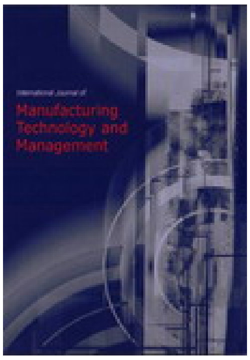

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Linyan Pan

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Dexterity control of multi-arm sorting robot based on machine learning

Linyan Pan

Intelligent Manufacturing College,
Anhui Wenda University of Information Engineering,
Hefei, Anhui 230000, China
Email: xiaoshitoumama99@126.com

Abstract: In order to overcome the problems of large dexterity control error of manipulator joint and poor sorting and positioning accuracy, this paper designs a dexterity control method of multi manipulator sorting robot based on machine learning. Firstly, the attitude of the multi manipulator coordinate system on the rigid body is obtained. Secondly, the translation matrix is constructed by using the translation transformation method. Then, the rotation matrix is constructed to determine the inverse motion law of the robot. Finally, determine the dexterity parameters of the manipulator joint, introduce the machine learning algorithm to calculate the dexterity parameter control error, and correct the error through the activation function to complete the dexterity control. The experimental results show that the error of this method is always less than 0.1% and the positioning accuracy is higher than 90%, which shows that the dexterity control effect of this method is good.

Keywords: machine learning: multi-manipulator; robot; dexterity; translation transformation; rotation matrix; activation function.

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Biographical notes: Linyan Pan received his Master's in Control Engineering from the Hefei University of Technology in 2019 and is now a Lecturer in the School of Intelligent Manufacturing of Anhui Wenda University of Information Engineering. His main research directions are intelligent manufacturing, automatic control, artificial intelligence and so on.

1 Introduction

In the recent years, automation technology has become more and more widely used in all aspects of society. Various developments have been achieved in urban labour-intensive scenarios, unmanned retail, cargo sorting, and large-scale warehouse sorting. Automation technology has become the key technology to replace traditional manual and semi-manual (Wilson et al., 2021). Among them, the emergence of sorting robots provides new solutions for sorting problems in many fields such as industrial enterprise warehousing. Under the background of traditional manual sorting, the sorting of warehousing products, especially the sorting of large-scale items, requires a large amount of labour, and the sorting efficiency and work quality show low efficiency. The emergence of multi-manipulator sorting robots has provided a new business model for the high-cost labour industry, which has rapidly improved production efficiency and labour efficiency (Yan et al., 2020). The speed and scale of the modern e-commerce industry are getting faster and faster, and the order volume of the warehouse centre is showing a rapid growth. The sorting of warehouse items has become a key factor for fast delivery. The multi-arm robot quickly locates the position of the sorted items through the set program, and obtains the target through a fast decision-making method, so as to realise the rapid sorting of the target item (Vecchietti et al., 2020). This greatly improves the speed and status of item sorting, and lays a good foundation for the rapid development of modern society and economy.

A multi-arm robot is a robot working mode that combines multiple working links such as handling, sorting, and packaging. In this working mode, various items are sorted according to certain requirements according to the sorting target. In this process, it is necessary to carry out multiple links such as decision-making of sorting goods, mobile grabbing and information interaction (Garate et al., 2021). Among them, the dexterity of the sorting motion in the multi-manipulator robot is the precondition to complete the sorting process. With the continuous increase of sorting target categories and the continuous change of workload, it is very easy to cause the dexterity of multi-manipulator robot sorting to continue to decline, which affects the completion of multi-manipulator robot work tasks (Cao et al., 2020). For this reason, many researchers have done a lot of research on this problem, and got some solutions.

