

23 oct 2001

MPC Primer

I. Numerical Methods

- Parametric Opt.

$$\mathbb{R}^n \ni u, \mathbb{R}^+ \ni \min_u L(x, u) \quad \text{st. } f(x, u) = 0$$

- + dynamics

$$\rightarrow \min_u \phi(t_f, x(t_f)) + \int_{t_0}^{t_f} L(x, u, t) dt$$

$$\text{st. } \dot{x} = f(x, u), x(t_0)$$

II. MPC

A) Problem Statement

B) Proofs of Stability

Recall: $L: \mathbb{R}^n \rightarrow \mathbb{R}^+$, $\Omega \subset_{\text{open}} \mathbb{R}^n$

Solve $\min_{u \in \Omega} L(u)$ /

Know u^* is an extremum \Rightarrow

$$\frac{\partial L}{\partial u}(u^*) = 0, \quad \frac{\partial^2 L}{\partial u^2}(u^*) \geq 0$$

Descent Algorithms

1) 1st order gradient

2) Conjugate directions (L is quadratic)

3) Successive 2)

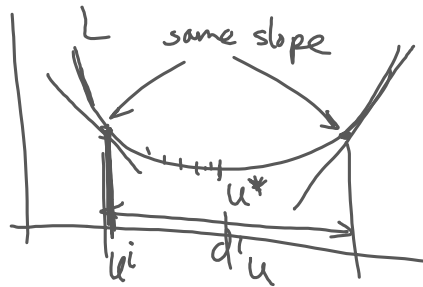
idea $\frac{\partial L}{\partial u} \perp \{L = \text{const.}\}$
 is greatest decrease direction

$$\Leftarrow \frac{\partial^2 L}{\partial u^2}(u^*) > 0$$

1) Steepest Descent (gradient) : improve guess u^* until $\frac{\partial L}{\partial u}$ "small"

alg. a) $i=0$, guess u^i , compute $\frac{\partial L}{\partial u}(u^i)$

b) $u^{i+1} = u^i - d_i \left(\frac{\partial L}{\partial u}(u^i) \right)$ $0 < d_i < 1$



$$L(u^{i+1}) = L(u^i - d_i \left(\frac{\partial L}{\partial u}(u^i) \right)) \approx L(u^i) - \frac{\partial L}{\partial u}(u^i)^T d_i \frac{\partial L}{\partial u}(u^i) \leq L(u^i)$$

$$d_{i+1} = d_i$$

$$d_{i+1} = \frac{1}{k}$$

if $L(u^{i+1}) < L(u^i)$ —

, k smallest integer s.t. \bullet

2) conjugate directions

solve $\min_u \{ \hat{L} = u^T A u + B u + c \}$

$A > 0$, get \min_u in n -steps $u \in \mathbb{R}^n$

3) Successive approx.

at u^0 , approx L by \hat{L} , get u' from
Conj. direc. $u^0 \leftarrow u'$. Repeat until $u^0 \approx u'$

Add Equality Constraints: $\min_u L(x,u) \text{ s.t. } f(x,u)=0$

$$\Leftrightarrow \min H(x,\lambda,u)$$

Result: extremal $z^* \triangleq (x^*, \lambda^*, u^*)$ of H

$$H = L + \lambda^T f$$

$\left(\left. \frac{\partial H}{\partial x} \right|_{z^*} = 0, \left. \frac{\partial H}{\partial \lambda} \right|_{z^*} = 0, \left. \frac{\partial H}{\partial u} \right|_{z^*} = 0 \right)$ is extremal of L holding $f=0$

$$L_x + \lambda^T f_x = 0$$

$$\lambda^T = -L_x f_x^{-1}$$

$$\left. \frac{\partial L}{\partial u} \right|_{\text{s.t. } f=0} = 0$$

$$\frac{\partial H}{\partial u} = 0 = \frac{\partial L}{\partial u} + \lambda^T \frac{\partial f}{\partial u}$$

Revision of 1st order gradient:

(a) guess u^i , $i = 0$

(b) compute x^i from $f(x^i, u^i) = 0 = \frac{\partial H}{\partial \lambda}$

(c) $\frac{\partial H}{\partial x} = 0 \rightarrow \lambda^i = \left[- \left(\frac{\partial L}{\partial x} \right) \frac{\partial f}{\partial x}^{-1} \right]^T$

(d) $\left(\frac{\partial H}{\partial u} \right)^i = \left(\frac{\partial L}{\partial u} \right) + \lambda^{iT} \left(\frac{\partial f}{\partial u} \right)$ ($\neq 0$ in general)

(e) $u^{i+1} = u^i - k \left[\left(\frac{\partial H}{\partial u} \right)^i \right] \Rightarrow J^{i+1} \approx J^i - k \left(\frac{\partial H^i}{\partial u} \right)^T \left(\frac{\partial H^i}{\partial u} \right)$

(f) repeat (b) - (e) until $\left[\left(\frac{\partial H^i}{\partial u} \right)^T \left(\frac{\partial H^i}{\partial u} \right) \right]$ is small

$$\min_u \left\{ \phi(x(t_f), t_f) + \int_{t_0}^{t_f} L(x, u, t) dt \right\} \quad \text{s.t. } \underline{\dot{x} = f(x, u)}, x(t_0) \text{ given}$$

$(x, u) (\cdot)$ functions over $[t_0, t_f]$

Note:

$$\left. \begin{array}{l} \delta J \Big|_{\text{varying } \delta u \text{ only}} \neq \int_{t_0}^{t_f} L_u \delta u dt \end{array} \right\}$$

$$\delta J = \int_{t_0}^{t_f} (H_u \delta u) dt$$

$$H = L + \lambda^T f$$

"Computing the gradient by the adjoint."

variation of
J w.r.t. u
holding $\dot{x} = f(x, u)$

Problem Statement

Nonlinear two-point Boundary-Value Problem

Find:

$$\left. \begin{array}{l} (a) \quad x(t) \in \mathbb{R}^n \\ (b) \quad \lambda(t) \in \mathbb{R}^n \\ (c) \quad u(t) \in \mathbb{R}^m \end{array} \right\} t \in [t_0, t_f]$$

that simultaneously solve:

$$\begin{array}{l} (i) \quad \dot{x} = f(x, u), \quad x(t_0) \in \mathbb{R}^n \\ (ii) \quad \dot{\lambda} = -f_x^T \lambda - L_x, \quad \lambda(t_f) = \left[\frac{\partial \phi}{\partial x(t_f)} \right]^T \\ (iii) \quad \frac{\partial H}{\partial u} = 0 \in \mathbb{R}^m \\ (iv) \end{array}$$

