AN INTRODUCTION TO THE MOMENT APPROACH FOR OPTIMAL CONTROL

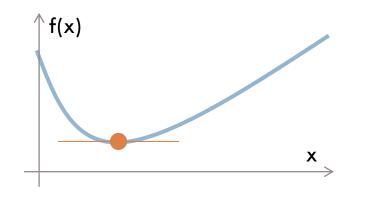
<u>MATHIEU CLAEYS</u> DIDIER HENRION JEAN-BERNARD LASSERRE

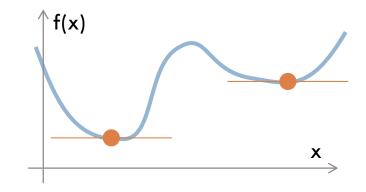
LAAS-CNRS and University of Toulouse

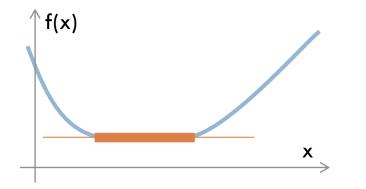
This presentation

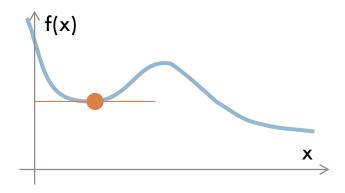
- Compute lower bounds on the cost of optimal control problems
 - For a large class of problems
 - Systematically
 - On a computer
- Solve the problemSometimes only!

The idea







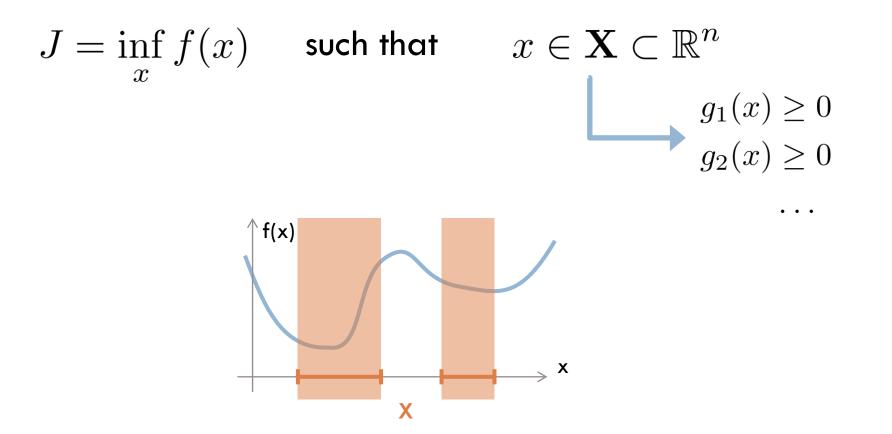


Presentation outline

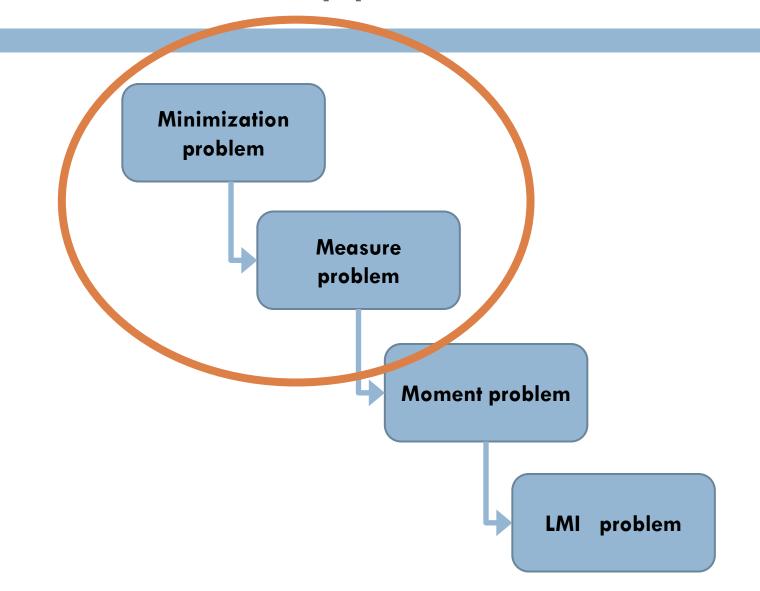
1. Introduction

- 2. Static optimization
- 3. Optimal control: impulsive controls
- 4. Perspectives