Tang and Liu (2021) designed a PLC-based sorting robot motion flexibility control optimisation method. Firstly, by constructing the kinematic mathematical model of the sorting robot, the basic working mode and principle of the sorting robot are determined. Then the main control core hardware of the robot is designed, and the flexibility parameters of different moving parts are determined according to different design modules. Finally, PLC address allocation is introduced to compile the moving terrain map. This method improves the sorting speed of the sorting robot, and the sorting efficiency is high, but the detailed flexibility optimisation of its core part is not carried out, and further improvement is required. Yu et al. (2021) designed a visual servo control method of sorting robot with improved BP neural network to improve the flexibility of sorting robot. The method introduces the particle swarm algorithm, analyses the basic principle of the algorithm, improves the BP neural network by means of the crossover, mutation and other operations in the algorithm, and optimises the manipulator dexterity parameters and operating threshold of the sorting robot to realise the design of the method. This method effectively improves its running speed, but the improvement of the dexterity of the manipulator is insufficient. Zou and Tao (2022) designed a method for improving the flexibility of multi-manipulator cooperation. Analyse the space change law when multiple manipulators work together, determine the change law of singular points in the space through the envelope method, construct the cooperative coordinate system of its motion, extract the points in the work space, and analyse the changes of the manipulator in each joint. Design a flexibility optimisation method for its changes. This method has strong pertinence, but the construction space is more complicated, and it has the disadvantage of being difficult to operate.

Aiming at the problems existing in the above methods, this paper proposes a dexterity control method for a multi-manipulator sorting robot based on machine learning. In this paper, by analysing the kinematics principle of the multi-manipulator sorting robot, and setting parameters according to the running trajectories of its different manipulators, machine learning is introduced to complete the dexterity control method of the multi-manipulator sorting robot. The main technical routes studied in this paper are:

First, the forward kinematics analysis of multi manipulator sorting robot. In the fixed three-dimensional region, the posture of the multi manipulator coordinate system on the rigid body is obtained, and the cosine positions of different coordinates are calculated to determine the forward motion law of the multi manipulator sorting robot.

Secondly, the inverse kinematics analysis of multi manipulator sorting robot. The two coordinates are mapped to the corresponding points by means of translation transformation, the vector of any point is extracted, the translation matrix is constructed, the translation transformation is completed, the rotation matrix is constructed, and the reverse motion law of the multi manipulator sorting robot is determined.

Then, the dexterity of the sorting robot is controlled. Through the above two sections, the forward and inverse kinematics laws are obtained to determine the dexterity parameter changes of the robot arm joints of the multi arm sorting robot. The neural network in machine learning is introduced. The dexterity parameter control error is calculated by neurons, and the error structure is corrected by activation function. The dexterity control function of the multi arm sorting robot is constructed to complete the dexterity control.

Finally, the dexterity control effect of the multi-manipulator sorting robot is verified by the two indicators of joint dexterity control error and sorting and positioning accuracy, and the conclusion is drawn.

2 Kinematics analysis of the multi-arm sorting robot

2.1 Forward kinematics analysis of the multi-arm sorting robot

It is necessary to analyse the kinematics of multi manipulator sorting robot in motion. Kinematics refers to the correspondence between the movement of objects and the amount of movement. The main analysis of the kinematics of multi manipulator sorting robot is mainly the analysis of the dexterity between its link levers. In order to improve the dexterity and control accuracy of the multi manipulator sorting robot, it is necessary to obtain the position parameters, moving speed, acceleration and other parameters. Therefore, this paper first analyses these two motion modes, and the analysis of this mode plays a prerequisite and foundation role for subsequent research (Ma et al., 2021).

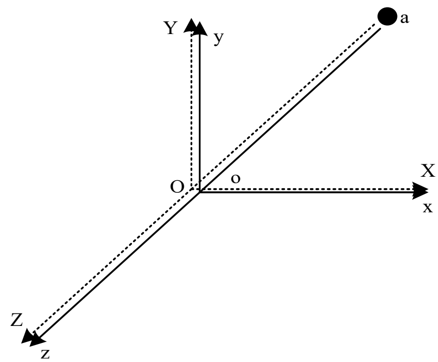
In the forward kinematics analysis of the multi-manipulator sorting robot, the change of its three-dimensional attitude is mainly analysed. Objects existing in three-dimensional space are determined by six point coordinates, mainly rotation coordinates and movement coordinates. The state position of these coordinate points is also the position and attitude state of the multi-manipulator sorting robot when it is moving. In the fixed three-dimensional area, set any one of the point coordinates a, and represent it as a three-dimensional vector of its position. The schematic diagram of the coordinate system of its positive motion is shown in Figure 1.

