1. INTRODUCTION

Control of door manipulators

The problem of controlling a door manipulator involves the coordination of multiple degrees of freedom, such as those associated with the actuator, hinge, and position of the door itself. This control problem is complex due to the non-linear dynamics and uncertainties in the system. The objective is to develop a control strategy that can adapt to varying conditions and ensure smooth, efficient, and safe operation.

The proposed approach involves an adaptive motion control strategy that learns from the environment and adjusts its behavior accordingly. This approach is particularly useful in scenarios where the door's characteristics or the environment are not precisely known or change over time.

The paper presents a novel method for adaptive motion control of a door manipulator, which combines elements of model predictive control (MPC) and reinforcement learning (RL). The MPC module predicts future states and takes actions to minimize a cost function, while the RL component learns optimal policies through interaction with the environment.

The adaptive control scheme is evaluated through simulations and experimental tests, demonstrating its effectiveness in handling various door configurations and environmental challenges.

In conclusion, the proposed adaptive motion control approach offers significant advantages over traditional control methods, particularly in dynamic and uncertain environments. Further research is needed to extend the methodology to more complex systems and to improve the robustness and efficiency of the control algorithm.

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APPENDICES

[Appendix A: Additional mathematical formulations]
[Appendix B: Experimental setup and results]

REFERENCES

We are able to compute the characteristic equation of the system to obtain the poles of the transfer function. By solving the characteristic equation, we can find the roots of the denominator polynomial of the transfer function, which are the eigenvalues of the system matrix. These eigenvalues determine the stability and dynamics of the system.

Therefore, the poles of the transfer function can be expressed as:

\[ \lambda_1, \lambda_2, \ldots, \lambda_n \]

where \( n \) is the order of the transfer function.

For a given input function \( y(t) \), the output function \( x(t) \) can be computed using the transfer function matrix \( H(s) \).

The system is stable if all the eigenvalues have negative real parts. Otherwise, the system is unstable.

In summary, the analysis of the control system dynamics involves calculating the poles of the transfer function, which determine the system's stability and response characteristics.

Control of Robot Manipulators
In the following, let us consider the following equation:

\[ \frac{\partial \mathbf{y}}{\partial P} \left|_{x^*} \right. = \left( \mathbf{y} - \mathbf{y}^* \right) \mathbf{P}^{-1} \mathbf{P} \mathbf{y} \mathbf{x} \mathbf{A} \mathbf{y} = \mathbf{0} \]

where \( \mathbf{P} \) is the precision matrix and \( \mathbf{x} \) are the covariances. If \( \mathbf{P} \) is invertible, we can express the conditional expectation \( \mathbf{E} \left[ \mathbf{y} | \mathbf{x} \right] \) as:

\[ \mathbf{E} \left[ \mathbf{y} | \mathbf{x} \right] = \mathbf{P} \mathbf{y} \mathbf{x} \mathbf{A} \mathbf{y} \]

In this case, the conditional expectation is a function of \( \mathbf{x} \) only.

To ensure that the expectation is a function of \( \mathbf{x} \) only, we need to ensure that the precision matrix \( \mathbf{P} \) is invertible and that the covariances \( \mathbf{A} \) are positive definite.

In practice, we can use numerical methods to estimate the conditional expectation from data.

Such an equation representation of the learned model is essential for understanding the relationships between variables.

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**Control of Robot Manipulators**

In the context of robot manipulators, the control strategy often involves minimizing the joint torques subject to the kinematic and dynamic constraints of the robot. This can be formulated as an optimization problem:

\[ \min \quad \sum_{i=1}^{n} \left( \mathbf{T}_i \right)^T \mathbf{T}_i \]

subject to

\[ \mathbf{T}_i \mathbf{q} = \mathbf{T}_d, \quad \mathbf{q} \mathbf{q}^T \mathbf{q} = \mathbf{I} \]

where \( \mathbf{T}_d \) represents the desired torque vector, and \( \mathbf{q} \) is the vector of joint angles.

This problem can be solved using numerical optimization techniques, such as gradient descent or quasi-Newton methods, to find the joint angles that minimize the joint torques while satisfying the constraints.

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**Conclusion**

In conclusion, the representation of the learned model is crucial for the control of robot manipulators. Understanding the relationships between variables not only improves the efficiency of the system but also enhances its robustness and adaptability to changing environments.
Theorem 1. If \( f \) is a differentiable function in an interval \( (a, b) \) and \( f' \) is continuous in \( (a, b) \), then \( f \) is absolutely continuous in \( (a, b) \).

**Proof.** Let \( a = x_0 < x_1 < \cdots < x_n = b \) be a partition of \( (a, b) \), and let \( \epsilon > 0 \) be given. We need to show that there exists a positive number \( \delta \) such that for any finite collection of disjoint subintervals \( [x_i, x_{i+1}] \) of \( (a, b) \), the sum of the lengths of these subintervals is less than \( \delta \), and the sum of the absolute values of the differences of the function values at the endpoints of these subintervals is less than \( \epsilon \).

Choose \( \delta = \min \{ \frac{\epsilon}{2n}, \frac{1}{2} \sum_{i=0}^{n-1} (x_{i+1} - x_i) \} \). Then, for any partition \( a = x_0 < x_1 < \cdots < x_n = b \) of \( (a, b) \), we have

\[
\sum_{i=0}^{n-1} (f(x_{i+1}) - f(x_i)) = \sum_{i=0}^{n-1} \int_{x_i}^{x_{i+1}} f'(t) dt.
\]

By the Mean Value Theorem, there exists a \( c_i \in (x_i, x_{i+1}) \) such that

\[
f(x_{i+1}) - f(x_i) = f'(c_i)(x_{i+1} - x_i).
\]

Thus,

\[
\sum_{i=0}^{n-1} (f(x_{i+1}) - f(x_i)) = \sum_{i=0}^{n-1} f'(c_i)(x_{i+1} - x_i) \leq \sum_{i=0}^{n-1} \|f'(c_i)\| (x_{i+1} - x_i) \leq \frac{1}{2} \sum_{i=0}^{n-1} (x_{i+1} - x_i)^2 \leq \frac{1}{2} \sum_{i=0}^{n-1} (x_{i+1} - x_i).
\]

Hence,

\[
\sum_{i=0}^{n-1} |f(x_{i+1}) - f(x_i)| \leq \frac{1}{2} \sum_{i=0}^{n-1} (x_{i+1} - x_i) \leq \frac{1}{2} \sum_{i=0}^{n-1} (x_{i+1} - x_i).
\]

Therefore, the sum of the absolute values of the differences of the function values at the endpoints of these subintervals is less than \( \epsilon \) when the partition is fine enough, as required. This completes the proof of Theorem 1.
\[
\begin{align*}
&(\lambda \theta(\lambda \theta(x)) - (\lambda \theta(x)) - (\lambda \theta(x)))
\end{align*}
\]
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