

# Sensitivity analysis for optimization and optimal control problems

J. Frédéric Bonnans

INRIA-Saclay & CMAP, Ecole Polytechnique, France

Kick-off meeting, GDR 3273 MOA, Paris, June 24, 2009



## 1 General framework

- Main questions
- Tangent sets

## 2 Upper estimates of the value function

- general upper estimates
- Lower estimates

## 3 State constrained optimal control problems

- Framework
- Sensitivity: framework
- Main result

## 4 Open problems

# Families of optimization problems

Generic framework:

$$\underset{x}{\text{Min}} \ f(x, u); \quad G(x, u) \in K \quad (P_u)$$

with

- $U, X, Y$ : Banach spaces
- $K$  closed convex subset of  $Y$
- $f : X \times U \rightarrow \mathbb{R}$  and  $G : X \times U \rightarrow Y$ , smooth ( $C^\infty$ ).

# Examples

- $K = \{0\}_{\mathbb{R}^p} \times \mathbb{R}_+^q$ : finitely many equalities and inequalities. If  $X = \mathbb{R}^n$ : **Nonlinear programming**.
- **Semi definite programming**:  $X = \mathbb{R}^n$  and  $K = \mathcal{S}_+^p$ , with  $\mathcal{S}^p$  set of symmetric matrices of order  $p$ , or more generally

$$K = \mathcal{S}_+^{p_1} \times \cdots \mathcal{S}_+^{p_q}$$

- **Semi infinite programming**:  $X = \mathbb{R}^n$ ,  $\Omega$  compact metric,  $Y = C(\Omega)$ ,  $K = C(\Omega)_+$ :
- **Optimal control of ODEs**
- **Optimal control of PDEs**

# Notations

$$\underset{x}{\text{Min}} \ f(x, u); \quad G(x, u) \in K \quad (P_u)$$

- Set of feasible points:  $F(u) = G^{-1}(\cdot, u)(K)$ . Value

$$\text{val}(u) := \inf\{f(x, u); x \in F(u)\}$$

Set of solutions

$$S(u) := \{x \in F(u); f(x, u) = \text{val}(u)\}.$$

# Questions

- Stability of solutions:

$$\text{dist}[S(u'), S(u)] = O(\|u' - u\|) \text{ or } O(\|u' - u\|^{1/2})$$

- Expansion of (approximate) solutions along a path

$$u_\tau := \bar{u} + \tau v, \quad \tau \in \mathbb{R}_+$$

$$S(u_\tau) = \bar{x} + \tau^\gamma h + o(\tau^\gamma), \quad \gamma = 1 \text{ or } 1/2$$

- Expansion of value function: find subproblems  $(L)$  and  $(Q)$  such that

$$\text{val}(u_\tau) = \text{val}(\bar{u}) + \tau \text{val}(L) + \frac{1}{2}\tau^2 \text{val}(Q) + o(\tau^2).$$

# First and second order tangent cones

Nominal problem:  $f(x) = f(x, \bar{u})$ ,  $G(x) = G(x, \bar{u})$ .

Here  $\mathcal{K} \subset X$ , possibly nonconvex, e.g.  $\mathcal{K} = G^{-1}(K)$ :

- **(Interior) tangent cone:**  $y \in \mathcal{K}$

$$T_{\mathcal{K}}(x) = \{y \in X; \text{dist}(x + \tau y, \mathcal{K}) = o(\tau), \tau \geq 0\}$$

- **(Interior) second order tangent set:**  $x \in \mathcal{K}, y \in T_{\mathcal{K}}(x)$ .

$$T_{\mathcal{K}}^2(x, y) = \{z \in Y; \text{dist}(x + \tau y + \frac{1}{2}\tau^2 z, \mathcal{K}) = o(\tau^2), \tau \geq 0\}$$

# Second-order necessary condition

Nominal problem again:

$$\underset{x}{\text{Min}} \ f(x); \quad x \in \mathcal{K} \subset X.$$

Use

$$\begin{aligned} f(x + \tau y + \frac{1}{2}\tau^2 z) = & \quad f(x) + \tau Df(x)y \\ & + \frac{1}{2}\tau^2 [Df(x)z + D^2f(x)(y, y)] + o(\tau^2) \end{aligned}$$