In this coordinate system, the vector $\overrightarrow{Oa}$ is represented as:

$$\overrightarrow{Oa} = \begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} \tag{1}$$

Among them, O_x, O_y, O_z represent the different components of point a in this space.

Figure 1 Schematic diagram of the positive motion coordinate system of the multi-arm sorting robot



In view of the positive movement of the manipulator, it is not only necessary to analyse the forward coordinate position of the multi-manipulator sorting robot, but also to describe the specific change rule of the multi-manipulator sorting action according to the change of the coordinate point (Van and Ge, 2020). The running posture of the manipulator can represent the specific change law of the sorting action of the multi-manipulator. At this time, the coordinate system of the multi-manipulator is set on the rigid body, and there are three coordinate quantities x_Q, y_Q, z_Q in this coordinate system. At this time, the cosine position of these three coordinates at each different position can represent its specific change (Zhao and Iwasaki, 2020). Therefore, construct the cosine matrix ${}_D^C E$ as:

$${}_D^C E = \left[C_{x_D}, C_{y_D}, C_{z_D} \right] = \begin{bmatrix} e_{11} & e_{12} & e_{13} \\ e_{11} & e_{22} & e_{23} \\ e_{31} & e_{32} & e_{33} \end{bmatrix} \tag{2}$$

Among them, ${}_D^C E$ represents the rotation matrix, and C and D represent different three-dimensional coordinate position points.

When the sorting robot rotates around these three point axes, the rotation generates an angle, which is the centre point $E(z, \omega)$ of the rotation matrix in its forward kinematics, and then we get:

$$E(z, \omega) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\omega & -\sin\omega \\ 0 & \sin\omega & \cos\omega \end{pmatrix} \tag{3}$$

In the forward kinematics analysis of the multi-manipulator sorting robot, in a fixed three-dimensional area, set the coordinates of any point, determine the forward motion coordinate system, obtain the posture of the multi-manipulator coordinate system on the rigid body, and calculate the different coordinates Cosine position to complete the determination of the forward motion law of the multi-manipulator sorting robot.

2.2 Inverse kinematics analysis of multi-arm sorting robot

After the forward kinematics analysis of the multi-manipulator sorting robot, its movement pattern is not only a forward study, but also has a reverse movement, which also affects the dexterity of its movement. To this end, this paper further analyses the inverse kinematics of the multi-arm sorting robot. In the inverse kinematics of the multi-manipulator sorting robot, each joint of each manipulator has a certain influence on the control of the end (Juang and Bui, 2020). In this process, the coordinates of its inverse operation need to be changed to construct the coordinates and the end coordinates. In the reverse operation, the translation transformation is used first and then the rotation transformation is used to determine the reverse motion law of the multi-manipulator sorting robot. In its translation transformation, set the coordinate system point in the three-dimensional space as F, G, and use translation transformation to map these two coordinates to the corresponding points. Suppose the vector $\overrightarrow{OF_W}$ of a point W at any of these two points can be expressed as:

$$\overrightarrow{OF_W} = (X, Y, Z, W) \tag{4}$$

Among them, the mapped vector is represented as $\overrightarrow{OF_W}$ and (X, Y, Z, W) represents the mapped point coordinate position.

At this time, the vector relationship $\overrightarrow{O_F O_G}$ of these two coordinates in the three-dimensional space after mapping can be expressed as:

$$\overrightarrow{O_F O_G} = f_i + g_i + u_i \tag{5}$$

Among them, $\overrightarrow{O_F O_G}$ represents the vector relationship in the three-dimensional space, f_i and g_i respectively represent the result value of the coordinate system point after F, G is mapped by translation transformation, and u_i represents the deviation point of reverse motion after translation change.

