# Semidefinite relaxations for optimal control problems with oscillation and concentration effects

Mathieu Claeys, Cambridge, UK Didier Henrion, LAAS-CNRS, France Martin Kružík, UTIA, Czech Republic

July 8, 2014

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- Solve by semi-definite relaxations (2000s-2010s: Lasserre, ...).

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What if  $U = \mathbb{R}^m$ ?

## Example: concentration effects

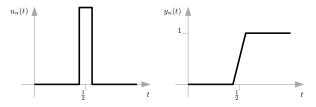
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s.t.  $\dot{y} = u$ ,  
 $y(0) = 0$ ,  $y(1) = 1$   
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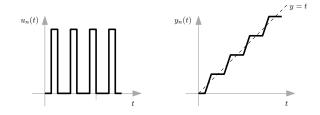
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July 8, 2014 4 / 25

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- How to treat those problems with Lasserre hierarchy, as for the bounded control case [Lasserre et al.: '08].
- Use DiPerna-Majda measures ['87] as relaxed control objects.

 $\implies$  extends [Kružík, Roubíček: '98] for non-convex problem.

### Table of contents



#### 2 Semi-definite hierarchy





Define appropriate [DiPerna, Majda: '87] compactification of control space  $\mathbb{R}^m$  by  $\gamma \mathbb{R}^m$ .

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#### Theorem (DiPerna and Majda)

For bounded  $\{u_k\}_{k\in\mathbb{N}}$  in  $L^p([t_0, t_f]; \mathbb{R}^m)$ ,  $\exists$  subsequence,  $\sigma \in \mathcal{M}^+([t_0, t_f])$ and  $\nu(\mathrm{d}\bar{u}|t) \in \mathcal{P}(\gamma\mathbb{R}^m)$  defined  $\sigma$ -a.e. such that for any  $g \in C([t_0, t_f])$ and any  $w \in \mathcal{R}$ :

$$\lim_{k\to\infty}\int_{t_0}^{t_f}g(t)v(u_k(t))\mathrm{d}t \ = \int_{t_0}^{t_f}\int_{\gamma\mathbb{R}^m}g(t)w(\bar{u})\nu(\mathrm{d}\bar{u}|t)\sigma(\mathrm{d}t) \ ,$$

where  $v(\bar{u}) = w(\bar{u})(1 + |\bar{u}|^p)$ .

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where  $v(\bar{u}) = w(\bar{u})(1 + |\bar{u}|^p)$ .

Example: to  $u \in L^p$  corresponds  $\sigma = (1 + |u(t)|^p) dt$  and  $\nu = \delta_{u(t)}(d\bar{u}|t)$ .

#### Relaxed OCP

$$J = \min_{u} \int_{t_0}^{t_f} h(t, y(t), u(t)) dt$$
  
s.t.  $\dot{y} = f(t, y(t), u(t))$   
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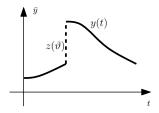
Relaxed as:

$$J_r = \min_{\sigma,\nu} \int_{t_0}^{t_f} \int_{\gamma \mathbb{R}^m} \frac{h(t, y(t), \bar{u})}{1 + |\bar{u}|^p} \nu(\mathrm{d}\bar{u}|t) \sigma(\mathrm{d}t)$$
  
s.t.  $\dot{y} = \int_{\gamma \mathbb{R}^m} \frac{f(t, y(t), \bar{u})}{1 + |\bar{u}|^p} \nu(\mathrm{d}\bar{u}|t) \sigma,$   
 $(\sigma, \nu) \in \mathcal{DM}^p([t_0, t_f]; \mathbb{R}^m)$ 

See [Kružík, Roubíček: '98].

