# Collaborative Control Analysis of Dual Arm Robots

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**Abstract.** The collaborative control technology of dual arm systems does play a crucial role in the field of robotics. This technology enables robots to exhibit extremely high efficiency and accuracy in handling complex, dangerous, or delicate tasks by precisely coordinating the movements of two robotic arms. With the shortage of labor and the continuous increase in labor costs, there are more and more fields that require the use of robots, and the quantity is also increasing. For many application scenarios, tasks are complex and varied, and application environments and conditions are also different. Single arm collaborative robots can no longer meet the requirements, and multi arm collaborative robot systems have emerged and become an important field for future development. However, the dual arm robot is a strongly coupled, highly nonlinear, and uncertain system, and its collaborative control problem is a challenging topic. This review provides a detailed summary of the collaborative control methods for dual arm systems, including classic methods such as master-slave control, force/position hybrid control, and impedance control during collaborative handling; Intelligent control methods based on neural networks and fuzzy systems; The progress of reinforcement learning based control methods in robot control. Finally, the future development trends of dual arm systems were discussed.

**Keywords:** Mechanical arm, dual arm robots, cooperative control, intelligent control.

## 1. Introduction

In foreign countries, some developed countries have been conducting research on robot motion control technology for a long time. After the NGC (The Next Generation Work Station/Machine Control) research program in the United States, OMAC (Organization for Machine Automation and Control) arranged for an independent research and development plan to develop modular control systems, thereby reducing the research and maintenance costs of robot control systems; In Europe, the OSACA (Open System Architecture for Control within Automation) program initiated by Germany and France is researching the architecture of layered system platforms, aiming to expand the openness of control systems; Many Japanese companies have also jointly implemented the OSEC program (Open System Environment for Controller) with the aim of obtaining a structurally flexible and lightweight motion control system [1]. The research on motion control technology for robotic arms in China is relatively lagging behind, with a short development time and still staying at the level of control algorithms and planning strategies. There is a significant gap with foreign countries, and in certain specific fields, it still relies on foreign imports. Research on open control systems is still in its infancy.

At present, dual arm collaborative robots have received widespread attention from academia and industry, especially when facing challenges brought by unstructured environments. They not only solve the intelligence needs that cannot be met or are difficult to meet with a single arm, but also improve work efficiency and have good human-machine collaboration capabilities. There are usually three forms of dual arm collaboration: 1. Using two robotic arms to simultaneously operate a common object, such as a larger momentum or volume object [2], this type is called tightly coupled cooperation; 2. Operate the same component sequentially in a shared workspace, such as adjusting the posture of the component with both arms during transportation; 3. Operate different objects in a shared workspace to complete specific tasks, such as collaborating on pouring water, folding clothes, etc. [3, 4], the latter two being loosely coupled collaboration. Tight coupling collaboration focuses on the force control problem between the two arms and the grasped object, while loose coupling collaboration considers more motion planning and task planning problems. Although the dual arm system has many advantages such as wide application scenarios, greater flexibility, and the ability to complete complex tasks, the difficulty of system modeling and controller design has also significantly increased. It is not only a simple combination of two robotic arms, but also requires coordination and cooperation to avoid collisions while completing complex tasks [5].

This review will investigate and analyze the collaborative control strategies of dual arm robots from traditional collaborative control methods and intelligent collaborative control methods of dual arm systems.

## 2. Dual Arm Collaborative Control Strategy

The collaborative control of dual arm systems is more complex than traditional single arm robots, as it not only requires consideration of task coordination but also obstacle avoidance between the two arms

### 2.1. Classic Control Methods

### 2.1.1. Master-slave control method

The master-slave control method involves designing a controller for the main arm based on task requirements, with the other robotic arm serving as a slave arm. The motion of the slave arm is calculated based on the trajectory of the main arm and specific constraint relationships. The main robot adopts pure position control, while the slave robot adopts compliant force control. The slave robot obtains the contact force magnitude through force sensors and calculates the motion trend generated by the main robot based on the force information, thereby performing compliant following. Nakano et al. first suggested a dual arm control strategy based on master-slave mode and applied it to dual arm collaborative handling [6]. Su Yue adopted a master-slave approach for collaborative handling, analyzed the motion constraints of dual arm cooperation, established a dynamic model, and designed the position control of the master robot and the force control of the slave robot separately [7]. The position control of the master robot was added with the flexibility control of the slave robot to complete the collaborative handling task. The master-slave control mode requires fast response and strong flexibility from the force control of the robot.