On this basis, the inverse translation transformation $\overrightarrow{O_F O_G'}$ of the coordinates of two points in the three-dimensional space of the multi-manipulator robot is:

$$\overrightarrow{O_F O_G'} = \begin{bmatrix} 1 & 0 & 0 & f \\ 0 & 1 & 0 & g \\ 0 & 0 & 1 & f \\ 0 & 0 & 0 & 1 \end{bmatrix} \overrightarrow{f_i} + g_i + u_i \tag{6}$$

Among them, $\overrightarrow{O_F O_G'}$ represents the result of inverse translation transformation.

After the multi-manipulator sorting robot moves in the reverse direction and translates the three-dimensional coordinate points, it performs effective rotation on this basis, and rotates it according to the centre point of the orbit. The orbiting rotation matrix $R(F, G)$ is set as:

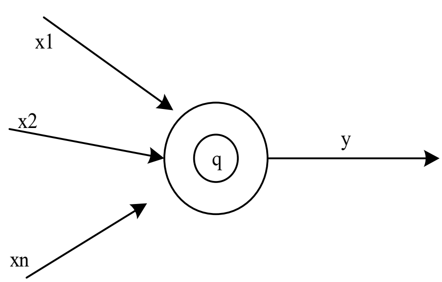
$$R(F,G)=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & \cos F & -\sin F & 0\\ 0 & \sin G & \cos G & 0\\ 0 & 0 & 0 & 1\end{bmatrix} \tag{7}$$

In the inverse kinematics analysis of the multi-manipulator sorting robot, the coordinate system points in the three-dimensional space are determined, the two coordinates are mapped to the corresponding points by means of translation transformation, the vector of any point is extracted, and the translation matrix is constructed to complete the translation transformation (Peng et al., 2020), based on the construction of the rotation matrix again, to determine the inverse motion law of the multi-manipulator sorting robot.

3 Dexterity control algorithm of multi-manipulator sorting robot based on machine learning

On the basis of the above-determined motion law of the multi-manipulator sorting robot, in order to realise the design of its dexterity control algorithm, this paper introduces the machine learning method to realise the design of the algorithm in this paper. Machine learning algorithm is a key algorithm that has been widely used in industrial production in recent years. Its basic theoretical core is to extract a small number of features, and to study the relationship between them based on the basic feature data, so as to realise the effective control of research and other operations. Among them, the most extensive machine learning algorithm realises the final control through the input and processing of a variety of neural networks, and each layer of nerves can be extracted hierarchically through relevant complex multi-dimensional information, and the extracted results are the results of the research. In the control of robot dexterity in this paper, the main object is the multi-arm sorting robot. Therefore, the research on dexterity in this study is mainly aimed at the joint dexterity of the robotic arm (Dong et al., 2021). The core of machine learning algorithms is the processing function of neurons, and the basic structure of neurons is shown in Figure 2.

Figure 2 Basic structure of neurons



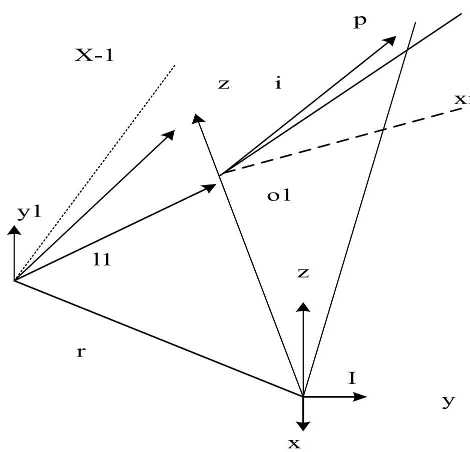
In Figure 2, x1/x2/xn represent the input parameters of the research object with different characteristics, q represents the core position of the neuron, and y represents the output result of the final neuron processing feature parameters. The calculation formula is:

$$y = v\left(\sum_{i=1}^{n} w_i x_i - q\right) \tag{8}$$

where w_i represents the sum of the input and output weights.

