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A Survey on Application of Data-driven Model Predictive Control in Robot Control

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Abstract: Robotics has rapidly advanced, revolutionizing manufacturing, healthcare, agriculture, and logistics industries. These advances have enabled robots to perform increasingly complex tasks with greater efficiency and adaptability. However, robotic control remains a major challenge due to robotic systems' complex dynamics, nonlinearities, and uncertainties. Traditional control methods often rely on accurate mathematical models, which are difficult to obtain for complex robots. Data-driven model predictive control (DD-MPC) is a promising solution that overcomes the limitations of traditional methods by leveraging data to learn system dynamics. Unlike model-free methods that lack safety guarantees or model-based methods that struggle with complexity, DD-MPC offers a balance between flexibility and performance. It facilitates real-time optimization, adeptly manages multifaceted constraints, and exhibits adaptability to spatiotemporal dynamic changes. This survey explores the application of DD-MPC in robotic control, highlighting its advantages over other control strategies and its potential to address current challenges in the field.

Keywords: Data-driven, Model Predictive Control, Robot Control

1. Introduction

In recent years, robotics has significantly advanced, transforming industries like manufacturing, healthcare, and logistics. However, traditional control methods struggle with robots' complex dynamics, nonlinearity, and uncertainty. For example, Saviolo et al. [1] highlighted the need for self-supervised learning to adapt to dynamic changes. Traditional PID controllers, relying on accurate models, often fail in complex systems due to their inability to handle uncertainty [2]. Data-driven model predictive control (DD-MPC) has emerged as a promising solution. It leverages data-driven models and advanced techniques like rapidly exploring random trees (RRT) to improve task performance and safety [3]. By combining data-driven flexibility with MPC's optimization capabilities, DD-MPC balances adaptability and performance, enabling real-time optimization and constraint handling, making it suitable for complex robotic systems [4, 5]. This paper reviews DD-MPC's application in robot control.

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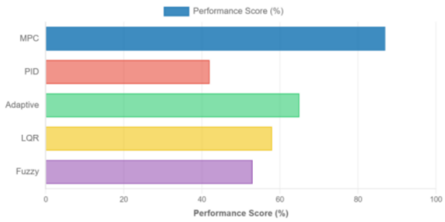

Figure 1: MPC shows superior performance in complex constrained scenarios

This study examines DD-MPC's efficacy in robotic applications through comprehensive literature review, evaluating its comparative advantages and implementation constraints. The analysis synthesizes current developments and research trajectories to advance robust control methodologies in complex robotic systems.

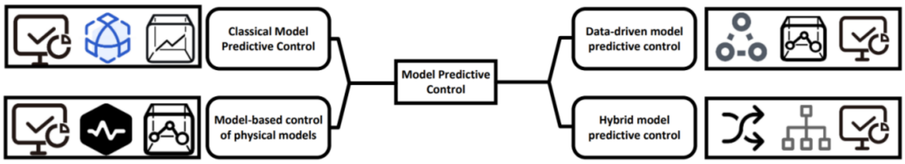

Figure 2: Classification of MPC

Figure 2 shows the classification of MPC. Model predictive control can be divided into classic model predictive control, data-driven model predictive control, physical model predictive control, and hybrid model predictive control. This article mainly introduces data-driven model predictive control. DD-MPC is commonly used in this article.

2. Research status

2.1. Robot control challenges

Robotics is widely used in industrial manufacturing, medical services, home assistants, and exploration of unknown environments. However, as the application scenarios and task complexity increase, its control faces many challenges. Traditional control methods (such as PID control and state feedback control) perform well in simple tasks, but are insufficient in complex tasks [6,7]. The nonlinearity and high dimensionality of robot dynamics, as well as the uncertainty in the operating environment [8,9] (such as external interference, sensor noise, and system parameter changes) have a significant impact on control performance, especially in dynamic and unknown environments. Traditional methods are difficult to meet the needs of rapid adaptation. Real-time robotic control faces challenges in applications requiring rapid computation, like high-speed motion and obstacle avoidance. Traditional methods often struggle with computational complexity, hindering performance and real-time execution. Task heterogeneity demands flexible, robust control systems. These challenges drive research into adaptable, efficient strategies, with data-driven model predictive control (DD-MPC) as a key focus.

2.2. The rise of data-driven model predictive control (DD-MPC)

Conventional model predictive control (MPC) leverages system models to forecast future states and optimize control inputs, demonstrating efficacy in managing multivariable constraints. However, its reliance on precise mathematical models curtails applicability, particularly in robotics where dynamics are nonlinear, high-dimensional, and uncertainty-laden. The computational demands of online optimization further impede real-time implementation. Data-driven MPC has emerged to

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address these limitations [10]. Data-driven MPC (DD-MPC) integrates data-driven methods with the MPC framework, utilizing system data for model construction or control optimization. DD-MPC demonstrates adaptability, online learning, and enhanced optimization efficiency in robotic control. Recent advancements include neural network and reinforcement learning-based strategies, augmenting system adaptability and robustness. DD-MPC addresses nonlinearity, uncertainty, and real-time challenges, advancing control theory. Future deep learning advancements promise enhanced robustness, interpretability, and computational efficiency. Integrating DD-MPC with deep reinforcement learning enables efficient decision-making, while transfer learning improves cross-task adaptability. Combining DD-MPC with adaptive or sliding mode control optimizes system performance, significantly impacting robotic control and fostering robotic technology advancements.