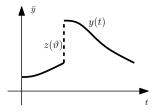
#### Occupation measures

Fix admissible  $(\sigma, \nu, y)$ :



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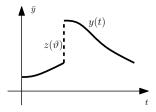
Fix admissible  $(\sigma, \nu, y)$ :



$$\xi(B|t) := \begin{cases} \delta_{y(t)}(B) & \text{if } t \notin J \\ \int_0^{d_t} I_B(z_t(\vartheta))/d_t \, \mathrm{d}\vartheta & \text{otherwise} \end{cases}$$

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 $\mu(\mathrm{d} t \mathrm{d} \bar{y} \mathrm{d} \bar{u}) := \xi(\mathrm{d} \bar{y} | t) \, \nu(\mathrm{d} \bar{u} | t) \, \sigma(\mathrm{d} t)$ 

# Weak ODE integration

#### Test $\mu$ with $v \in C^1(T \times Y)$ along trajectories of admissible.

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#### Test $\mu$ with $v \in C^1(T \times Y)$ along trajectories of admissible.

# Proposition $v(t_f, x(t_f^+)) - v(t_0, x(t_0^-)) = \langle \frac{\partial v}{\partial t} \frac{1}{1 + |\bar{u}|^p} + \frac{\partial v}{\partial \bar{y}} \frac{f(t, \bar{y}, \bar{u})}{1 + |\bar{u}|^p}, \mu \rangle$

### The measure LP

Convex relaxation:

$$\begin{split} J_{meas} &= \inf_{\mu} \ \langle \frac{h(t,\bar{y},\bar{u})}{1+|\bar{u}|^{p}}, \mu \rangle \\ \text{s.t.} \ \forall v \in C^{1}(T \times Y) : \\ v(t_{f},y(t_{f}^{+})) - v(t_{0},y(t_{0}^{-})) &= \langle \frac{\partial v}{\partial t} \frac{1}{1+|\bar{u}|^{p}} + \frac{\partial v}{\partial \bar{y}} \frac{f(t,\bar{y},\bar{u})}{1+|\bar{u}|^{p}}, \mu \rangle \\ \mu \in \mathcal{M}^{+}(T \times Y \times \gamma \mathbb{R}^{m}). \end{split}$$

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Compare this with [Vinter, Lewis: SICON '78] or [Vinter: SICON '93].

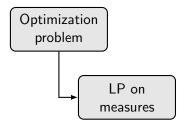
### Table of contents

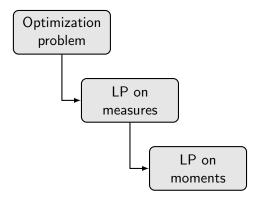


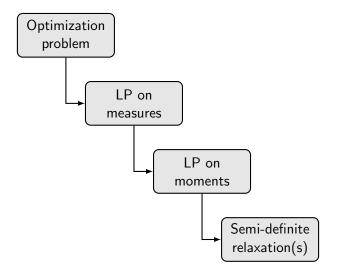
#### 2 Semi-definite hierarchy











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#### Moments

• Moments: 
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• Moment matrix: 
$$M(z) = \begin{bmatrix} z_0 & z_1 & z_2 & \cdots \\ z_1 & z_2 & z_3 & z_4 \\ z_2 & z_3 & z_4 & \\ \vdots & & \ddots \end{bmatrix}$$

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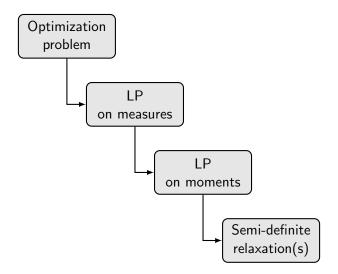
• Let 
$$\mathbf{X} := \{x \in \mathbb{R}^n : g_i(x) \ge 0, \quad i = 1, ..., m\}$$

Theorem (Putinar)

 $\mu \in \mathcal{M}^+(\mathbf{X}) \text{ iff:}$  $M(z) \succeq 0, \qquad M(g_i * z) \succeq 0 \quad \forall i$ 

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Use only  $(z_{\alpha})_{|\alpha| \leq 2r}$ .

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#### Theorem (Lasserre)

#### $J_{mom}^r \uparrow J_{meas}$

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Each relaxation is a standard semi-definite program. Can be solved by dedicated software.

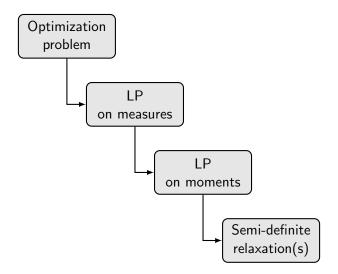
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GloptiPoly [Henrion et al.]: toolbox for automatic generation of the SDP relaxations from the measure LP.