**First-order necessary condition:**

$$Df(\bar{x})h \geq 0, \quad \text{for all } h \in T_{\mathcal{K}}(x)$$

**Second-order necessary condition:** for all  
 $h \in C(\bar{x}) := T_{\mathcal{K}}(x) \cap Df(\bar{x})^\perp$ :

$$Df(\bar{x})z + D^2f(\bar{x})(h, h) \geq 0, \quad \text{for all } z \in T_{\mathcal{K}}^2(x, h)$$

# Robinson's Qualification Condition

Robinson's qualification condition (RQC) for  $G(x) \in K$ :

$$\text{For some } \varepsilon > 0, \quad \varepsilon B \subset G(x) + \text{Im}[DG(x)] - K \quad (\text{RQC})$$

Specific cases:

- Equality constraints:  $K = \{0\}$ , reduces to  $DG(x)$  onto
- $\text{int}(K) \neq \emptyset$ , reduces to

$$\text{For some } h \in X, \quad G(x) + DG(x)h \in \text{int}(K)$$

## Normal cone

$$N_K(y) = \{y^* \in Y^*; \langle y^*, y' - y \rangle \leq 0, \text{ for all } y' \in K\}$$

# Calculus of first and second order tangent cones

If (RQC) holds then we have

$$\begin{aligned} G(x + \tau y + \frac{1}{2}\tau^2 z) = & \quad G(x) + \tau DG(x)y \\ & + \frac{1}{2}\tau^2 [DG(x)z + D^2G(x)(z, z)] + o(\tau^2) \end{aligned}$$

- **Tangent cone:**  $y \in \mathcal{K}$

$$T_{\mathcal{K}}(x) = \{y \in Y; DG(x)y \in T_{\mathcal{K}}(G(x))\}$$

- **Second order tangent set:**  $x \in \mathcal{K}, y \in T_{\mathcal{K}}(x)$ .

$$\begin{aligned} T_{\mathcal{K}}^2(x, y) = & \{w \in Y^*; DG(x)z + D^2G(x)(y, y) \\ & \in T_{\mathcal{K}}^2[G(x), DG(x)y]\} \end{aligned}$$

# First-order necessary conditions

If (RQC) holds; **Tangent directions**

$$T_K(\bar{x}) = \{h \in X; DG(\bar{x})h \in T_K(G(\bar{x}))\}$$

If (RQC) holds; **Critical cone**

$$C(\bar{x}) = \{h \perp Df(\bar{x}); \quad DG(\bar{x})h \in T_K(G(\bar{x}))\}$$

**Lagrangian function:**  $L(x, \lambda) := f(x) + \langle \lambda, G(x) \rangle.$

**Set of Lagrange multipliers** non empty and bounded at local solutions

$$\Lambda(\bar{x}) := \{\lambda \in N_K(G(\bar{x})); \quad D_x L(\bar{x}, \lambda) = 0\}.$$

Robinson 76, Zowe and S. Kurcyusz 79

# second-order necessary conditions ||

(Cominetti 90) **Primal form:**

For all  $h \in C(\bar{x})$ ,  $\text{val}(Q_h) \geq 0$ , where

$$\begin{aligned} Df(\bar{x})z + D^2f(\bar{x})(h, h) &\geq 0 \text{ if} \\ DG(\bar{x})z + D^2G(\bar{x})(h, h) &\in T_K^2[G(x), DG(x)h] \end{aligned} \quad (Q_h)$$

Support function:  $\sigma(\lambda, K) := \sup\{\langle \lambda, w \rangle; w \in K\}$