Static optimization



The moment approach

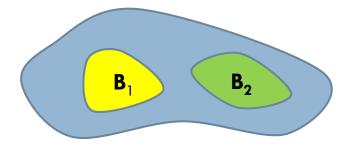


Measures: geometric viewpoint

 \square Measure space $(\mathbf{X}, \Sigma, \mu)$

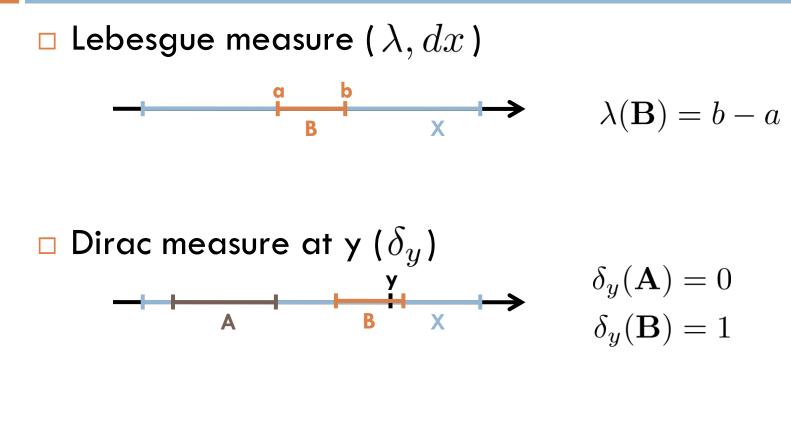
Notation
$$\mu(\mathbf{B}) \text{ or } \int_{\mathbf{B}} 1 \, \mathrm{d}\mu(x)$$

 $\begin{array}{ll} \square \mbox{ Properties } & \mu(\emptyset) = 0 \\ & \mathbf{B} \in \mathcal{B} \implies \mu(\mathbf{B}) \ge 0 \\ & \mathbf{B}_i \mbox{ disjoints } \implies \mu(\mathbf{B}_1 \cup \mathbf{B}_2 \cup \ldots) = \mu(\mathbf{B}_1) + \mu(\mathbf{B}_2) + \ldots \end{array}$





8



Probality measure

 $\mu(\mathbf{X}) = 1$

Measures: relation with integration

The Lebesgue integral
$$\int_{\mathbf{X}} f(x) \, d\lambda(x)$$
 is the completion of its Riemann counterpart $\int_{\mathbf{X}} f(x) \, dx$

Integration w.r.t. Dirac measure:

$$\int_{\mathbf{X}} f(x) \, d\delta_{x^*}(x) = f(x^*)$$

Measures: functional analysis viewpoint

□ Let :

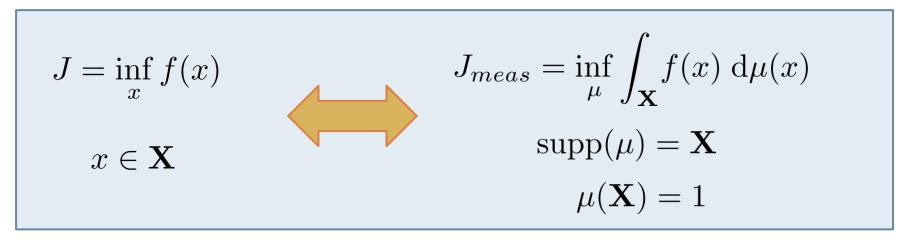
• C(X), bounded continuous functions, $||f|| = \sup_{x \in X} f(x)$

