

Primal-dual optimization methods for solving optimal control problems with saddle-point structure

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¹joint work with Yurii Nesterov

Problem statement

We have two objects with motion given by equations

$$\frac{dx(t)}{dt} = A_x(t)x(t) + B(t)u(t), \quad \frac{dy(t)}{dt} = A_y(t)y(t) + C(t)v(t),$$

$(x(0), y(0)) = (x_0, y_0)$. $x(t) \in \mathbb{R}^n$, $y(t) \in \mathbb{R}^m$, $u(t) \in P \subset \mathbb{R}^p$,
 $v(t) \in Q \subset \mathbb{R}^q$, $t \in [0, \theta]$.

P, Q closed convex sets.

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Performance index:

$$F(u, v) + \Phi(x, y) = \int_0^\theta \tilde{F}(\tau, u(\tau), v(\tau)) d\tau + \Phi(x(\theta), y(\theta)). \quad (1)$$

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We are looking for $u(t) \in L_2([0, \theta], P)$, $v(t) \in L_2([0, \theta], Q)$ s.t. (u, v) is the saddle point of (1).

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$$\mathcal{B} : L_2([0, \theta], P) \rightarrow \mathbb{R}^n, \quad \mathcal{C} : L_2([0, \theta], Q) \rightarrow \mathbb{R}^m:$$

$$x(\theta) = V_x(\theta, 0)x_0 + \int_0^\theta V_x(\theta, \tau)B(\tau)u(\tau)d\tau = x_0 + \mathcal{B}u,$$

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- **A1** The sets P, Q are bounded.
- **A2** In performance index $F(u, v) + \Phi(x, y)$ the functional $F(\cdot, v)$ is convex for any fixed v , $F(u, \cdot)$ is concave for any fixed u , $\Phi(\cdot, y)$ is convex for any fixed y , $\Phi(x, \cdot)$ is concave for any fixed x .

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Hence $x(\theta), y(\theta)$ are bounded and we can assume that

$x(\theta) \in X, y(\theta) \in Y$, where X, Y are closed convex bounded.

Transform problem

We get the problem:

$$\min_{u \in \mathcal{U}} \left[\max_{v \in \mathcal{V}} \{F(u, v) + \Phi(x, y) : y = y_0 + Cv\} : x = x_0 + Bu \right]$$

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Adjoint problem:

$$\begin{aligned} & \min_{\lambda} \max_{\mu} \left\{ \min_{u \in \mathcal{U}} \max_{v \in \mathcal{V}} [F(u, v) - \langle \mu, Bu \rangle + \langle \lambda, Cv \rangle] + \right. \\ & \left. + \min_{x \in X} \max_{y \in Y} [\Phi(x, y) + \langle \mu, x \rangle - \langle \lambda, y \rangle] - \langle \mu, x_0 \rangle + \langle \lambda, y_0 \rangle \right\} = \\ & = \min_{\lambda} \max_{\mu} \psi(\lambda, \mu) \end{aligned}$$

Finite-dimensional VI problem

Denote $z = (\lambda, \mu)$. The problem is to find z^* s.t.

$$\langle g(z), z - z^* \rangle \geq 0 \quad \forall z \in \mathbb{R}^n \times \mathbb{R}^m,$$

where $g(z) = (\psi'_\lambda(\lambda, \mu), -\psi'_\mu(\lambda, \mu))$ – bounded and monotone ($\langle g(z_1) - g(z_2), z_1 - z_2 \rangle \geq 0$) operator.

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Some auxiliary objects

- Prox-function $d(z)$ – strongly convex with parameter $\sigma > 0$ ($d''(z) - \sigma I \succeq 0$)
- $D : d(z^*) \leq D$
- $\mathcal{F}_D = \{z \in S : d(z) \leq D\}$
- $\pi_\beta(s) = \arg \min_{z \in S} \{-\langle s, z \rangle + \beta d(z)\}$
- for the sequences $\lambda_i \geq 0, z_i \in S, g_i, i = 0, \dots, k$

$$\delta_k(D) = \max_z \left\{ \sum_{i=0}^k \lambda_i \langle g_i, z_i - z \rangle : z \in \mathcal{F}_D \right\}$$

- sequence $\hat{\beta}_i$: $\hat{\beta}_0 = \hat{\beta}_1 = 1, \hat{\beta}_{i+1} = \hat{\beta}_i + \frac{1}{\hat{\beta}_i}. (\hat{\beta}_k \sim \sqrt{2k})$

Simple Dual Averages Method [Yu. Nesterov, 2009]

Initialization $s_0 = 0, z_0, \gamma > 0$

Step $k \geq 0$

- 1 $g_k = g(z_k). \quad s_{k+1} = s_k + g_k.$
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- 1 $\delta_k(D) \leq \hat{\beta}_{k+1} \left(\gamma D + \frac{L^2}{2\sigma\gamma} \right)$
- 2 If the solution z^* exists, then $\|z_k - z^*\|^2 \leq \frac{2}{\sigma} d(z^*) + \frac{L^2}{\sigma^2\gamma^2}$

Equivalent problem

- Denote

$$\phi(u, x, v, y) = \min_{\lambda} \max_{\mu}$$

$$\{F(u, v) + \Phi(x, y) + \langle \mu, x - x_0 - \mathcal{B}u \rangle + \langle \lambda, y_0 + \mathcal{C}v - y \rangle :$$

$$d_{\lambda}(\lambda) \leq D_{\lambda}, d_{\mu}(\mu) \leq D_{\mu}\}$$

- Then our problem is equivalent to $\min_{u \in \mathcal{U}, x \in X} \max_{v \in \mathcal{V}, y \in Y} \phi(u, x, v, y)$.