**Support function of second-order tangent set** (Curvature term)

$$\Xi(\lambda, h) := \sigma(\lambda, T_K^2[G(\bar{x}), DG(\bar{x})h])$$

**Lagrangian of  $(Q_h)$ :**

$$D_x L(x, \lambda)z + D_x^2 L(x, \lambda)(h, h) - \Xi(\lambda, h).$$

**Dual form of second-order necessary conditions:**

$$\max_{\lambda \in \Lambda(\bar{x})} D_{xx}^2 L(x, \lambda)(z, z) - \Xi(\lambda, h) \geq 0.$$

# Sign of $\sigma(\lambda, T_K^2(g, \delta g))$

When  $\lambda \in N_K(G(\bar{x})$ ,  $\lambda \perp \delta g$  and  $w \in T_K^2(g, \delta g)$ :

$$0 \geq \langle \lambda, g + \tau \delta g + \frac{1}{2} \tau^2 w + o(\tau^2) \rangle = \tau^2 [\langle \lambda, w \rangle + o(1)]$$

and so we always have  $\Xi(\lambda, h) \leq 0$ . In particular, the second-order necessary condition is weaker than the condition

$$\max_{\lambda \in \Lambda(\bar{x})} D_{xx}^2 L(x, \lambda)(z, z) \geq 0.$$

Cases when  $\Xi(\lambda, h) = 0$ :

- (a)  $K$  polyhedron
- (b)  $K$  pointed cone and  $G(\bar{x}) = 0$ .

**Reduction theory:** rewriting of  $(P)$  such that (b) holds  
(FB and Shapiro 2000)

# Example: inequality constraints I

For  $K = \mathbb{R}_+^q$ , assuming (RCP)  $\equiv$  Mangasarian-Fromovitz

Define sets of active constraints

$$\begin{aligned} I(x) &:= \{1 \leq i \leq q; G_i(x) = 0\} \\ I(x, y) &:= \{i \in I(x); DG_i(x)y = 0\} \end{aligned}$$

- **Tangent cone:**  $x \in \mathcal{K}$ ,

$$T_{\mathcal{K}}(x) = \{y \in X; DG_i(x)z \leq 0, i \in I(x)\}$$

## Set of Lagrange multipliers

$$\Lambda(\bar{x}) := \{\lambda \in \mathbb{R}_+^p; \lambda \cdot G(x) = 0; Df(\bar{x}) + DG(x)^\top \lambda = 0\}$$

# Example: inequality constraints II

- **Second order tangent cone:**  $x \in \mathcal{K}, y \in T_{\mathcal{K}}(y)$ .

$$T_{\mathcal{K}}^2(x, y) = \{z \in X; DG_i(x)z + D^2G_i(x)(y, y) \leq 0, i \in I(x, y)\}$$

## Second order necessary conditions

$$\max_{\lambda \in \Lambda(\bar{x})} D_{xx}^2 L(\bar{x}, \lambda)(h, h) \geq 0.$$

# Example: semidefinite programming I

For  $K = \mathcal{S}_-^p$ , we have

- Qualification:  $G(x) + DG(x)\hat{y} \in \mathcal{S}_{--}$  (negative definite) for some  $\hat{y}$
- $E p \times s$  matrix whose columns are an orthonormal basis of the kernel of  $A = G(x)$ . **Tangent cone**:

$$T_{\mathcal{S}_-^p}(A) = \{H \in \mathcal{S}^p; E^\top H E \preceq 0\}$$

- $F s \times k$  matrix whose columns are an orthonormal basis of the eigenspace associated with the largest eigenvalue of  $E^\top H E$ .

**Second order tangent cone**:  $x \in \mathcal{K}$ ,  $y \in T_{\mathcal{K}}(x)$ .

$$T_{\mathcal{S}_-^p}^2(A, H) = \{W \in \mathcal{S}^p; F^\top E^\top W E F \preceq 2F^\top E^\top H A^\dagger H E F\}$$

with  $A^\dagger$  pseudo-inverse of  $A$ .