 $\square \mathcal{M}(X)$, sufficiently regular measures

□ Riesz: then positive linear functionals on C(X)"are" $\mathcal{M}(X)$

□ We note
$$\langle f, \mu \rangle = \int_{\mathbf{X}} f(x) \ d\mu(x)$$

Towards a measure problem

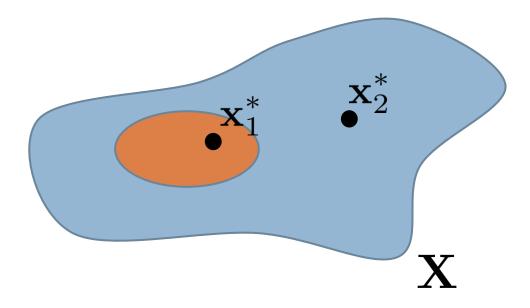


□
$$J \ge J_{meas}$$
: take $\mu = \delta_x$
□ $J \le J_{meas}$: by definition $J \le f(x)$, $\forall x \in X$
then $\int J d\mu(x) \le \int f(x) d\mu(x)$

then
$$\int_X J d\mu(x) \le \int_X f(x) d\mu(x)$$

What does it measure?

12



Properties of the measure problem

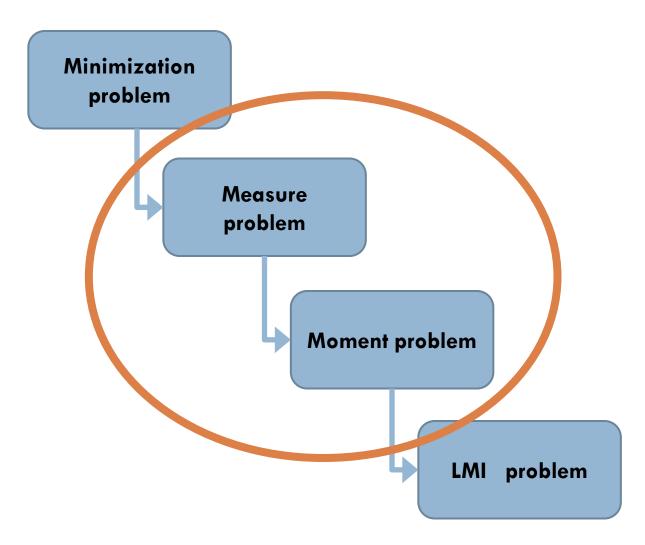
□ The problem is linear!

The set of admissible solutions is convex

The set of optimal solutions is convex

The infimum is a minimum!

The moment approach



Moments

15

• Moments
$$y_{\alpha} = \int_{\mathbf{X}} x^{\alpha} d\mu(x)$$

 \square Moment sequence $(y) = (y_0, y_1, y_2, \ldots)$

$$\square \text{ Moment matrix } M(y) = \begin{bmatrix} y_0 & y_1 & y_2 & \cdots \\ y_1 & y_2 & y_3 & \\ y_2 & y_3 & y_4 & \\ \vdots & & \ddots \end{bmatrix} = \int_{\mathbf{X}} \begin{bmatrix} 1 & x & x^2 & \cdots \\ x & x^2 & x^3 & \\ x^2 & x^3 & x^4 & \\ \vdots & & \ddots \end{bmatrix} d\mu(x)$$

 \Box Localizing matrix at e.g. $4-x^2$

$$M_{4-x^2}(y) = \int_{\mathbf{X}} \begin{bmatrix} 1 & x & \cdots \\ x & x^2 & \\ \vdots & \ddots \end{bmatrix} (4-x^2) \, \mathrm{d}\mu(x) = \begin{bmatrix} 4y_0 - y_2 & 4y_1 - y_3 & \cdots \\ 4y_1 - y_3 & 4y_2 - y_4 & \\ \vdots & \ddots \end{bmatrix}$$

Properties of moments matrices

$$\square \qquad M(y) \succeq 0 \qquad \qquad M(hy) \succeq 0$$

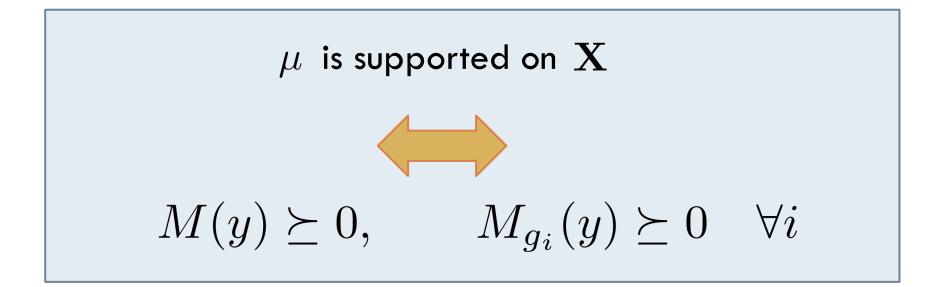
Proof:
$$0 \leq \int p^2 d\mu = \int (\sum a_i x^i)^2 d\mu = a' M a$$

□ Is the converse true?

