

# Lecture 18 : MPC Variations : Code Generation, Robust, Stochastic

goals:

- Code gen techniques for MPC
- Robust + stochastic MPC

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## Fast MPC via Code Generation

- MPC: Repeatedly solve open-loop planning problem, often a convex problem
- general parser-solver (e.g. CVX, YALMIP) ok for prototyping, but can do much better using a custom solver in a low-level language (usually C) tailored to problem structure
- useful/necessary when
  - need to run many simulations for performance verification (Monte Carlo)
  - implementation on a real system (e.g. robot w/ low-cost, low-power embedded processor)

## Options:

- ① manually write solver in C code
- ② use recent code generation techniques to automatically generate custom solvers!
  - can exploit problem structure + hardware platform characteristics for speed + reliability

Ex CVXGEN by Mattingly + Boyd (~2012)

- used in SpaceX Falcon 9 landing system

Forces Pro by Embotech GMBH (~2012)

\* both have academic licenses

- highlights of Mattingly's CVXGEN slides

## Summary

- extremely fast + reliable custom solvers for convex optimization problems
- exploits repeated problem structure, hardware
- appropriate + necessary for extensive simulations, implementation on embedded systems

# Robust + Stochastic MPC

→ Lecture 10

- combination of robust/stochastic optimization with model predictive control
- on research boundary, state-of-the-art<sup>^</sup> in many application areas (or beyond!)

$$\underline{\text{Ex}} \quad \text{minimize} \quad \sum_{t=0}^{T_h-1} g_t(x_t, u_t) + g_{T_h}(x_{T_h})$$

$$\text{subject to} \quad x_{t+1} = Ax_t + Bu_t + w_t \quad t=0, \dots, T_h-1$$

$$\left. \begin{array}{l} Fx_t \leq h \\ Gu_t \leq d \end{array} \right\} \quad \forall t=0, \dots, T_h, \quad \boxed{\forall w_t \in W}^*$$

with variables  $u_0, \dots, u_{T_h-1}, x_1, \dots, x_{T_h}$

parameters  $g_t, A, B, T_h, F, h, G, d, W$

uncertain variable  $w_t \in W$

- if  $W$  is polytopic, can reformulate exactly using duality w/ linear constraints (see Lecture 10)
- repeatedly solve robust optimization problem
- same idea for different uncertainty sets, or for various types of stochastic constraints