# Example: semidefinite programming II

**Support function of second-order tangent set:** quadratic function

$$\Xi(\lambda, h) = -h^\top \mathcal{H}(\bar{x}, \lambda)h$$

with, setting  $G_i(\bar{x}) = \partial G(\bar{x})/\partial x_i$ :

$$[\mathcal{H}(\bar{x}, \lambda)]_{ij} = -2\lambda \circ \left( G_i(\bar{x})[G(\bar{x})^\dagger]G_j(\bar{x}) \right)$$

Ref. A. Shapiro, 1997.

# Upper estimates: first-order

Generic framework: path  $u_\tau := \bar{u} + \tau v$

$$\underset{x}{\text{Min}} \quad f(x, u); \quad G(x, u) \in K \quad (P_u)$$

$\bar{x} \in S(\bar{u})$ ; **Linearized problem**

$$\begin{aligned} \text{Min}_{h \in X} \quad & Df(\bar{x}, \bar{u})(h, v); \\ & DG(\bar{x}, \bar{u})(h, v) \in T_K[G(\bar{x}, \bar{u})]. \end{aligned} \quad (LP)$$

Lagrangian function:  $L(x, u, \lambda) := f(x, u) + \langle \lambda, G(x, u) \rangle$ .

If (RQC):  $\text{val}(LP) = \text{val}(LD)$  where

$$\underset{\lambda \in \Lambda(\bar{x})}{\text{Max}} \quad D_u L(\bar{x}, \bar{u}, \lambda)v \quad (LD)$$

Set of dual solutions:  $S(LD)$ . **First-order upper estimate**

$$\text{val}(u_\tau) \leq \text{val}(\bar{u}) + \tau \text{val}(LP) + o(\tau).$$

# Upper estimates: second-order, pseudo quadratic problem

## Pseudo Quadratic problem: primal formulation

$\text{val}(QP_h) \geq 0$ , where

$$\begin{aligned} \text{Min}_{z \in X} \quad & D_x f(\bar{x}, \bar{u})(z, z) + D^2 f(\bar{x}, \bar{u})(h, v)^2 \\ & D_x G(\bar{x}, \bar{u})z + D^2 G(\bar{x}, \bar{u})(h, v)^2 \\ & \in T_K^2[G(\bar{x}, \bar{u}), DG(\bar{x}, \bar{u})(h, v)]. \end{aligned} \quad (QP_h)$$

Curvature term for the perturbation problem

$$\Xi(\lambda, v, h) := \sigma(\lambda, T_K^2[G(\bar{x}, \bar{u}), DG(\bar{x}, \bar{u})(h, v)])$$

## Pseudo Quadratic problem: dual formulation

$$\text{Max}_{\lambda \in S(DL)} \quad D_{xx}^2 L(\bar{x}, \bar{u}, \lambda)(h, v)^2 - \Xi(\lambda, v, h) \quad (QD_h)$$

# Upper estimates: second-order

If (RQC):

$$\text{val}(QP_h) = \text{val}(QD_h), \quad \text{for all } h \in S(LP).$$

## Second-order Upper Estimates:

$$\text{val}(u_\tau) \leq \text{val}(\bar{u}) + \tau \text{ val}(LP) + \frac{1}{2}\tau^2 \text{ val}(QD_h) + o(\tau^2).$$

Best estimate:

$$\underset{h \in S(LP)}{\text{Min}} \text{ val}(QD_h). \quad (QD)$$

$$\text{val}(u_\tau) \leq \text{val}(\bar{u}) + \tau \text{ val}(LP) + \frac{1}{2}\tau^2 \text{ val}(QD) + o(\tau^2).$$

## Lower estimates: first-order

Let  $x_\tau$  be a  $o(\tau)$  solution of  $(P_{u_\tau})$ :

Use the previous first-order upper estimate and  $\lambda \in N_K[G(\bar{x}, \bar{u})]$ :

$$\begin{aligned} f(x_\tau, u_\tau) - f(\bar{x}, \bar{u}) &= \text{val}(u_\tau) - \text{val}(\bar{u}) + o(\tau) \leq \tau \text{val}(LD) + o(\tau) \\ \langle \lambda, G(x_\tau, u_\tau) - G(\bar{x}, \bar{u}) \rangle &\leq 0. \end{aligned}$$