The converse

17

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

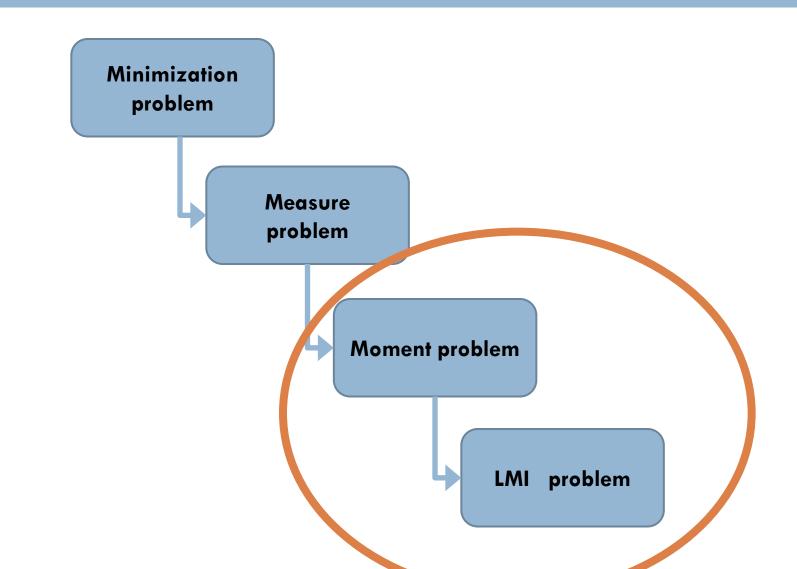


Proof: Riesz-Haviland + Putinar's Positivstellensatz

From a measure to a moment problem

$$\begin{split} J_{meas} &= \inf_{\mu} \int_{\mathbf{X}} f(x) \, d\mu(x) & J_{mom} = \inf_{(y)} c \cdot y \\ &\text{such that} & \text{such that} \\ &\sup p(\mu) = \mathbf{X} & M(y) \succeq 0 \quad M(a_i \, y) \succeq 0 \\ &\int_{\mathbf{X}} 1 \, d\mu(x) = 1 & y_0 = 1 \end{split}$$

The moment approach



From a moment to a LMI problem

 (Lasserre) relaxations: optimize only on moments of order up to 2r

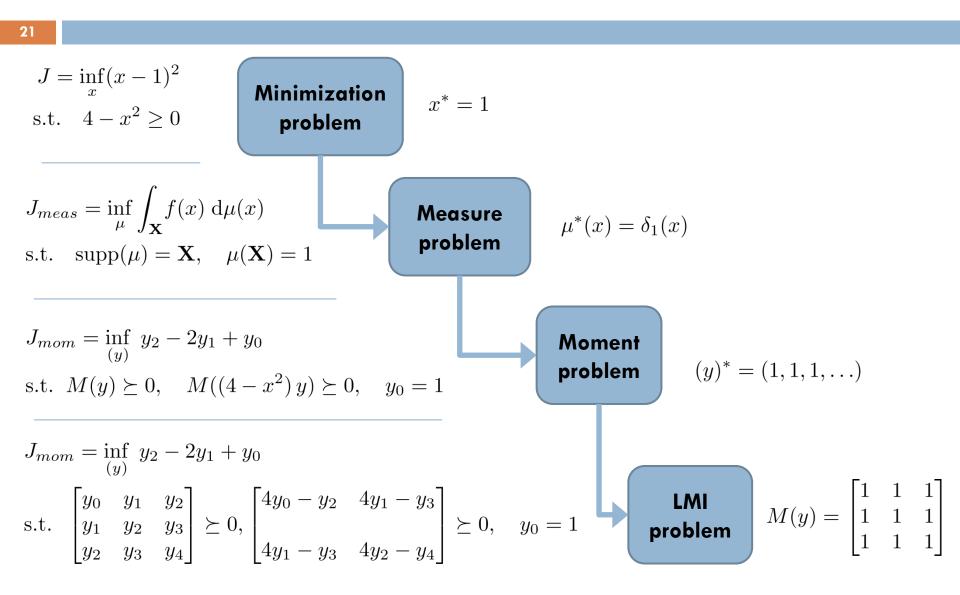
$$\Box \quad J_{mom}^1 \le J_{mom}^2 \le \dots \le J_{mom}^{r \to \infty} = J_{mom}$$

