Model-based and Model-Free Robot Control: A Review

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Abstract. Robot control is one of the key aspects of robotics research. Models are essential tools in robotics, such as robot's own body dynamics and kinematics models, actuator/motor models, and the models of external controllable objects. In this paper, we review the latest advances in model-based and model-free approaches with a strong focus on robot control. Based on the designed search strategy, several prevailing control approaches are classified and discussed according to their control strategies. An insight into the gripper control is also explored. Then the research problems and applicability of the control methods are discussed by investigating their merits and demerits. Based on the discussion, we summarize the challenges and future research trends of robot control.

Keywords: Model-based, Model-free, Robot Control, Impedance, Admittance, Machine Learning, Gripper

1 Introduction

Robot control methods have always been a topic of great concern. Current high-precision control requirements bring new challenges that the traditional control methods may not be applicable. For example, the requirement that robots work in a complex unstructured environment or be able to work collaboratively with humans or other robots. Many new controllers have been developed that are flexible and suitable for complex non-institutional environments [1], and some controllers can also be effectively applied in complex human-computer interaction scenarios [2].

Robot controllers can be classified into two categories: model-based and model-free. The former is a controller that developed based on a model (Robot model, environment model, motor/actuator model, etc.). Considering the uncertainties and disturbances in the real-world scenarios, such as parametric uncertainties, wear of the machine, manipulation influenced by gravity, errors of the motor, the influence of the noisy environment, which make the established model inaccurate to be used to control the real robots. In this regard, researchers have developed many model-based controllers to adapt or suppress these model uncertainties [3][4]. Furthermore, to solve these problems, many studies adopt machine learning techniques to develop new control systems [5]. And examples of machine learning can also be found in model-free control [6].

Another type of controller is based on model-free approaches. This type of controller usually does not consider whether the model is accurate and the uncertainty of the model, but achieves the purpose of control through learning or training [7]. One way of learning and training is to help robots learn through human-computer interaction. It is also possible to use some learning frameworks to through training the input and output data, such as the neural learning enhanced control studied in [8].

Among the controllers, there are two classic controllers often mentioned, which are impedance control and admittance control. Impedance control is a control system that inputs displacement and then outputs force [9]. In contrast, admittance control is a control system that inputs force and outputs displacement [9]. In addition, admittance control has some advantages that make it suitable for position control systems. Many researchers have been proposing new designs based on these two controllers in order to obtain better control performance. More information will be introduced in other parts of this paper.

In this paper, some latest studies on control methods of soft robots will also be discussed. The soft robots and the rigid robots are very different, for example, the state space of the soft robot is infinite [10], it is difficult to model and other characteristics, as such, the control methods are also different from the rigid robots. In addition, some recent advances in control different grippers (electric gripper and pneumatic gripper) will be investigated.

The paper is structured as follows: Section 2 introduces the methods and criterions adopted for searching and ranking the latest references discussed in this paper Section 3 classifies the references according to the type of controllers and clarifies the basic implementation ideas of the controllers. Section 4 expands the discussions based on Section 3. Finally, conclusions of this paper are given in Section 4.

2 Search strategy

In this section, the methods of literature search and screening criteria will be described. The method of selecting keywords is mainly based on different control types, such as model-based control, model-free control, etc. We also choose keywords for different types of robots, such as rigid robots, soft robots, etc. Keywords such as electric gripper control, pneumatic gripper control are adopted for gripper control selection. To cover more types of control methods, the following keywords are also used: impedance control, admittance control, inference control, adaptive control, data-based control, force control, using feedback control for a robot, etc. Since controllers are generally complicated, controllers will have different design methods, which means that even if "model-based control" is used as a keyword, many other types of controllers may be found, which will improve the search coverage for articles. The discussion will be provided with good support.

The choice of a search database is another concern. In this search, the main sources of literature in this paper are: IEEE, ScienceDirect and SAGE. Due to a large number of robot-related publications on these sites (The ranking is shown in figure 1, the data source comes from Google Scholar). As such, these sites are selected as the main source of references. Furthermore, considering the nature of this paper, the search time should be limited to the literature of the past two years, which means that the publication time is between 2019-2020. In this way, the article can show the latest and most advanced research direction and research trends. However, several excellent articles were still selected although the publication time was in 2017.