3. Application of DD-MPC in robot control

3.1. Application of DD-MPC in autonomous vehicle steering control

Data-Driven Model Predictive Control (DD-MPC) offers notable benefits for autonomous vehicle steering by circumventing intricate modeling via a data-centric strategy, diminishing computational demands, and enhancing control precision. A 2023 Tongji University study introduced a DD-MPC-based steering algorithm, validated in Carsim-Simulink, demonstrating its superiority over PID control and kinematics-based MPC in control error and computation time. DD-MPC optimizes prediction time domain and control input in real-time, adeptly manages complex road conditions, and elevates lateral stability and trajectory tracking fidelity .

3.2. Continuous jumping control of humanoid robots

In 2024, the Beijing General Artificial Intelligence Research Institute and the Leju Humanoid Robot Joint Laboratory validated a center of mass dynamics model-based model predictive control (CDM-MPC) framework for continuous jumping control in humanoid robots. Empirical results from a 1.2-meter robot hardware platform demonstrated high-dynamic jumps and stable landings, even amidst external perturbations. This research underscores the efficacy of dynamics-aware MPC in intricate systems, offering novel insights for humanoid robot deployment in sectors such as intelligent manufacturing and disaster mitigation [11].

4. DD-MPC advantages and limitations

4.1. Advantages

The following will introduce the advantages of DD-MPC from a mathematical perspective.

In the field of robot control, data-driven model predictive control (DD-MPC) has shown significant advantages, especially when dealing with complex robot systems, its performance and practicality are particularly outstanding.

First, DD-MPC avoids the reliance on accurate dynamic models. Traditional robot control methods usually require accurate dynamic models to design controllers. However, for complex robot systems (such as multi-joint robots or quadruped robots), accurate modeling is often very difficult and time-consuming. DD-MPC uses input and output data to build system models directly in a data-driven way. For example, assuming that the robot's input is the control signal u(k) and the output is the joint angle y(k), DD-MPC can obtain an approximate linear model through data fitting:

$$y(k+1) = Ay(k) + Bu(k) \tag{1}$$

The matrix is learned from data. This method greatly simplifies the modeling process and reduces the requirements for accurate modeling of the system, especially for complex robotic systems.

DD-MPC performs well in trajectory tracking. By optimizing the objective function, DD-MPC can minimize the trajectory tracking error while limiting the rate of change of the control input to avoid actuator overload. The objective function can usually be expressed as:

$$\mathrm{J} = \sum_{\mathrm{k}=1}^{\mathrm{N_p}} \| \mathrm{y}(\mathrm{k}) - \mathrm{y_{ref}}(\mathrm{k}) \|_{\mathrm{Q}}^{2} + \sum_{\mathrm{k}=0}^{\mathrm{N_e}-1} \| \Delta \mathrm{u}(\mathrm{k}) \|_{\mathrm{R}}^{2} \tag{2}$$

Among them, $\mathrm{N_p}$ is the prediction range, $\mathrm{N_c}$ is the control range, $\mathrm{y_{ref}}(\mathrm{k})$ is the desired trajectory, and Q and R are the weight matrices. By optimizing this objective function, DD-MPC is able to generate the optimal control input sequence within the prediction horizon, making the output of the robot system as close to the desired trajectory as possible.

Moreover, DD-MPC has good real-time and fast response capabilities. In each control cycle, DD-MPC can quickly solve the optimization problem and update the control input in real time:

$$\mathrm{u}(\mathrm{k}) = \underset{\mathrm{u}}{\mathrm{argmin}} \mathrm{J}(\mathrm{u}) \tag{3}$$

This real-time nature enables DD-MPC to quickly adapt to dynamic changes in robot motion, improving the response speed and stability of the control system.

DD-MPC can also adapt to environmental changes and system uncertainties. Through online learning and data updates, DD-MPC can adjust control strategies in real time to compensate for unknown disturbances and system parameter changes. For example, assuming that the system is subject to an unknown disturbance d(k), DD-MPC can respond by updating the data-driven model:

$$\mathrm{y}(\mathrm{k}+1) = \mathrm{Ay}(\mathrm{k}) + \mathrm{Bu}(\mathrm{k}) + \mathrm{d}(\mathrm{k}) \tag{4}$$

This approach improves the robustness of the control system, enabling it to operate stably under different environmental conditions.