□ If at some relaxation

$$\operatorname{rank}\left(M_{j-1}\right) = \operatorname{rank}\left(M_{j}\right) = k$$

Then μ is k-atomic and we can extract its k support points

A simple example



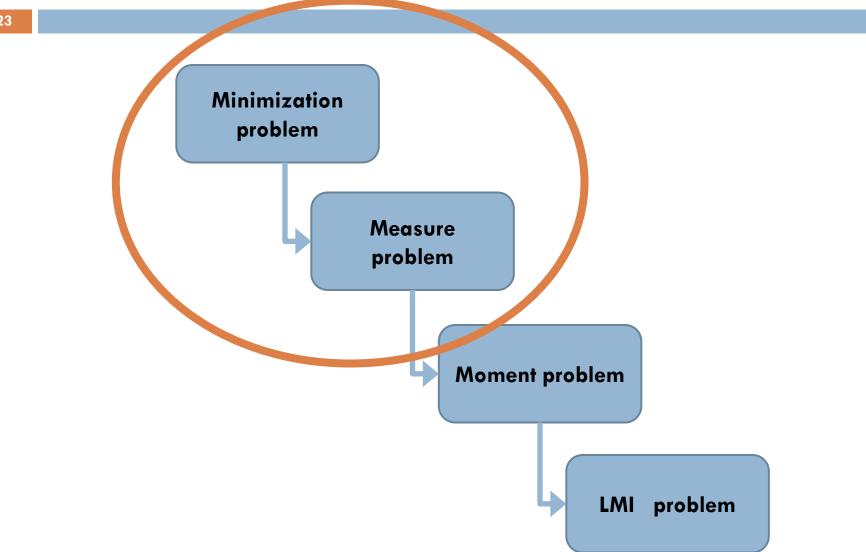
A GloptiPoly snippet

22

```
>> mpol x; % define optimization variable
>> P = msdp(min((x-1)^2), x^2 <= 4, 2); % define problem: criterion, constraint, order
>> [flag, obj] = msol(P) % solve problem
flag =
     1
obj =
 2.8868e-009
>> double(x) % extract solution(s)
ans =
   1.0000
>> double(mmat(meas(1))) % show moment matrix
ans =
   1.0000
          1.0000 0.9999
   1.0000
          0.9999
                    0.9999
```

0.9999 0.9999 0.9998

The moment approach



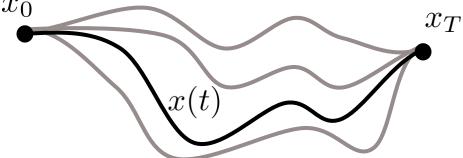
Presentation outline

- 1. Introduction
- 2. Static optimization
- 3. Optimal control: impulsive controls
- 4. Perspectives

