676	Local convergence
5	68.395	2	0.092	
6	57.883	4	32.275	Local convergence
7	58.135	3	0.557	
8	54.786	0	0	
9	57.537	2	0.208	
10	56.038	0	0	

Table 3 Grasping success rate on different speeds of conveyor belts

Speeds of conveyor belts (m/s)	Number of bricks grasped (pieces)	Number of foam grasped (pieces)	Number of wood grasped (pieces)	Grasping success rate (%)
0.10	20	18	20	96.7
0.15	20	18	20	96.7
0.20	19	19	20	96.7
0.25	20	19	20	98.3
0.30	19	18	19	93.3
0.35	18	18	19	91.7

3.3 Real system experiment on sorting efficiency

A method based on kinematic analysis has been proposed recently, acceleration and the independent parameters between the actuator joint and the conveyor belt are deduced by using the vector dot product and cross product operation[20]. In this paper, the robot kinematics parameters are optimized through real system experiments.

The sorting experiment of randomly distributed objects on the production line is set up, and the robot kinematics parameters according to the actual sorting conditions are analyzed, including the interpolation speed of the robot, acceleration/deceleration time (i.e., acceleration), and the conveyor speed. The effect of all of the parameters on the grasping success rate is discussed.

Because of the limitations of the mechanical structure of the robot and the load of the motor, the range of its kinematics parameters is constrained: the range of the interpolation speed v is (0.5–1.5 m/s); the acceleration/deceleration time t in (0.3–0.5 s); and the speed of the conveyor belt v_b is (0.15–0.35 m/s).

Experimental procedure: The working conditions are grouped according to the above parameters. In order to get the maximum efficiency of the robot, 30 objects are set in each group to be randomly placed with a distance less than 0.45 m between each other (to perform a full-load grasp without waiting), and the number of grasped objects is recorded. A total of 27 sets of experiments are performed. Since the sorting efficiency is also an important evaluation indicator of production efficiency, the total time T of the grasping process of each group is recorded. The grasping results are shown in Table 4. The sorting efficiency is mainly affected by the interpolation speed, and the setting of the acceleration/deceleration time has a small effect. As long as the time for placing the object is appropriate, the speed of the conveyor does not affect the sorting efficiency.

It can be concluded from Table 4, that as the interpolation speed increases, the grasping time is significantly shortened; as the acceleration/deceleration time decreases, the grasping time is partially reduced, and the speed of the conveyor belt mainly controls the locating accuracy, thereby affecting the grasping success rate of the object, but do nothing to the grasping time. The sorting efficiency is mainly affected by the interpolation speed, and the setting of the acceleration/deceleration time has a small effect. As long as the time for placing the object is appropriate, the speed of the conveyor does not affect the sorting efficiency.

Furthermore, it was found during the experiment that when $v = 0.5$ m/s, the speed of the vibrations generated by the acceleration is close to the actual speed, causing the manipulator to resonate, resulting in a large jitter, which will reduce the grasping success rate. It is determined that the conveyor belt speed should be maintained at about 0.25 m/s, which can achieve better grasping performance. When the load is allowed, it is preferable to increase the speed and reduce the acceleration/deceleration. Currently, the sorting efficiency is at approximately 2 000 pieces per hour.

4 Conclusions

In this paper, we proposed an efficient robotic dynamic locating method based single grasping point, including grasping strategy and mathematical model in dynamic locating. Two algorithms based on iterative theory were used in the process of solving the mathematical model. The proposed method was superior to other methods for dynamic locating, it avoided the error of image acquisition caused by using end-effector based sensors and does not require complex trajectories and control while guaran-

Table 4 Grasping success rate and processing time in different working conditions

t (s)	v (m/s)	v_b (m/s)						$\overline{T}$ (s)
		0.15		0.25		0.35		
		Number of grasped (pieces)	T (s)	Number of grasped (pieces)	T (s)	Number of grasped (pieces)	T (s)	
0.3	0.5	27	78.9	27	75.0	26	78.6	77.5
	1.0	28	61.1	28	59.1	29	62.5	60.9
	1.5	29	51.7	29	52.8	28	51.2	51.9
0.4	0.5	26	78.0	28	79.6	26	75.9	77.8
	1.0	29	62.1	28	60.2	27	61.2	61.2
	1.5	29	53.4	30	54.2	27	50.6	52.7
0.5	0.5	28	79.8	28	77.8	27	80.5	79.4
	1.0	29	64.1	30	62.8	29	63.6	63.5
	1.5	30	51.6	30	52.3	29	54.0	52.6
Grasping success rate (%)		94.4		95.6		91.9		

teeing high accuracy and real-time performance. The experimental results show the effectiveness of the proposed methods in dynamic grasping. After optimizing the robot kinematics parameters through real system experiments, the sorting efficiency can reach approximately 2 000 pieces per hour. However, the adaptability and reliability of robotic grasping for different materials can be improved, we will try to use visual sensors and deep learning methods to improve the adaptability of the algorithm in future work.

Acknowledgments

The authors are thankful for the financial support provided by the Science and Technology Project of Quanzhou (Nos. 2018C100R and 2019G003), the Science and Technology Cooperation Program of Quanzhou (No. 2018C001), the Science and Technology Cooperation Program of Fujian (No. 2018I1006), the Joint Innovation Project of Industrial Technology in the Fujian Province, and Subsidized Project for Postgraduates′ Innovative Fund in Scientific Research of Huaqiao University.

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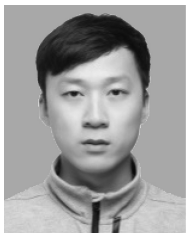

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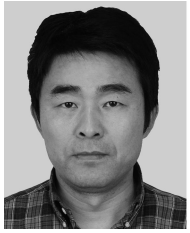

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