Therefore, based on the introduction of machine learning algorithms, it is necessary to determine the relevant parameter changes of the robotic arm joints of the multi-manipulator sorting robot. On this basis, the joint dexterity parameters are processed with the help of machine learning algorithms. The mechanical arm of the multi-manipulator sorting robot is long in length, light in weight, and heavy in load. Its flexible mechanical arm is prone to deformation during the sorting process, which affects the sorting speed and operation stability of the mechanical arm. The dynamic response and vibration suppression of the flexible manipulator are the key parameters of its influence (Chen and Shen, 2020). Therefore, it is very important to determine the flexible deformation parameters of the manipulator. The flexible body structure of the multi-manipulator sorting robot is shown in Figure 3.

Figure 3 Schematic diagram of the flexible body structure coordinates of the multi-arm sorting robot



In Figure 3, I represent the inertial coordinate system, which is the joint origin near the flexible body of the manipulator, the tangent to the flexible body is the x axis, and the direction of the joint rotation axis is z. The coordinates of each mechanical linkage position constructed at this time are $o_i x_i y_i$, and its joints the rotation angle of is φ_i and the inertial position vector of each joint is expressed as r.

Set point h to be any point in the flexible body, then the position vector r_h of this point in the inertial coordinate system is:

$$r_h = r + I\left(a_i + u_i\right) \tag{9}$$

Among them, u_i represents the random transformation point of the vector coordinates, and a_i represents the transformation matrix of the manipulator joint in the random transformation (Chen et al., 2020).

Assuming that the flexible joint of the multi-arm sorting robot moves, its parameter change Q_i is set as:

$$Q_i = \sigma_i \tau_i \tag{10}$$

Among them, σ_i is the vector of joint deformation, and τ_i is the generalised coordinate of joint deformation.

Select the generalised coordinates, attitude coordinates and deformation generalised coordinates in the joints of the manipulator respectively, and the attitude quaternion array δ_i of its joint parameters is expressed as:

$$\delta_i = [\delta_0, \delta_1, \delta_2, \delta_3]^T \tag{11}$$

According to the quaternion of the posture, the angular relationship of its joint motion is determined as:

$$\delta_i = \left[\cos\frac{\theta}{2}, v_x \sin\frac{\theta}{2}, v_y \sin\frac{\theta}{2}, v_z \sin\frac{\theta}{2}\right]^T \tag{12}$$

Among them, θ represents the Euler axis vector of the motion of the manipulator, and v represents the rotation angle.

The flexible body of the manipulator arm of the multi-manipulator sorting robot will also generate elastic potential energy during the strain process, that is to say, the change of the flexible body that affects the flexibility of the manipulator arm joint during its movement will lead to changes in the internal force of the manipulator arm, thereby affecting the manipulator arm dexterity. The calculation formula of the internal force change γ_i in the elastic deformation of the manipulator is:

$$\gamma_i = -\int_v^{\mu^t} \varepsilon dv [\varepsilon dv]^T \tag{13}$$

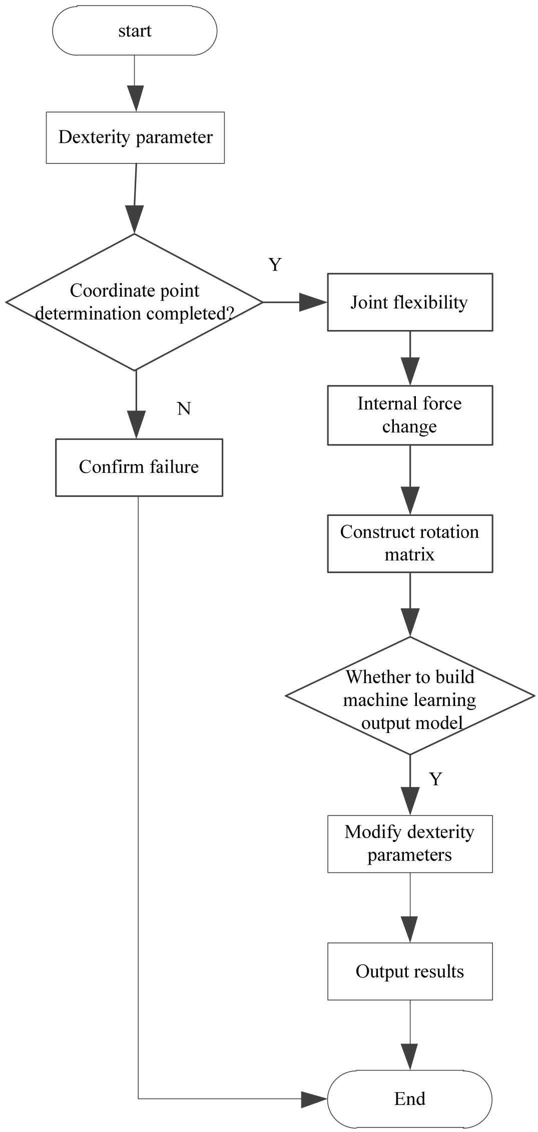
Among them, γ_i represents the change value of the elastic deformation internal force of the manipulator, ε represents the elastic body stress, and v represents the elastic modulus.

According to the above-determined parameters affecting the dexterity of the multi-manipulator sorting robot, a machine learning algorithm is introduced in this paper, through which the dexterity control function of the multi-manipulator sorting robot is constructed, and the dexterity parameters of the multi-manipulator sorting robot are input into the constructed In the machine learning machine, the revised dexterity parameters of the multi-manipulator sorting robot are output to realise the dexterity control of the multi-manipulator sorting robot.

When the machine learning algorithm is applied to dexterity control, based on a single neuron, the neuron from the previous layer is set to s_i (i = 1, 2, 3 …n), the part linked to this setting is set to k_i, and a weighted calculation is performed to obtain the weighted function α:

$$\alpha = f\left(d_i \sum_{i=1}^{f} s_i k_i - \beta\right) \tag{14}$$

Figure 4 The dexterity control process of the multi-arm sorting robot



Among them, d_i represents the input of multiple manipulator dexterity parameters; f represents the activation function, and β represents the neuron weight in machine learning.

When the weighting of the dexterity parameters of the multi-manipulator sorting robot is completed, the learning parameters in the machine learning are also set to obtain:

$$(a, b) = \left(a^i, b^i\right) \tag{15}$$

where (a, b) represents the offset intercept.

Activate the neurons in the machine learning, use the activated neurons to activate the dexterity parameter of the multi-manipulator sorting robot, and the output result of the multi-manipulator sorting robot dexterity parameter is the final control value a^i, the result obtained for:

$$a^i = f\left(b^i x\right) + b^i \tag{16}$$

$$h(a, b, w) = f\left(w^i a^i + b^i\right) \tag{17}$$

Among them, $h(a, b, w)$ represents the dexterity parameter of the output control, and w^i represents the error of the control value. The dexterity control process of the multi-arm sorting robot based on machine learning is shown in Figure 4.

4 Experimental analysis

4.1 Experimental design

Experimental testing is the most effective way to validate a design method. Therefore, this paper selects a multi-arm robot model D3P-1100-P3 produced by a company as the research object, and uses this research object for experimental analysis. In the experiment, the robot was applied to a large warehouse to effectively sort food goods in the warehouse. The food that needs to be sorted in this warehouse is packed in cartons, and the size and weight of each carton are different. The robot is used for effective sorting, and these goods are mainly sorted into three categories, large carton goods (weight 1 KG, The length, width and height of the carton are 120*100*80 respectively), the medium-sized carton goods (weight is 0.8KG, the length, width and height of the carton are 80*90*65), and the small carton goods (the weight is 0.5 KG, the length, width and height of the carton are respectively 40*80*55). All the robot parameters in the specific experiments are shown in Table 1.