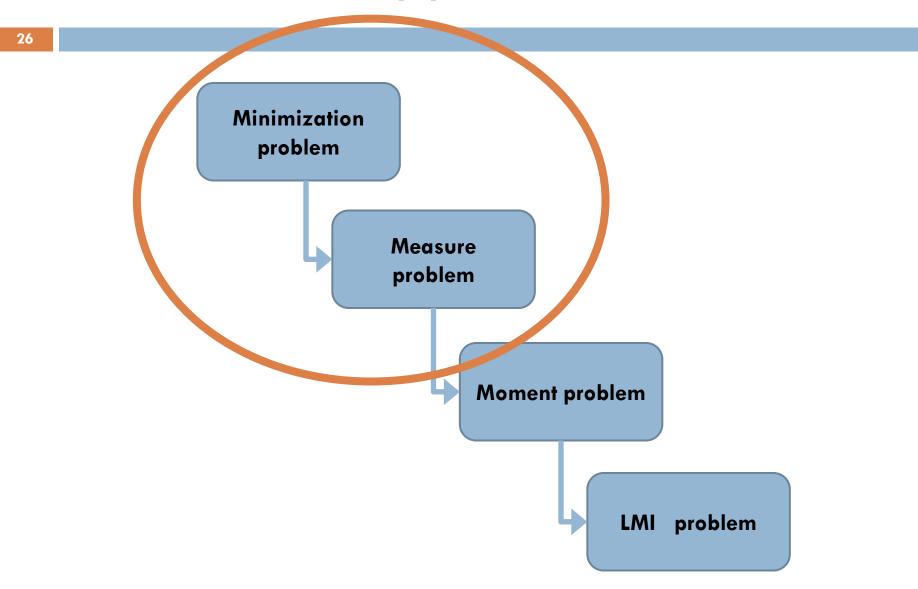
Our problem

25

$J = \inf_{u(t)} \int_0^T (h(t, x(t)) + H(t) u(t)) dt$
such that :
$\dot{x}(t) = f(t, x(t)) + G(t) u(t)$
$x(0) = x_0, x(T) = x_T$
$x(t) \in \mathbf{X}, u(t) \in \mathbb{R}^m$
$x_0 \qquad \qquad x_T$



The moment approach



Measure for impulses

27

We embed

$$\dot{x}(t) = f(t, x(t)) + G(t) u(t)$$

in

$$dx(t) = f(t, x(t))dt + G(t) dw(t), \quad w(t) \in BV([0, T])$$

where w(t) can be decomposed as

$$dw(t) = u_{L_1}(t) dt + \sum_{j \in J} u_{t_j} \delta_{t_j}(dt)$$

Occupation measures

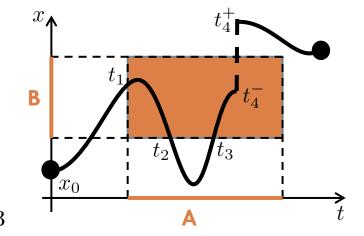
$$\square$$
 Fix $(w(t), x(t))$

 \square Define $\xi_t(B) = P(x(t) \in B)$

Occupation measure:

 $\mu_{w(t),x(t)}(\mathbf{A} \times \mathbf{B}) = t_2 - t_1 + t_4 - t_3$

Control measure: $\nu_{w(t),x(t)}(\mathbf{A} \times \mathbf{B}) = w(t_2) - w(t_1) + \frac{w(t_4^+) - w(t_4^-)}{2} - w(t_3)$



Weak formulation of dynamics

29

 \Box For each continuous v(t, x(t)):

$$v(T, x_T) - v(0, x_0) \left(= \int_0^T dv(t, x(t)) \right) =$$

$$\int_{[0,T]\times\mathbf{X}} \left(\frac{\partial v}{\partial t} + \frac{\partial v}{\partial x} \cdot f\right) d\mu_{w(t),x(t)}(t,x) + \int_{[0,T]\times\mathbf{X}} \frac{\partial v}{\partial x} \cdot G \cdot d\nu_{w(t),x(t)}(t,x)$$

This is a relaxation!