Table 1. Ranking of top 5 publications in Robotics from Google Scholar Metrics

Rank	Name
1	IEEE International Conference on Robotics and Automation
2	IEEE/ASME Transactions on Mechatronics
3	The International Journal of Robotics Research
4	IEEE Transactions on Robotics
5	IEEE/RSJ International Conference on Intelligent Robots and Systems

3 Results

3.1 Overview of the Results

The classification of the selected papers is shown in Table 2. All screened papers are classified. The representative articles are discussed in subsections 3.2-3.4.

Table 2. Literature classification

Category	Method keywords	Related literature
Model-based control	Model-based learning	[4][3][5][11]
	Control based on neural network	[12][8]
	Data-based control	[13]
	Based on admittance control	[2][14][9][15]
	Impedance based control	[16][17][18]
	Based on different feedback signals: tactile, visual, etc.	[10][19][6][20][21]
	Novel methods	[22][23][24][25][26]
Model-free control	Data-driven, neural network, adaptive learning, iterative learning, reinforcement learning	[27][28][29][30][31][32][33][34][35][36][37]
Gripper control	electric	[38][39]
	pneumatic	[40]

3.2 Model-based Control and Model-Free Control

Model-based control. In the control problems, it is difficult to establish the model due to the uncertainty of the model such as wear, friction, materials and so on that hinder the accuracy of the dynamic model [32]. Therefore, the model-based controller is usually used to adapt or suppress the uncertainty of the model. In [4] the researchers described a general method based on factor graphs. The method can effectively meet the needs of customized robot kinematics models. In this method, the researchers developed a kinematics model based on general factor graphs. Since the kinematics model involves fine-tuning of parameters, they chose to complete the task of fine-tuning parameters through data-driven learning methods. Finally, the control task of the robot arm is realized.

Data-based learning methods are increasingly used in robot control. In [5] the researchers extended the model predictive path integral (MPPI) algorithm. MPPI is a sampling-based algorithm that can be optimized for general cost standards. In the article, the author demonstrates how to derive the updated law used in MPPI through the information theory framework without the assumption of controlled affine, which means that model learning in the MPPI framework can be completely driven by data. In the simulation, the researchers tested the MPPI controller using purely learned neural network dynamics, and the results showed that its performance was in line with the requirements. Another study proposed a position/force tracking impedance control scheme based on adaptive Jacobian and neural network [12]. The control scheme is divided into two parts: outer loop control and inner loop control. In the outer loop, the traditional impedance relationship is combined with a PID-like scheme to quickly eliminate force tracking errors [12]. In the inner loop, an adaptive Jacobian method is proposed to estimate the uncertainty due to system kinematics, the adaptive radial basis function neural network (RBFNN) compensates for uncertainties in system dynamics and adaptive Jacobian determinants [12]. Then, a robust term is designed to compensate for the external interference and approximation error of RBFNN. In this way, the commanded position trajectory generated by the outer ring force impedance controller can be finally tracked, so that the contact force tracking performance can be achieved indirectly in the force direction.

In addition, admittance control and impedance control are two common model-based control methods. In [2], researchers propose a novel control method that combines adaptive filtering with admittance control to overcome the disadvantages of constant admittance controllers. The basic idea of this control method is that once the filter detects oscillation, the admittance control parameters can be modified passively. Finally, this method can be used to solve the problem of vibration during cooperative manipulation. In order to solve the problem that the identification of the inertia and damping matrix in the dynamic admittance model is very time-consuming, a fuzzy-based admittance control is proposed in [14]. The controller directly calculates the speed of the end effector through an external wrench (force/torque) and the power transmitted by the robot. In addition, the fuzzy reasoning mechanism is mainly used to eliminate the identification of inertia and damping matrix. The composition of the fuzzy relationship can adaptively adjust the relationship between the speed of the end effector and the power transmitted by the external wrench and the robot. Two variable admittance control schemes were introduced for position control robots in [9] the first scheme is variable admittance control for direct intention, which changes the damping by estimating the direct intention to achieve fast and accurate motion. The second scheme is variable admittance control for indirect intention, similar to the virtual fixture guidance method, changing the admittance to guide people. There are also controllers that are based on impedance control. In order to achieve the active compliance of collaborative robots, [16] proposed an impedance controller based on torque feedback. The controller is divided into two parts, the torque controller and the impedance controller. The torque controller is used to compensate the robot dynamics, and the impedance controller is used to adjust the joint stiffness and damping. This controller can be applied to flexible joint robots and robots that cannot be accurately modelled. In [17], the researchers proposed an impedance sliding mode control method with adaptive fuzzy compensation. The control scheme is divided into inner loop control and outer loop control. The outer loop control uses impedance control, and the inner loop control uses sliding mode control. Due to the chatter caused by sliding mode gain switching, an adaptive fuzzy logic system is introduced to solve this problem. Finally, solve the position/force control problem caused by model uncertainty.