### 2.1.2. Distributed force/position hybrid control method

Compared to master-slave control, distributed force/position hybrid control no longer has a master-slave distinction for dual robots, and both have equal status. Force/position hybrid control decouples position control from force control, controlling separately in independent subspaces, using position control in free space, and switching to force control when constrained. However, during the transition process of switching, the system is prone to instability. It was originally created by M H. Raibert and J J. The flexible motion control method for robotic arms proposed by Craig mainly solves the problem of relative motion between the robotic arm and the contact surface, and is widely used in engineering practice [8]. By decoupling the force and position of the end effector into two separate subspaces—position control directed toward the cutting surface in contact with the environment and force control directed toward the normal surface in contact with the environment—force/position hybrid control operates. In contrast to master-slave control, Uchiyama et al. suggested a symmetrical force/position hybrid control technique to address the issue of two robots controlling the same item [9]. For the coordinated control problem of dual arm robots, Zhou et al. proposed a fuzzy force/position hybrid control strategy based on genetic algorithms [10]. They then confirmed the efficacy of the fuzzy force/position hybrid control strategy in simulation experiments and dual arm collaborative box handling. Yi et al. proposed a new dual arm cooperative adaptive control method, which achieves internal force and contact force tracking through force/position hybrid control under dynamic and closed-loop motion uncertainties [11].

### 2.1.3. Impedance control method

Impedance control is a classic force control algorithm, which generally sets the robot end as a virtual compliant mass spring damping system. After collecting force information through a six dimensional force sensor, the position error is calculated based on the mass spring damping system for position compensation. It is a high-performance second-order response force control. Impedance control is a force control method proposed by Neville Hogan in 1984 [12]. Macroscopically speaking, impedance control aims to present the dynamic characteristics of a second-order system of mass spring damping in a robotic arm. By adjusting the inertia, damping, and stiffness matrices in the impedance model, the impedance characteristics of the robot can be changed to achieve the effect of controlling the contact force with the external environment [5]. Caccavale et al. conducted a joint force analysis on the collaborative operation of objects using a dual six axis robotic arm and proposed an object-oriented internal and external impedance control method, ultimately achieving a reduction in both internal and external forces, and safely and effectively performing collaborative object operations [13].

## 2.2. Intelligent Control Methods

Intelligent control is an emerging technology developed in recent years, mainly using intelligent optimization algorithms to improve force control technology, such as fuzzy logic control, neural network optimization, and some biological intelligence algorithms. When performing tightly coupled tasks with both arms, even small position errors can generate huge internal forces, causing damage to the operated object and the robotic arm. The dual arm system not only needs to consider external interference, but also internal force factors. Therefore, precise motion control of the dual arm system is particularly important. In fact, when using a real robotic arm, the arm manufacturer will provide accurate kinematic parameters, but it is difficult to obtain dynamic parameters. At this point, utilizing the fitting ability of intelligent control methods such as neural networks and fuzzy logic can effectively compensate for dynamic uncertainty [5]. Kong et al. proposed an adaptive fuzzy neural network strategy to solve the dual arm cooperative control problem in the case of unknown dual arm dynamics model and contact environment [14]. Among them, fuzzy neural networks are used to approximate unknown dynamic models, and an integral barrier Lyapunov function is introduced to avoid violating constraint conditions. Specifically, impedance learning is used to adjust the control input to improve the interaction between the robotic arm and the environment, enabling it to track the desired trajectory. Yang et al. considered the kinematic uncertainty problem of dual arm systems and proposed a dual arm robot control strategy that integrates adaptive fuzzy logic systems and Approximate Jacobian Matrix (AJM) techniques [15]. This strategy ensures that the tracking error converges within a limited time.

In order to achieve good dual arm coordination ability in dual arm robots, it is necessary to deal with nonlinear problems in the dynamic system. There is a common assumption in the literature on humanoid robot control that the output lag problem can be ignored. However, the output lag phenomenon is widely present, which seriously affects the motion and force performance of the dual arm system. An adaptive neural control approach that considers computational efficiency and uncertain output hysteresis was presented by Liu et al [16]. Finally, the Lyapunov stability theory was used to prove that the motion error converges to a smaller neighborhood of the origin, while ensuring that the internal forces are bounded and the error can be arbitrarily small. A method that combines neural networks and impedance control was presented by Dong et al. Neural networks are used to approximate the uncertainty of robots, while impedance control improves the interaction performance between robots and the external environment [17]. Theoretical analysis verified that the error signal can converge to a bounded set, and the designed controller can better cope with changes in unknown environments compared to classical PD controllers.

Traditional control methods rely on complex kinematic and dynamic models of robotic arms, and have poor generalization ability for tasks. In recent years, data-driven learning methods have attracted the attention of many researchers for achieving end-to-end control of robotic arms without the need for system modeling [18-20]. Especially in 2016, the Google DeepMind team introduced the AlphaGo Go robot in Nature and used it to defeat the world Go champion, leading to a surge in research on reinforcement learning. Reinforcement learning is the interaction between an intelligent agent and its environment, continuously improving its decision-making ability through trial and error.

At the current time $t$, the intelligent agent receives the state information $S_t$ of the environment, selects an appropriate action $A_t$ to act on the environment based on the policy function π, and then receives the next state $S_{t+1}$ and timely reward $R_{t+1}$ feedback from the environment. Therefore, reinforcement learning is a sequential decision-making process whose state follows a Markov process, meaning that the state at the next moment is only related to the state at the current moment and is independent of all states before the current state. Almost all reinforcement learning can be represented as a Markov Decision Process (MDP). The process was shown in the Figure 1.