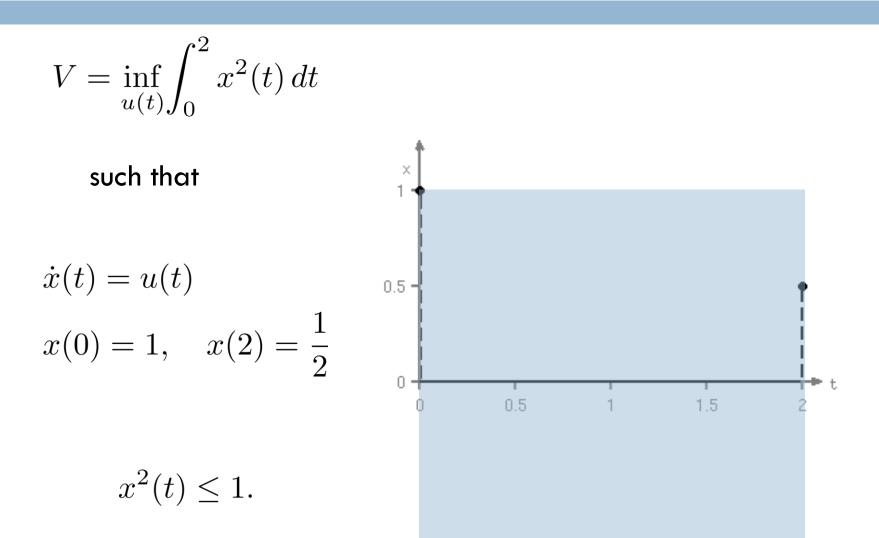
$$\dot{x} = (t-1)^2 u$$
$$\dot{y} = u$$

$$u(t) \ge 0$$
$$x(t) = 0$$
$$y(0) = 0$$
$$y(2) = 1$$

$$dx = (t - 1)^2 dw^+(t)$$
$$dy = dw^+(t)$$

$$w^{+}(t) = y(t)$$

A basic example (1/2)



A basic example (2/2)

$$V = \inf_{u(t)} \int_0^2 x^2(t) \, dt$$

such that

$$\dot{x}(t) = u(t)$$

 $x(0) = 1, \quad x(2) = \frac{1}{2}$

$$x^2(t) \le 1.$$

$$V_{meas} = \inf_{\substack{\mu,\nu}} \int x^2 \, \mathrm{d}\mu$$
$$[0,T] \times \mathbf{X}$$

such that

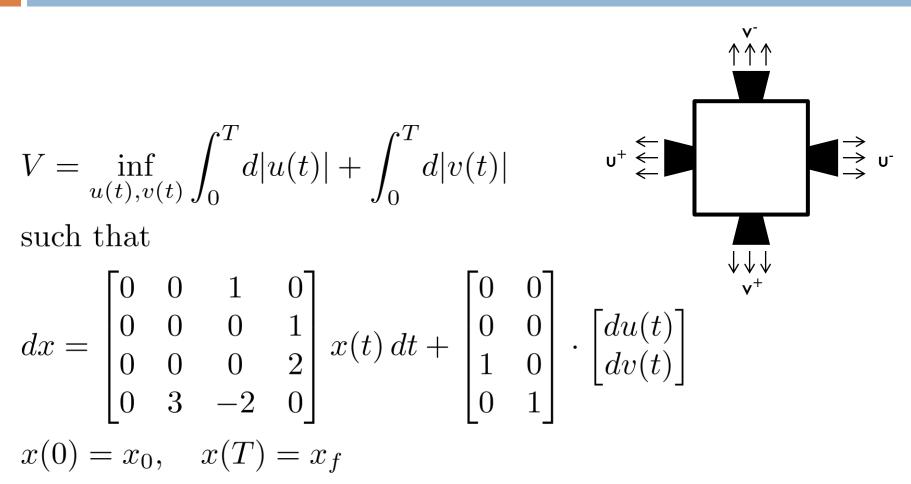
$$v(T, x_T) - v(0, x_0) = \int \frac{\partial v}{\partial t} d\mu + \int \frac{\partial v}{\partial x} d\nu$$

$$v(T, x_T) - v(0, x_0) = \int \frac{\partial v}{\partial t} d\mu + \int \frac{\partial v}{\partial x} d\nu$$

$$v(T, x_T) - v(0, x_0) = \int \frac{\partial v}{\partial t} d\mu + \int \frac{\partial v}{\partial x} d\nu$$

$$X = \left\{ x \in \mathbb{R} : 1 - x^2 \ge 0 \right\}$$

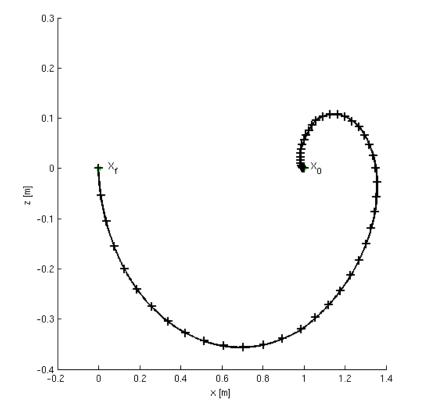
Orbital rendez-vous, I₁-induced norm



On Carter's third example

 $x(0) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}, \quad x(2\pi) = \begin{bmatrix} 0 & 0 & 0 & 0.427 \end{bmatrix}$

