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Dual adaptive MPC using application-oriented set-membership identification

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MPC under model uncertainty

- MPC: Optimization based control, ensures state and input constraint satisfaction
- Tube MPC: Incorporates model uncertainty into the optimization, guarantees robustness
- Adaptive MPC: A novel technique, to reduce the model uncertainty online using measurements

Features of Adaptive MPC

Systems with linear, time-invariant dynamics and parametric uncertainties in the state space matrices and additive disturbances

> $x_{k+1} = A(\theta)x_k + B(\theta)u_k + w_k,$ $(A(\theta), B(\theta)) = (A_0, B_0) + \Sigma_i (A_i, B_i) \theta_i$

- The parameters and disturbances are assumed to be bounded $w \in W, \theta \in \Theta_0$
- Constraint satisfaction ensured using tube MPC
- Uncertain parameters are bounded by sets of non-increasing size using set-membership ID
- Identification is *passive* (**PAMPC**)

Set-membership identification

- Applicable when systems are subject to bounded noise, even with unknown properties
- Compute feasible parameters at each time step: $\Delta_k := \{\theta | x_{k+1} - A(\theta) x_k + B(\theta) u_k \in W\}$
- Update parameter set such that Θ_k has predefined hyperplane directions and $\Theta_k \supseteq \Theta_{k-1} \cap \Delta_k, \qquad \Theta_k \coloneqq \{\theta | H_\theta \theta \le h_{\theta_k}\}$ Can be performed by solving linear programs

Contribution

Augment Adaptive MPC with active exploration: Dual AMPC (DAMPC)

Main features

- Addresses the exploration-exploitation tradeoff: informative data vs. control performance
- Enables reference tracking under uncertain input setpoints
- Preserves guarantees of constraint satisfaction and recursive feasibility

Predicted parameter set

Using a parameter estimate $\bar{\theta}_{k}$, predict the next state measurement as a function of u_k

$$f_{1|k} = A(\bar{\theta}_k)x_k + B(\bar{\theta}_k)u_k$$

The predicted state measurement defines a feasible parameter set as

 $\widehat{\Delta}_{1|k} := \{\theta | \widehat{x}_{1|k} - A(\theta) x_k + B(\theta) u_k \in W\}$

• The identification at the next time step can be approximated as

$$\widehat{\mathfrak{D}}_{1|k} \coloneqq \mathfrak{O}_k \cap \widehat{\Delta}_{1|k}$$



Safe active exploration

- Construct state tubes using homothetic sets $X_{l|k} = z_{l|k} \oplus \alpha_{l|k} X_0$
- Decouple robustness and exploration:
 - Robust state tube: constraint satisfaction
 - **Predicted state tube**: worst case performance as MPC cost function



Numerical Example

- Monte Carlo simulation study
- Compare performance of PAMPC and DAMPC*

We consider a 2nd order syst

$$A_0 = \begin{bmatrix} 0.85 & 0.5\\ 0.2 & 0.7 \end{bmatrix}, B_0 = \begin{bmatrix} 0.4 & 0\\ 0.4 & 0 \end{bmatrix}, B_0 = \begin{bmatrix} 0.4 & 0\\ 0.4 & 0 \end{bmatrix}$$

$$A_{2} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad B_{2} = \begin{vmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix},$$

Parameter, disturbance and constraint sets

 $||\theta|$

$$\begin{aligned} ||\theta||_{\infty} &\leq 1, \qquad ||w| \\ ||x||_{\infty} &\leq 3, \qquad ||u| \end{aligned}$$

- 50 random realizations of true $\theta \in \Theta_0$
- 4 random disturbance sequences $w_k \in W$
- Finite horizon reference tracking, 100 timesteps
- Prediction horizon: 8 steps

A. Parsi, A. Iannelli and R. S. Smith, "Active exploration in adaptive model predictive control," 2020 59th IEEE Conference on Decision and Control (CDC)

A. Parsi, A. Iannelli and R. S. Smith, "An explicit dual control approach for optimal tracking of uncertain systems," IEEE Transactions on Automatic Control (submitted), 2021

*The code is available in the public repository: https://gitlab.ethz.ch/aparsi/active-exploration-ampc-cdc-2020



```
em of the form:
             0.41
            0.6
      0.2
            0.2
           0.35
     \mid_{\infty} \leq 0.1
||u||_{\infty} \leq 2
```