Table 1 Details of sample robot parameters

Parameter	Content
Number of axes	4
Maximum load	3 KG
Weight	90.5 KG
Workspace width	1,200 mm
Location	0.05 mm
Rotation angle	0.1
The highest frequency of exercise	700 pp/min
Rotation range	360°
Swing up	24.5°
Hem	74.5°

According to the above parameters, the method of Tang and Liu (2021), the method of Yu et al. (2021) and the method of this paper are used for experimental verification.

4.2 Experimental index setting

According to the experimental plan and experimental parameters set above, the experimental indicators selected in the experiment are the control error of the joint dexterity of the manipulator and the accuracy of cargo sorting and positioning. These two indicators reflect the control effect of the joint dexterity of the manipulator. In the experiment, three methods were used to optimise the sorting process and joint dexterity parameters by comparison.

1 Dexterity control error R_{oo}. The higher the dexterity control error, the worse the dexterity control effect of the manipulator joints. On the contrary, the higher the dexterity control error is, the better the control effect of the manipulator joint dexterity is. The specific calculation formula is as follows:

$$R_{oo} = \sqrt{\left(x_i - x_i'\right)^2 + \left(y_i - y_i'\right)^2} \tag{18}$$

In the formula, (x_i, y_i) is the actual coordinate of the joint pose of the manipulator, and (x_i', y_i') is the estimated coordinate of the joint pose of the manipulator.

2 Sorting and positioning accuracy cr_k. The higher the sorting and positioning accuracy, the better the control effect of the joint dexterity of the robot arm. On the contrary, the higher the sorting and positioning accuracy is, the worse the control effect of the joint dexterity of the robot arm is. The specific calculation formula is as follows:

$$cr_k = \frac{T_p}{T_p + F_p} \tag{19}$$

In the formula, the accuracy cr_k represents the proportion of samples that are correctly predicted in the samples sorted and positioned as positive examples by the robotic arm, and T_p represents the number of positive samples that are correctly positioned as positive classes in the robotic arm joint dexterity control, F_p represents the number of falsely localised samples of negative class as positive class in robotic arm joint dexterity control.

4.3 Analysis of experimental results

4.3.1 Manipulator joint dexterity control error

The control error of the joint dexterity of the robot arm is the key to the effective control of the direct response method. For this reason, the method in this paper is designed in the experiment, Yu et al. (2021) method and Zou and Tao (2022) method are designed to control the joint dexterity error of the robot arm in the sorted goods, and the obtained results are shown in Figure 5.

By analysing the results in Figure 5, it can be seen that with the continuous change of the number of goods sorted, the dexterity control errors of the manipulator joints in the sorted goods are different by using the methods in this paper, Yu et al. (2021) and Zou and Tao (2022). When the number of experiments is 20, the robot joint dexterity control error of Yu et al. (2021) method is 0.122%, the robot joint dexterity control error of Zou and Tao (2022) method is 0.135%, and the robot joint dexterity control error of this method is only 0.053%; when the number of experiments is 100, the robot joint dexterity control error of Yu et al. (2021) method is 0.186%, the robot joint dexterity control error of Zou and Tao (2022) method is 0.162%, and the robot joint dexterity control error of this method is only 0.082%; The control errors of the three methods are within a reasonable range, but through comparison, it can be seen that the control error of this method is the lowest, and is always lower than 0.1%, which shows the effectiveness of this method.