Sum of above inequalities:

$$L(x_\tau, u_\tau, \lambda) - L(\bar{x}, \bar{u}, \lambda) \leq \text{val}(u_\tau) - \text{val}(\bar{u}) \leq \tau \text{val}(LD) + o(\tau)$$

Take  $\lambda \in S(DL)$ : then  $\text{val}(L) = D_u L(\bar{x}, \bar{u}, \lambda)$  and so

$$L(x_\tau, u_\tau, \lambda) - L(\bar{x}, \bar{u}, \lambda) = \tau \text{val}(LD) + O(\tau^2 + \|x_\tau - \bar{x}\|^2)$$

If (stability result)  $\|x_\tau - \bar{x}\| = o(\tau^{1/2})$  deduce the **marginal cost** (in direction  $v$ )

$$\text{val}(u_\tau) = \text{val}(\bar{u}) + \tau \text{val}(LD) + o(\tau).$$

## Lower estimates: second-order I

Assume existence of  $x_\tau$ ,  $o(\tau^2)$  solution of  $(P_{u_\tau})$ , with  
 $\|x_\tau - \bar{x}\| = O(\tau)$

$$\begin{aligned} L(x_\tau, u_\tau, \lambda) - L(\bar{x}, \bar{u}, \lambda) &\leq f(x_\tau, u_\tau) - \text{val}(\bar{u}) \\ &\leq \tau \text{val}(LD) + \frac{1}{2}\tau^2 \text{val}(QD) + o(\tau^2). \end{aligned}$$

For  $\lambda \in S(DL)$ , the l.h.s. is equal to

$$\tau \text{val}(LD) + \frac{1}{2} D_{(x,u)^2}^2 L(\bar{x}, \bar{u}, \lambda)(x_\tau - \bar{x}, \tau v)^2 + o(\tau^2).$$

Cancelling first-order terms and setting  $h_\tau := (x_\tau - \bar{x})/\tau$ , get:

$$\max_{\lambda \in S(DL)} D_{(x,u)^2}^2 L(\bar{x}, \bar{u}, \lambda)(h_\tau, v)^2 \leq \text{val}(QD) + o(1)$$

# Passing to the limit in the solution

- If  $h_\tau \rightharpoonup \bar{h}$  (weak convergence, for an extracted sequence):  
 $\bar{h} \in S(LP)$ .
- **Legendre** positively homogeneous form  $Q : X \rightarrow \mathbb{R}$ : w.l.s.c.  
and

$$h_\tau \rightharpoonup \bar{h} \text{ and } Q(h_\tau) \rightarrow Q(\bar{h}) \text{ implies } h_\tau \rightarrow \bar{h}.$$

- If  $h \mapsto \max_{\lambda \in S(LD)} D_{xx}^2 L(\bar{x}, \bar{u}, \lambda)(h, h)$  is Legendre then by previous expansions and  $\Xi(\lambda, v, h) \leq 0$ :

$$\text{val}(QD_h) = \max_{\lambda \in S(LD)} D_{xx}^2 L(\bar{x}, \bar{u}, \lambda)(\bar{h}, \bar{h}) \leq \text{val}(QD)$$

But if  $\Xi(\lambda, v, \bar{h}) = 0$  this implies  $h \in S(QD)$  !

(last hypothesis often obtained through reduction theory)

# Lower estimates: second-order II

## Theorem

Assume (i) (RQC), (ii) existence of  $x_\tau$ ,  $o(\tau^2)$  solution of  $(P_{u_\tau})$ , such that  $\|x_\tau - \bar{x}\| = O(\tau)$ , (iii)  $\text{val}(QD)$  finite, (iv)

$h \mapsto \max_{\lambda \in S(LD)} D_{xx}^2 L(\bar{x}, \bar{u}, \lambda)(h, h)$  Legendre, (v)  $\Xi(\lambda, v, \bar{h}) = 0$

Then

$$\text{val}(u_\tau) = \text{val}(\bar{u}) + \tau \text{val}(LP) + \frac{1}{2}\tau^2 \text{val}(QD) + o(\tau^2).$$

In addition  $(QD)$  has a unique solution  $\hat{h}$ , then  $\bar{h} = \hat{h}$  and  $x_\tau = \bar{x} + \tau \bar{h} + o(\tau)$ .