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$$\xi(u, x) = \max_{v \in \mathcal{V}, y \in Y} \phi(u, x, v, y)$$

$$\eta(v, y) = \min_{u \in \mathcal{U}, x \in X} \phi(u, x, v, y)$$

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- Then

$$\xi(u, x) \geq \phi(u^*, x^*, v^*, y^*) \geq \eta(v, y) \quad \forall u \in \mathcal{U}, v \in \mathcal{V}, x \in X, y \in Y$$

Main result

Denote

$$\hat{u}_{k+1} = \frac{1}{k+1} \sum_{i=0}^k u_i, \quad \hat{v}_{k+1} = \frac{1}{k+1} \sum_{i=0}^k v_i,$$
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Theorem 1

$$\xi(\hat{u}_{k+1}, \hat{x}_{k+1}) - \eta(\hat{v}_{k+1}, \hat{y}_{k+1}) \leq \frac{1}{k+1} \delta_k(D) = O\left(\frac{1}{\sqrt{k}}\right)$$

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Theorem 2

$$\|x_0 + \mathcal{B}\hat{u}_{k+1} - \hat{x}_{k+1}\| = O\left(\frac{1}{\sqrt{k}}\right), \quad \|y_0 + \mathcal{C}\hat{v}_{k+1} - \hat{y}_{k+1}\| = O\left(\frac{1}{\sqrt{k}}\right)$$

Numerical example

We have two objects with motion given by equations

$$\frac{dx(t)}{dt} = \begin{pmatrix} 1-t \\ 1 \end{pmatrix} u(t), \quad \frac{dy(t)}{dt} = \begin{pmatrix} 1-t \\ 1 \end{pmatrix} v(t), \quad u(t) \in P, v(t) \in Q$$

$$t \in [0, 1], \quad n = 2, \quad m = 2, \quad P = Q = [-1, 1].$$

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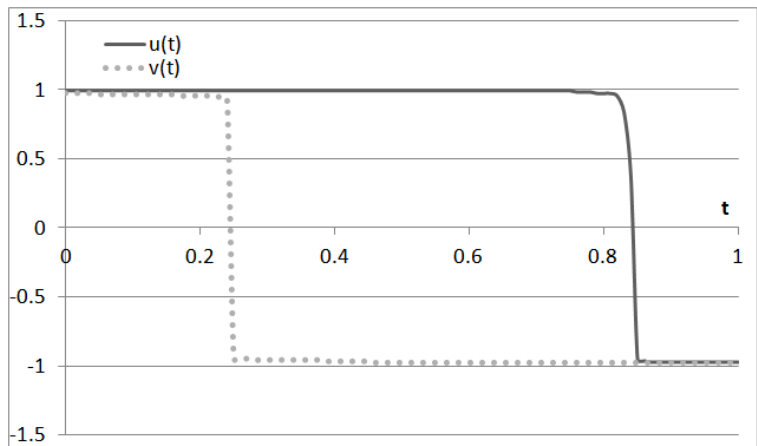
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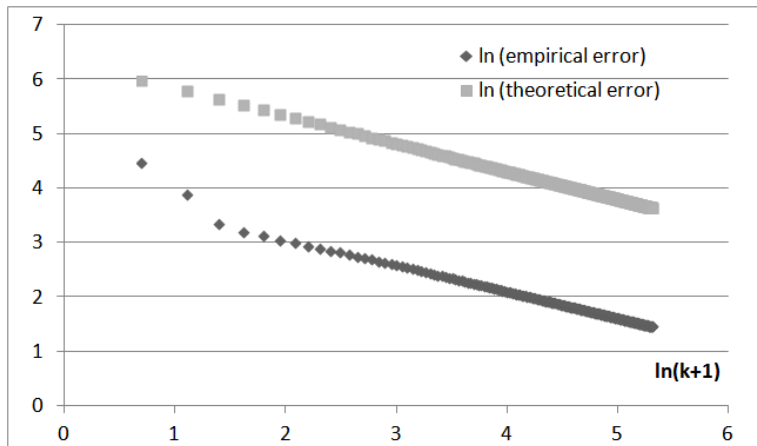
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$$J(u, v) = \frac{1}{2} \|x(1) - y(1)\|^2 - \|y(1) - a\|^2$$

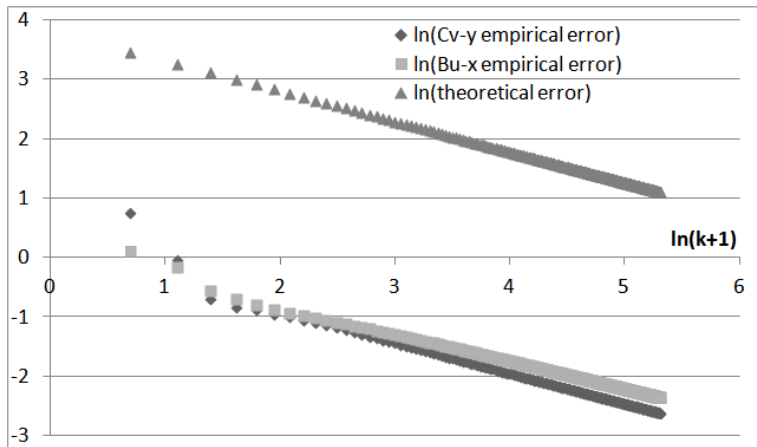
Controls



Error of funcional value



Error of equality constraint



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Thank you for your attention!