#### The moment approach



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$$\begin{split} \lambda_{\varepsilon}^{*} &= \min_{\tilde{\mu}, \lambda} \lambda \\ \text{s.t.} \; |z_{\alpha} - \langle x^{\alpha}, \tilde{\mu} \rangle| \leq \lambda \end{split}$$

Approximate support = non-zero atoms.

## Table of contents



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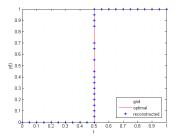
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$$\begin{split} \inf & \int_0^1 (t - \frac{1}{2})^2 u \, \mathrm{d}t & \sigma^*(\mathrm{d}t) = \mathrm{d}t + \delta_{\frac{1}{2}}(\mathrm{d}t) \\ \text{s.t.} & \dot{y} = u, \\ & y(0) = 0, \quad y(1) = 1 \\ & u \in L^1([0, 1]). & \nu^*(\mathrm{d}\bar{u}|t) = \begin{cases} \delta_0(\mathrm{d}\bar{u}) & \text{if } t \neq \frac{1}{2}, \\ \delta_{+\infty}(\mathrm{d}\bar{u}) & \text{if } t = \frac{1}{2}. \end{cases} \\ \end{split}$$

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 $\left( L_z(t^k) \right)_{k \in \mathbb{N}} = (2.0000, \ 1.0000, \ 0.5833, \ 0.3750, \ 0.2625, \ 0.1979, \ \ldots), \\ \left( \langle t^k, \sigma^* \rangle \right)_{k \in \mathbb{N}} = (2.0000, \ 1.0000, \ 0.5833, \ 0.3750, \ 0.2625, \ 0.1979, \ \ldots).$ 

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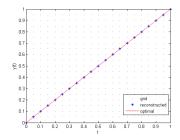
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$$\begin{split} \inf & \int_0^1 \left( \frac{u^2}{1+u^4} + (y-t)^2 \right) \mathrm{d}t & \sigma^*(\mathrm{d}t) = 2\mathrm{d}t \\ \text{s.t.} & \dot{y} = u & \nu^*(\mathrm{d}\bar{u}|t) = \frac{1}{2}\delta_0(\mathrm{d}\bar{u}) + \frac{1}{2}\delta_{+\infty}(\mathrm{d}\bar{u}) \\ & y(0) = 0 & & y^*(t) = t \\ & u \in L^1([0,1]). & y^*(t) = t \end{split}$$

 $\left( L_z(t^k) \right)_{k \in \mathbb{N}} = (2.0026, 1.0026, 0.6692, 0.5026, 0.4026, 0.3359, \ldots),$  $\left( \left\langle t^k, \sigma^* \right\rangle \right)_{k \in \mathbb{N}} = (2.0000, 1.0000, 0.6667, 0.5000, 0.4000, 0.3333, \ldots),$ 

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July 8, 2014 21 / 25

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## Table of contents

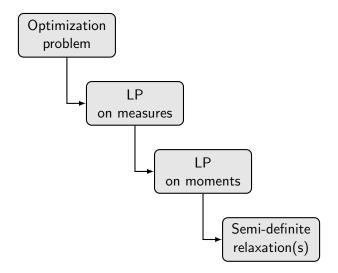


#### 2 Semi-definite hierarchy





#### The moment approach



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# Highlights of the method

• Common framework for concentration and oscillation effects.

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- Global resolution, even for non-convex problems.

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- Easy handling of state constraints.
- Straightforward to implement in GloptiPoly.
- Currently  $n+m \leq 5$ , but SDP solvers are getting faster (Mosek) ...

# Thanks!

• Presentation and paper version available at

http://mathclaeys.wordpress.com

- Mini-course on polynomial optimization: D. Henrion (Th. 10:30, A901), M. Putinar (Th. 11:30, A901), MC (Fr. 10:30, A901), M. Korda (Fr. 11:30, A901).
- This research was supported by the AVČR-CNRS project "Semidefinite programming for nonconvex problems of calculus of variations and optimal control".