d	V _d
1	0.0463
2	0.0680
3	0.2188
4	0.2972

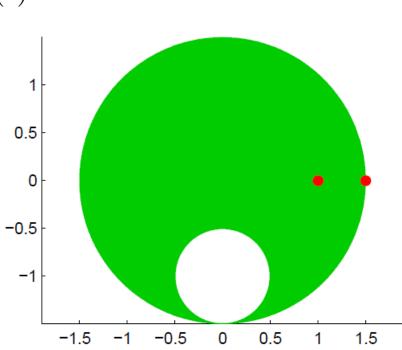


A non-convex example (1/2)

$$V = \inf_{u(t)} \int_0^T d|u(t)|$$

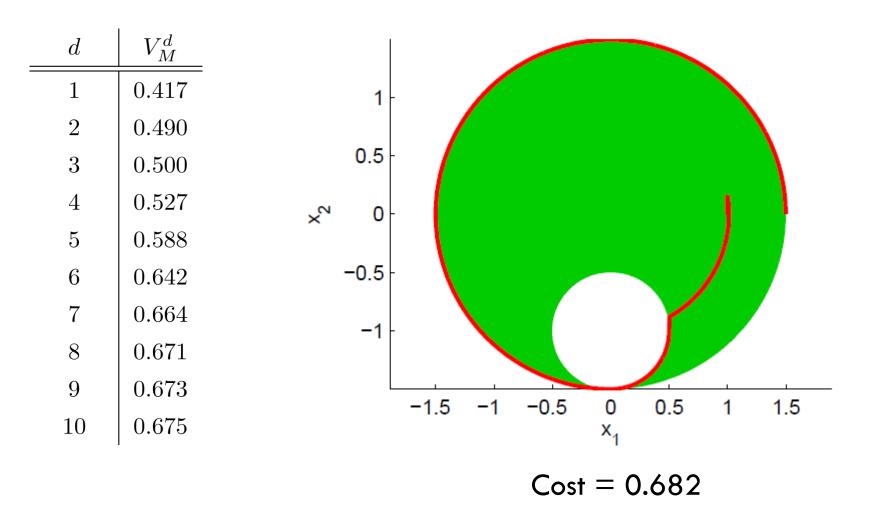
such that

$$dx = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} x(t) dt + \begin{bmatrix} 0 \\ 1 \end{bmatrix} du(t)$$
$$x(0) = x_0, \quad x(T) = x_f$$



A non-convex example (2/2)

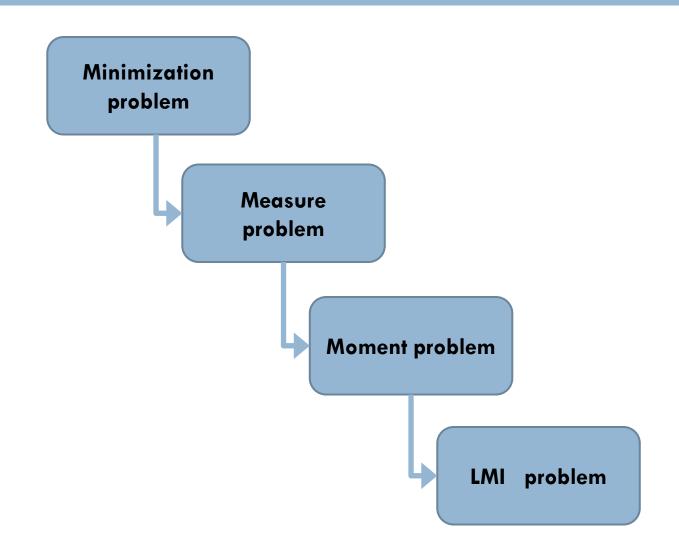
36



Presentation outline

- 1. Introduction
- 2. Static optimization
- 3. Optimal control: impulsive controls
- 4. Perspectives

The method, yet again





+	-
Global optimality	Extraction of solutions
Lower bounds	Finite convergence ?
Certificate of infeasibility	Relies on LMI solvers

The main problem...

40

 \square # of monomials of n variables up to degree 2r:

$$\binom{n+2r}{n}$$

□ Example with n=6

r	#
0	1
1	28
2	210
3	924
4	3003
5	8008
6	18564

Thank you!

Presentation available at:

http://homepages.laas.fr/mclaeys