Ref FB-Shapiro book (2000) + its refs

# Optimal control with state constraints

- State equation:  $y(t) \in \mathbb{R}^n, u(t) \in \mathbb{R}^m$

$$\dot{y}(t) = f(u(t), y(t)) \quad \text{p.p. } t \in [0, T], \quad y(0) = y_0 \quad (1)$$

- State constraint:

$$g_i(y(t)) \leq 0, \quad t \in [0, T], \quad i = 1, \dots, r. \quad (2)$$

- Same cost function: integral + final term

$$J(u, y) = \int_0^T \ell(u(t), y(t)) dt + \phi(y(T)). \quad (3)$$

- Optimal control problem

$$\underset{(u,y)}{\text{Min}} J(u, y) \quad \text{s.t. (1) and (2).} \quad (P)$$

- $C^\infty$ , Lipschitz data  $f, \ell, \phi, g$ .

# Order of the state constraint

- Total derivative of a scalar state constraint:

$$g^{(1)}(u, y) := g'(y)f(u, y).$$

While result does not depend on  $u$ , we can continue:

$$g^{(i+1)}(u, y) := g^{(i)}(y)f(u, y).$$

**Constraint order:**  $q$  smallest number such that

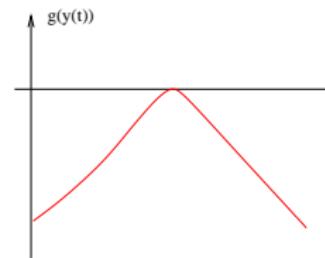
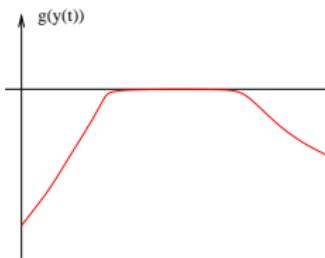
$$g_u^{(q)}(u, y) \neq 0$$

**Well-posed constraint order:** when

$$g_u^{(q)}(u, y) \neq 0, \quad \text{for all } (u, y)$$

# Constraint structure

- Contact set:  $\{t \in [0, T] ; g(y(t)) = 0\}$ .



boundary arc  $[\tau_{en}, \tau_{ex}]$       (isolated) touch point  $\{\tau_{to}\}$

- Question: If known structure: number, ordering of boundary arcs and touch points;  
 Then can we design a shooting algorithm ?  
 Will it be well-posed ?

# Junction points

- Set of junction points: closure of end-points of interior arcs
- Regular junction point: end-point of two arcs, of three types:
- Entry, exit points: end-points of a boundary arc
- Touch point: isolated contact points

# Sensitivity: Framework

$$(P^\mu) \quad \min_{(u,y) \in \mathcal{U} \times \mathcal{Y}} \int_0^T \ell^\mu(u(t), y(t)) dt + \phi^\mu(y(T))$$

s.c.       $\dot{y}(t) = f^\mu(u(t), y(t))$  p.p.  $[0, T]$  ;  $y(0) = y_0^\mu$   
 $g^\mu(y(t)) \leq 0$     on  $[0, T]$ .

- Rem. : scalar control  $u(t) \in \mathbb{R}$ .
- $\mu$  : perturbation parameter
- Hyp (A0) smooth data:  $C^\infty$ , Lipschitz (A1)  $g^{\mu_0}(y_0^{\mu_0}) < 0$ .

# Hypotheses I

$(\bar{u}, \bar{y})$  solution for  $\mu = \mu_0$ , with multipliers  $(\bar{p}, \bar{\eta})$ .