In addition to the above studies, some novel model-based control methods have also been proposed. In [22], they mainly studied the friction characteristics of the capsule system under dynamic conditions, especially the non-reversible drooping and hysteresis. The original intention of this research is because the friction model is still difficult for online implementation and control. The researchers in [23] mainly focused on the energy preserving in control. They based on passive dynamics to indirectly control the stick-slip motion caused by friction to achieve an improvement in overall driving distance and energy efficiency. [24] proposed A motion generation strategy for self-propelled robotic systems with viscoelastic joints is proposed, and an analytical two-stage motion profile is proposed based on the system response and dynamic constraint analysis. In [25], they studied the miniature hybrid capsule robot and proposed a new operation mode of the hybrid robot, namely the hybrid model and the anchoring model. In [26] they studied the problem of adaptive trajectory tracking control for under-driven vibration-driven capsule systems. The researchers designed two tracking control schemes using a closed-loop feedback linearization method and an adaptive variable structure control method with auxiliary control variables.

Model-free control. Model-based controllers are usually developed to suppress or compensate for model uncertainties. Another method is to use model-free control which is mainly based on data-driven approach.

For the rigid robot in [27], the researchers proposed an observer-based model-free adaptive terminal sliding mode controller based on data driving. The controller uses the concept of fully dynamic linearization to convert the nonlinear dynamics of the robot into an equivalent linear data model that only depends on the I/O data of the robot manipulator. Then use multiple observers to estimate the system output. Finally, based on the data-driven discrete-time nonlinear terminal sliding surface, a robust controller is designed. The researchers proposed a cascade-loop pHRI controller in [28], which consists of two parts. The outer loop is composed of two neural networks (NN) and is mainly used to predict human movement intentions. The inner loop applies the specified error dynamics with the help of a model-free neural adaptive controller that uses NN feedback to linearize the robot dynamics. This controller is used to improve the security and reliability of physical human-robot interaction（pHRI）.

Besides, reinforcement learning is also applied to model-free control. In [30], researchers proposed a model-less robot interactive control method using reinforcement learning. Learning only the best-expected force, without the need for impedance parameters corresponding to the environment but using force sensors to measure the contact force. They use force control to generate new position references and PID control to ensure position tracking. Then use feedback control principles to reduce the impact of unknown environmental dynamics. [31] proposed a model-free adaptive iterative learning controller based on iterative feedback tuning algorithm. The researcher used the principle of non-parametric dynamic linearization to establish a dynamic model, designed the controller based on this model, and then used the iterative feedback tuning (IFT) algorithm to adjust the parameters of the controller to optimize the performance of the system.

More model-free control methods, for example, an adaptive neural network tracking control scheme was proposed in [34] for the underactuated robot with matched and mismatched disturbances. A trajectory generation method based on Probabilistic Movement Primitives was discussed in [35] to improve the local trajectory optimization. A single trial classification method was studied in [36] based on ERD/ERS and Corticomuscular Coherence. A novel weakly-supervised approach was proposed in [37] for RGB-D-based nuclear waste object detection.

3.3 Gripper Control

The gripper plays an important role in the field of robot control research. Especially when collecting tactile signals, the gripper provides an irreplaceable role. For example, in [20], the researchers add tactile sensors to the gripper, and then analyzed the pressure data to grab the object and predict the hardness and softness of the object. Tactile feedback allows robots to perform dexterous manipulation tasks in unstructured environments [6].

The control methods of grippers are mainly divided into two categories according to the types of actuation of the gripper: electric and pneumatic. The electric gripper is a gripper driven by electric motors. For example, in [39], they describe an electric gripper called “blue gripper”. This gripper uses force control so that it can hold small objects of various weights safely. In another study, the researchers designed a five-finger robotic hand [38]. The grasping force of the robot is controlled by a force controller and combined with a tactile sensor to achieve the task of a multi-finger robot gripping an unknown object. Another control method is pneumatic. In [40] they proposed a two-finger robot based on PCP (pre-charged pneumatics). Due to the particularity of the pneumatic gripper, it is difficult to control the gripping speed and gripping force. So, in this study, they designed a closed-loop control strategy with feedback (distance and force) to alleviate this problem.