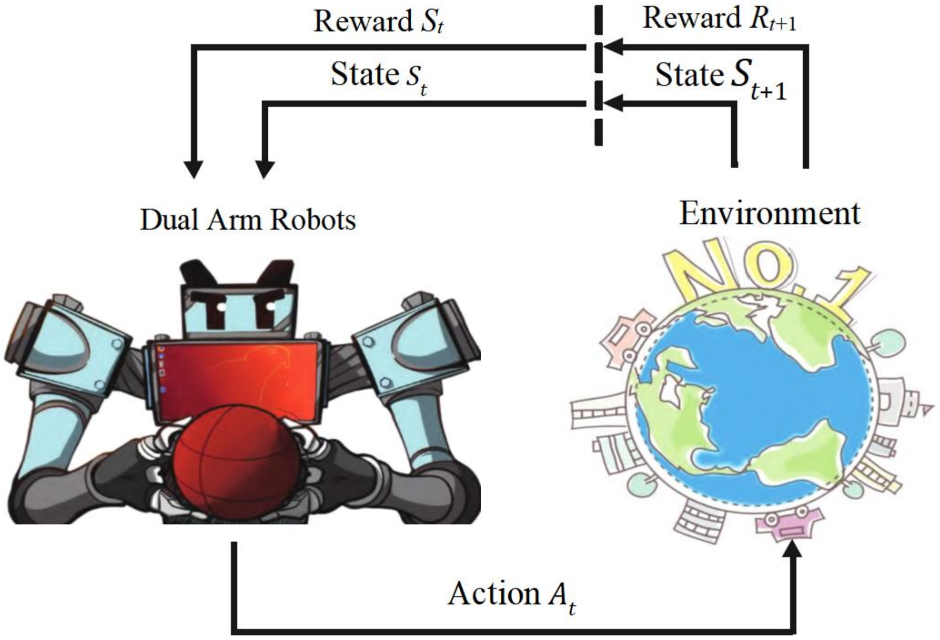

**Fig. 1.** Markov Decision Process [5]

## 3. Discussion

In the master-slave control mode, although the design is simple, the slave arm needs to track and assist the movement of the master arm based on the constraint relationship between the two arms. Therefore, when the master arm moves quickly, it is difficult for the slave arm to make a quick response, and the master-slave control method has a coupling relationship between the two arms, which is not conducive to the stability of the operation.

The force/position hybrid control strategy does not require precise dual robotic arm models and complete environmental constraint information, but achieves collaborative operation tasks of dual arm robots through high-precision position servo and force feedback. The disadvantage of force/position hybrid control is also obvious, that is, it cannot simultaneously control the magnitude of force in the direction of robot motion. Based on this limitation, impedance control has been derived.

The advantages and disadvantages of each method were shown in the Table 1, and with the development of the field of artificial intelligence, it seems possible to abandon complex robot dynamics models and turn to a way of constantly interacting with the environment to complete many tasks. Reinforcement learning is a promising and powerful technique that automatically obtains control strategies through trial and error. By processing raw sensor data (such as images), complex actions can be executed to achieve end-to-end control. At the same time, the strategies trained using reinforcement learning techniques have good generalization ability and can effectively manipulate unknown objects.

**Table 1**. Advantages and disadvantages of each method

| Method | Advantages | Disadvantages |
|---|---|---|
| Master-slave control method | simple design | Slow real-time response from the arm |
| Distributed force/position hybrid control method | Good stability and force control accuracy | Unable to control force in the direction of motion |
| Impedance control method | Good robustness in variable environments | Poor control accuracy |

## 4. Conclusion

This review investigates the collaborative control methods of dual arm systems, including classic methods such as master-slave control, force/position hybrid control, and impedance control during collaborative handling; The latest progress of intelligent control methods based on neural networks and fuzzy systems in robot control. With the emergence of more and more low-cost, safe, and reliable collaborative robotic arms, as well as the application of artificial intelligence technology in different fields, collaborative control of dual arm systems will inevitably become a research trend. In summary, in basic theoretical research, the advantages of current artificial intelligence should be utilized as much as possible and combined with the robotics that has been developed for decades.

Reviewed the latest developments in dual arm systems, particularly the transition from classical control algorithms to learning algorithms. With the emergence of more and more low-cost, safe, and reliable collaborative robotic arms, as well as the application of artificial intelligence technology in different fields, collaborative control of dual arm systems will inevitably become a research trend. Therefore, the control method of programming a robotic arm for different environments, tasks, and users appears cumbersome and impractical. However, the dynamic interactive reinforcement learning method compensates for this deficiency by not requiring manual programming and completing a certain task through continuous trial and error. In the process of strategy learning, dual arm robots will engage in extensive ineffective exploration, resulting in low efficiency in skill learning. Therefore, the combination of reinforcement learning and imitation learning greatly improves this phenomenon.

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