**(A2)**  $H^{\mu_0}(\cdot, \bar{y}(t), \bar{p}(t))$  uniformly strongly convex where

$$H(u, y, p, \mu) := \ell^\mu(u, y) + pf^\mu(u, y).$$

**(A3)** (Order 1 constraint) for all  $t$ :

$$|g_u^{(1)}(u(t), y(t))| \geq \gamma > 0.$$

# Hypotheses II

**(A4)**  $(\bar{u}, \bar{y})$  has a finite number of regular junctions.

**(A5)** Strict complementarity on boundary arcs:

$$\frac{d\bar{\eta}(t)}{dt} \geq \beta > 0, \quad \text{on interior boundary arcs.}$$

**(A6)** For all touch point (isolated contact point)  $\tau$ ,

$$\frac{d^2}{dt^2} g(\bar{y}(t))|_{t=\tau} < 0.$$

# Notion of quadratic growth condition

**Def:** The Quadratic Growth Condition (QGC) holds if, for all  $C^2$ -perturbation  $(P^\mu)$  of  $(P^{\mu_0})$ , there exists a neighborhood  $(V_u, V_\mu)$  of  $(\bar{u}, \mu_0)$ , and constants  $c, r > 0$  such that for  $\mu \in V_\mu$ , there exists a **unique local solution**  $(u^\mu, y^\mu)$  of  $(P^\mu)$  with  $u^\mu \in V_u$  satisfying

$$J^\mu(u, y) \geq J^\mu(u^\mu, y^\mu) + c \|u - u^\mu\|_2^2,$$

$$\forall (u, y) \text{ feasible for } (P^\mu), \|u - \bar{u}\|_\infty < r.$$

# Main result: statement

## Theorem

Let  $(\bar{u}, \bar{y}) = (u^{\mu_0}, y^{\mu_0})$  local solution of  $(P^{\mu_0})$  satisfying (A1)-(A6).  
 Then the following statements are equivalent:

- (i) The QGC holds
- (ii) The following second-order sufficient condition is satisfied: The tangent linear-quadratic problem (defined later) has  $v = 0$  as unique solution.

Under these conditions: local uniqueness of local solutions in  $\mathcal{U}$ .

Also: Boundary arcs are stable,

Touch point remain so, vanish or become boundary arcs.

# Main result (continued)

## Theorem (End of statement)

... If (i) or (ii) is satisfied, then  $\mu \mapsto (u^\mu, y^\mu, p^\mu, \eta^\mu)$  is locally Lipschitz in

$$\mathcal{U} \times \mathcal{Y} \times L^\infty(0, T; \mathbb{R}^{n*}) \times L^\infty(0, T; \mathbb{R})$$

and directionally differentiable in

$$L^r(0, T) \times W^{1,r}(0, T; \mathbb{R}^n) \times L^r(0, T; \mathbb{R}^{n*}) \times L^r(0, T)$$

for all  $1 \leq r < \infty$ . The directional derivative in direction  $d$  is the unique solution of a certain linear quadratic problem  $(P_d)$ .

# The linear quadratic problem

Space of linearized control and states

$$\mathcal{V} := L^2(0, T) \supset \mathcal{U}; \quad \mathcal{Z} := H^1(0, T; \mathbb{R}^n) \supset \mathcal{Y}.$$

$d = \mu - \mu_0$  : “given” direction of perturbation.

$$\begin{aligned}
 (\mathcal{P}_d) \quad & \min_{(v,z) \in \mathcal{V} \times \mathcal{Z}} \frac{1}{2} \int_0^T D_{(u,y,\mu)^2}^2 H^{\mu_0}(\bar{u}, \bar{y}, \bar{p})(v, z, d)^2 dt \\
 & + D^2 \phi^{\mu_0}(\bar{y}(T))(z(T), d)^2 + \int_0^T D^2 g^{\mu_0}(\bar{y})(z, d)^2 d\bar{\eta}(t)
 \end{aligned}$$

s.c.