Figure 5 Analysis of the control error of the joint dexterity of the manipulator by different methods (see online version for colours)

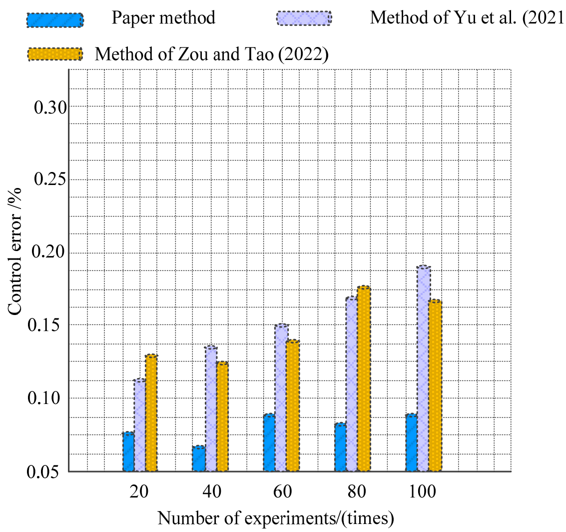
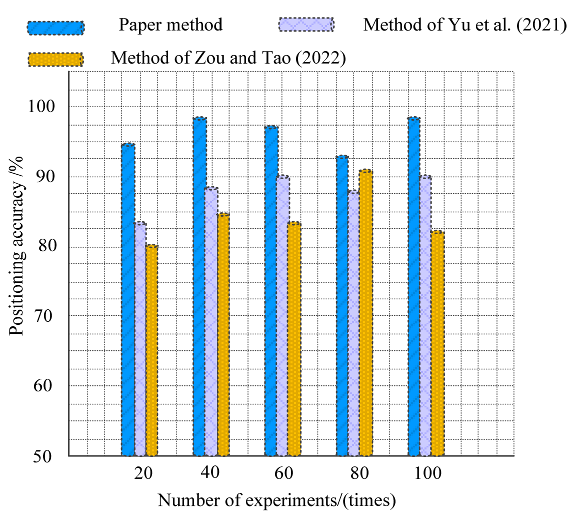


Figure 6 Analysis of the accuracy of cargo sorting and positioning by different methods (see online version for colours)



4.3.2 Goods sorting and positioning accuracy

In the experiment, the method in this paper, the Yu et al. (2021) method and the Zou and Tao (2022) method were compared for the experimental analysis of the accuracy of cargo sorting and positioning, and the results obtained are shown in Figure 6.

By analysing the experimental results in Figure 6, it can be seen that when the number of experimental iterations is 60, the accuracy of goods sorting and positioning of Yu et al. (2021) method is 90.2%, the accuracy of goods sorting and positioning of Zou and Tao (2022) method is 82.3%, and the accuracy of goods sorting and positioning of this method is as high as 98.1%; when the number of experimental iterations is 100, the accuracy of goods sorting and positioning of the method in Yu et al. (2021) is 90.2%, the accuracy of goods sorting and positioning of the method in Zou and Tao (2022) is 83.6%, and the accuracy of goods sorting and positioning of this method is as high as 98.5%; Based on the above data, it can be seen that the positioning accuracy of this method for the goods to be sorted is better, and is always higher than 90%, while the positioning accuracy of the other two methods is lower than this method. This is because the method in this paper has carried out many transformations for the coordinate points of the robot during sorting, and determined the law of its operation, so as to improve the positioning accuracy.

5 Concluding remarks

This paper proposes a dexterity control method for a multi-arm sorting robot based on machine learning. In a fixed three-dimensional area, set the coordinates of any point, obtain the posture of the multi-manipulator coordinate system on the rigid body, construct a rotation matrix, and determine the dexterity parameter changes of the manipulator joints of the multi-manipulator sorting robot. The dexterity parameter of the meta-computing method controls the error, and corrects the error structure through the activation function to complete the dexterity control. Experimental results show:

1 The control error of the method in this paper is always lower than 0.1%, which indicates that the method in this paper has a better control effect on the dexterity of the multi-manipulator sorting robot.

2 The positioning accuracy of the method in this paper is better for the goods to be sorted, and is always higher than 90%, and the dexterity control accuracy of the multi-manipulator sorting robot is high.

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