DD-MPC also excels in handling multivariable systems and constraints. It is able to optimize the relationship between multiple inputs and outputs simultaneously and incorporate constraints into the optimization problem. For example, assuming that the robotic system has m inputs and p outputs, DD-MPC can incorporate constraints into the optimization problem:

$$\begin{aligned} &\min_{\mathrm{u}} && \mathrm{J}(\mathrm{u}) \\ &\mathrm{s.t.} && \mathrm{u_{min}} \le \mathrm{u}(\mathrm{k}) \le \mathrm{u_{max}} \\ & && \mathrm{y_{min}} \le \mathrm{y}(\mathrm{k}) \le \mathrm{y_{max}} \end{aligned} \tag{5}$$

This method ensures that the control input and system output are within a safe range, improving the reliability and safety of the control system.

Finally, DD-MPC quickly solves the optimization problem through efficient optimization algorithms (such as gradient descent method, interior point method, etc.), reducing the computational complexity. For example, assuming that the objective function J(u) is a quadratic function, it can be directly solved by the gradient descent method:

$$\mathrm{u}(\mathrm{k}+1) = \mathrm{u}(\mathrm{k}) - \alpha \nabla \mathrm{J}\left(\mathrm{u}(\mathrm{k})\right) \tag{6}$$

Among them, α is the learning rate. The efficient optimization algorithm enables DD-MPC to complete the optimization calculation in a shorter time and is suitable for real-time control systems.

4.2. Limitations of data-driven model predictive control (DD-MPC)

Although data-driven model predictive control (DD-MPC) has significant advantages in robot control, its application also has some limitations. DD-MPC performance relies on data quality and generalizability but is susceptible to noisy, incomplete, or biased datasets that limit model generalization and control efficacy. Computational complexity persists despite modeling simplifications, especially with extended prediction horizons or high-dimensional systems, impeding real-time applications. Reliance on data-driven models for predictive accuracy is critical; model inaccuracies, particularly in nonlinear systems, degrade control performance.

5. Research progress

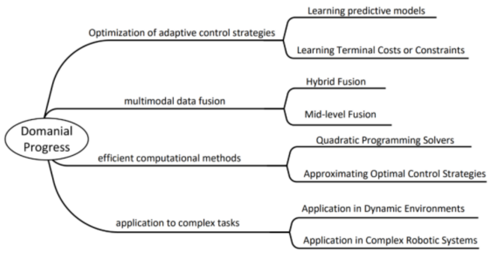

Figure 3: Domanial progress of DD-MPC

Figure 3 briefly shows the research progress in the field of DD-MPC.

5.1. Optimization of adaptive control strategies

DD-MPC approximates the dynamic equations of the system by learning a predictive model, such as Han et al. [12], thereby improving control accuracy in the prediction and optimization stages. This method is particularly suitable for complex systems that are difficult to obtain accurate physical models, such as soft robots and highly nonlinear biochemical processes. At the same time, DD-MPC can also learn more sophisticated terminal state constraints or terminal penalty functions through data analysis, which helps to improve the global performance of MPC and maintain good control effects when the dynamic characteristics of different operating points vary greatly.

5.2. Multimodal data fusion

DD-MPC employs mid-term and hybrid fusion strategies. Mid-term fusion enhances performance via multi-modal feature integration, exemplified by camera-radar data merging in autonomous driving for improved environmental perception. Hybrid fusion leverages early, mid-term, and late fusion advantages, exploiting multi-modal data complementarity and redundancy through network architecture and loss function regularization, thereby optimizing decision-making in complex environments.

5.3. Efficient calculation method

DD-MPC employs deep neural networks to approximate model predictive control (MPC) solutions, achieving optimization through learning. During online execution, rapid forward propagation yields approximate solutions, substantially reducing computational demands and enhancing real-time performance. DD-MPC often transforms optimization problems into quadratic programs (QP), leveraging efficient solvers like CasADi for swift resolution. In linear system MPC implementations, this approach facilitates rapid acquisition of optimal control inputs, thereby improving system response speed.

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5.4. Applied to complex tasks

DD-MPC exhibits considerable utility in intricate robotic systems and volatile environments. In quadruped robots, it optimizes control inputs for stable locomotion on uneven terrain, facilitating autonomous navigation and task execution. Furthermore, in autonomous driving, DD-MPC's real-time control input updates enhance system robustness and reliability by responding to dynamic changes in surrounding vehicles and road conditions.

6. Conclusion

This study deeply analyzed the application of DD-MPC in robot control and revealed its significant advantages in adaptive control optimization, multimodal data fusion, efficient computing and complex task execution. DD-MPC simplifies the traditional modeling process through data-driven, realizes high-precision trajectory tracking and dynamic control, significantly improves the performance and robustness of robots in complex tasks, and shows broad application prospects in intelligent manufacturing, logistics distribution, disaster relief and other fields. In the future, DD-MPC will continue to optimize in multimodal data fusion, efficient computing method development, generalization capability improvement and safety and reliability enhancement, and further promote the development of robot technology towards a smarter and more efficient direction.

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