$$\begin{aligned}
 \dot{z}(t) &= Df^{\mu_0}(\bar{u}, \bar{y})(v, z, d) \quad \text{sur } [0, T], \quad z(0) = Dy_0^{\mu_0} d \\
 Dg^{\mu_0}(\bar{y})(z, d) &= 0 \quad \text{on boundary arcs of } (\bar{u}, \bar{y}) \\
 Dg^{\mu_0}(\bar{y}(\tau))(z(\tau), d) &\leq 0, \quad \forall \tau \text{ isolated contact point of } (\bar{u}, \bar{y}).
 \end{aligned}$$

# Algorithmic consequences

- If no isolated touch point: Newton's method well-defined (with the “shooting parameters, see paper)
- Convergent homotopy algorithm taking into account transitions
- Touch point viewed as zero lenght boundary arc
- Backtracking over  $\mu$  if Newton's method non convergent.

# Expression of linearization of entry times

Linearize

$$\hat{g}^{(1)}(\bar{u}(\bar{t}^{en}), \bar{y}(\bar{t}^{en}), \mu_0) = 0$$

Denote by  $v$ ,  $z$ ,  $\sigma^{en}$  the directional derivative of control, state, entry point w.r.t. a variation of  $\mu$  in direction  $d$ , then

$$\begin{aligned} & D\hat{g}^{(1)}(\bar{u}(\bar{t}^{en}), \bar{y}(\bar{t}^{en}), \mu_0)(v(\bar{t}^{en-}), z(\bar{t}^{en}), d) \\ & + \sigma^{en} \frac{d}{dt} g^{(1)}(\bar{u}, \bar{y})|_{t=\bar{t}^{en-}} + 0, \end{aligned}$$

from which we can extract  $\sigma^{en}$ :

$$\sigma^{en} = -\frac{D\hat{g}^{(1)}(\bar{u}(\bar{t}^{en}), \bar{y}(\bar{t}^{en}), \mu_0)(v(\bar{t}^{en-}), z(\bar{t}^{en}), d)}{\frac{d}{dt} g^{(1)}(\bar{u}, \bar{y})|_{t=\bar{t}^{en-}}}$$

# Open problems

- Optimal control
- Variational problems
- Stochastic control

# Optimal control

- Initial-final state constraints, in the case of “bounded strong” minima, with nonunique multipliers:

$$\|u\|_\infty \leq M \text{ and } \|y - \bar{y}\|_\infty \leq \varepsilon.$$

- Same problem with additional control constraints.
- Idem, with distributed state constraints.
- Problems with control entering linearly
- Logarithmic penalty

See work by Milyutin, Osmolovskii, Dmitruk, Goh.

# Variational problems

Perturbation of a static plate problem with obstacle:

$$\underset{u}{\text{Min}} \frac{1}{2} \int_{\Omega} (\Delta u(x))^2 dx - \int_{\Omega} f(x)u(x)dx; \quad u(x) \geq \Psi(x)$$

with  $\Omega$  bounded smooth open in  $\mathbb{R}^2$ ,  $u = \partial u / \partial n$  over  $\partial\Omega$ .

see C. Pozzolini's thesis; Rao and Sokolowski, Mignot, Haraux.

# Stochastic control

State equation

$$dy_t = f(u_t, y_t)dt + \sigma(u_t, y_t)dW_t, \quad y_0 = y^0$$

Cost function

$$\int_0^T \ell(u_t, y_t)dt + \phi(y_T)$$

$W_t$  standard Brownian, all functions Lipschitz and bounded

Control adapted to the Brownian filtration

**Expansion of optimal control** (see Bensoussan's book (1988) in unconstrained case)

# References

- Alvarez, J. Bolte, J.F. B., F. Silva: *Asymptotic expansions for interior penalty solutions of control constrained linear-quadratic problems.* INRIA report RR 6863, Mar. 2009.
- J.F. B. and A.Hermant, *Second-order Analysis for Optimal Control Problems with Pure State Constraints and Mixed Control-State Constraints.* Ann. I.H.P. - Nonlin. Anal., 2009.
- J.F. B. and N.P. Osmolovskii, *Second-order analysis of optimal control problems with control and initial-final state constraints.* INRIA report RR 6707, 2008.