4 Discussions

4.1 Discussion on Model-based Control and Model-Free Control

The field of robot control can be divided into two directions, one is a controller based on model development, and the other is a model-free controller. It is not difficult to see from the results part of this article that there are advantages and disadvantages in both methods. Controllers developed based on models are usually highly dependent on the model, so the accuracy of the model directly affects the performance of the controller, and controllers developed based on the model are usually affected by many factors in the actual environment, such as machine wear and inertia torque etc. These problems will increase the uncertainty of the model and hinder the practical application of the controller. In order to solve these problems, many people tend to use machine learning, neural networks, adaptive fuzzy neural networks and other learning models combined with classical controllers to develop more powerful controllers. Because compared with classical controllers, controllers incorporating machine learning have the potential to improve control performance. Despite this, model-based methods still face many challenges when manipulation in unstructured dynamic environments. For example, how to avoid the accumulation of errors when training models is one of the challenges. Some people solve this problem by combining model prediction and machine learning, which may be a new direction for solving similar problems in the future.

The impedance control method and the admittance control method are two common control methods in model-based control. Classical impedance control methods fall into two categories: position-based impedance control and torque-based impedance control [12]. Therefore, if someone wants to design a simpler controller, the impedance control method may be extended to reduce the complexity of the controller. The opposite of the impedance controller is the admittance controller, which is widely used in the field of human-computer interaction. This may be because the admittance control scheme can mask the dynamic characteristics of the nonlinear robot and is easy to implement in practice.

Model-free control is just the opposite of model-based control. Model-free control is not highly dependent on the model and does not even need to know the model to complete the control of the robot. Because in practical applications, it is usually difficult to obtain an accurate model of the system, so some model-based control methods are only suitable for the simulation environment, so in order to make the controller independent of the system model, someone proposed the model-free control. Because the model-free control does not depend on the model, the step of building the model is omitted, thereby avoiding the uncertainty of the model. The alternative method, for example, converts the nonlinear dynamics of the robot into an equivalent linear data model that relies only on I/O data manipulated by the robot. Iterative feedback adjustment (IFT) is a data-driven method, which is used to adjust the parameters of the control system, and model-free adaptive control (MFAC), this method also requires I/O data. The effective research direction to convert nonlinear dynamics to equivalent linearity model. In addition, iterative control methods and model-free adaptive control are also two important research directions in the field of model-free control. Although the model-based control system reduces the dependence on the model, it also brings other problems. For example, in the model-free control method based on reinforcement learning (RL), the controller usually needs a lot of data to help learning, which reduces the applicability of the model-free controller.

4.2 Discussion on the Gripper

The gripper plays an equally important role in the field of robot control. Usually, in order to obtain control signals, such as tactile signals, researchers will install various types of tactile sensors on the gripper. In the gripper, people usually pay attention to how to control the gripper to achieve stable grasping of unknown or known objects. The gripper can also be combined with a tactile sensor to measure the hardness of the object. The control of the gripper usually uses the force controller, which has low cost and high practicality, so most research tends to use it. Relative to the hard gripper, to prevent the gripper from damaging the objects in contact, someone has designed pneumatic gripper. This type of gripper is usually used for highly adaptive robots due to its soft material compliance and adaptability. However, since pneumatic gripper is driven by inflation, it is difficult to achieve precise control. For precise control, someone designed the pre-charged pneumatics (PCP) gripper. Although it has not yet achieved perfect control, it may be used as a future research direction.

5 Conclusion

Accuracy is one of the key metrics of robot control. This paper investigates the latest advances in model-based and model-free control approaches and provides some insights into the gripper control. The paper selects some latest prevailing control methods for summarization and discussed the expected research direction in combination with some control methods. Although some methods increase the accuracy, they also increase the complexity of the calculation, especially some control methods that require large amounts of data for training. Therefore, future control methods need to control the computational complexity as much as possible while improving accuracy, which will bring great benefits to both control modes. Also, there is no unified measurement standard found in many works of literature, which may be related to different applications of different controllers, but if a general measurement standard can be formulated, it may play a key role in the performance measurement of the controller.

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