

# Minimizers that are not also Relaxed Minimizers

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# Outline of the Talk

- Relaxation
- The occurrence of an infimum gap
- Condition for existence of an infimum gap
- Implications for necessary conditions of optimality
- Concluding Remarks

(Joint work with Michele Palladino, ESR)

# The Optimal Control Problem

Consider

$$(P) \left\{ \begin{array}{l} \text{Minimize } g(x(0), x(1)) \\ \text{over absolutely continuous functions } x(\cdot) : [0, 1] \rightarrow \mathbb{R}^n \\ \text{satisfying} \\ \dot{x}(t) \in F(t, x(t)) \text{ a.e.,} \\ x(0) = x_0 \text{ and } (x(0), x(1)) \in C, \end{array} \right.$$

**Data:**  $g : \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $x_0 \in \mathbb{R}^n$ , a closed set  $C \subset \mathbb{R}^n \times \mathbb{R}^n$  and a multifunction  $F(\cdot, \cdot) : [0, 1] \times \mathbb{R}^n \rightsquigarrow \mathbb{R}^n$ .

**State trajectory**  $x(\cdot) : W^{1,1}$  function s.t.  $\dot{x}(t) \in F(t, x(t))$ , a.e.,  
 $x(0) = x_0$

$x(\cdot)$  is **feasible** if  $x(1) \in C$ .

$\bar{x}(\cdot)$  is a **minimizer** if

$$g(x(0), x(1)) \geq g(\bar{x}(0), \bar{x}(1))$$

for all state trajectories  $x(\cdot)$ .

$\bar{x}(\cdot)$  is a **strong local minimizer** if, for some  $\epsilon > 0$ ,

$$g(x(0), x(1)) \geq g(\bar{x}(0), \bar{x}(1))$$

for all state trajectories  $x(\cdot)$  such that  $\|x(\cdot) - \bar{x}(\cdot)\|_{L^\infty} \leq \epsilon$ .

# Standing Hypotheses

(H1) :  $F(t, x)$  is closed for all  $(t, x)$  and  $F(\cdot, x)$  is measurable.

(H2) : For given  $R > 0$ , there exist  $\varepsilon > 0$ ,  $k(\cdot) \in L^1$  and  $c(\cdot) \in L^1$  such that

$$F(t, x) \subset F(t, x') + k(t)|x - x'|B \quad \text{and} \quad F(t, x) \subset c(t)B$$

for all  $x, x' \in RB$ , a.e.  $t \in [0, 1]$ .

**Fact:** Assume (H1) and (H2). Suppose the set of feasible state trajectories is non-empty and bounded, and

**(C):**  $F(t, x)$  is convex for all  $(t, x)$ .

Then there exists a minimizer.

# Relaxation

## Relaxation:

'Enlarge the space of state trajectories to guarantee existence of minimizers'

Relaxed Problem:

$$(R) \begin{cases} \text{Minimize } g(x(1)) \\ \text{over } x(\cdot) : [0, 1] \in W^{1,1} \text{ s.t.} \\ \dot{x}(t) \in \text{co } F(t, x(t)) \text{ a.e.,} \\ x(0) = x_0 \text{ and } x(1) \in C, \end{cases}$$

( Refer to **relaxed state trajectories**, **relaxed minimizers**, etc. ).

**Fact:** Assume (H1) and (H2). Suppose the set of feasible relaxed state trajectories is non-empty and bounded.

Then there exists a relaxed minimizer.

( **Relaxed problem automatically has a convex velocity set**  $\text{co } F(t, x)$  ).

# Relaxation Theorem

## Relaxation Theorem:

Take any relaxed state trajectory  $\bar{x}(\cdot)$  and  $\epsilon > 0$ .  
Then there exist a state trajectory  $x(\cdot)$  such that

$$\|x(\cdot) - \bar{x}(\cdot)\|_{L^\infty} \leq \epsilon$$

**Caution:**  $x(\cdot)$  and  $\bar{x}(\cdot)$  close, but their velocities can be very different!

## Strategy for finding sub-optimal state trajectory:

**Step 1:** Solve relaxed problem (it has a solution)

**Step 2:** Approximate relaxed minimizer by a neighboring state trajectory  
(possible by relaxation theorem)

# Geometric Interpretation

Define **Reachable Set**:

$\mathcal{R} := \{(x(0), x(1)) \mid x(\cdot) \text{ is a feasible state trajectory}\},$

$\mathcal{R}_{relaxed} := \{(x(0), x(1)) \mid x(\cdot) \text{ is a feasible relaxed state trajectory}\}$

From Relaxation Thm:

$$\mathcal{R}_{relaxed} = \overline{\mathcal{R}}.$$

We have

$$\inf(P) = \inf\{g(x_0, x_1) \mid (x_0, x_1) \in \mathcal{R} \cap \mathcal{C}\},$$

$$\inf(R) = \inf\{g(x_0, x_1) \mid (x_0, x_1) \in \overline{\mathcal{R}} \cap \mathcal{C}\}$$



# The Infimum Gap

in general

$$\inf(R) \leq \inf(P).$$

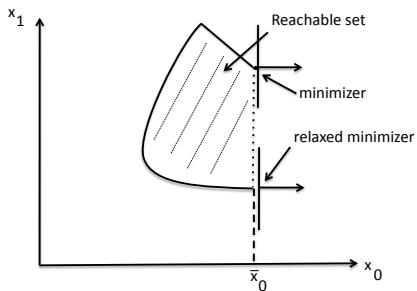
Important to identify situations when there is an **infimum gap**:

$$\inf(R) < \inf(P) \text{ (strict inequality!)}$$

because then

- Feasible trajectories cannot be closely approximated by feasible relaxed trajectories
- The dynamic programming methods yields only the relaxed infimum, not the 'true' infimum
- Numerical methods are often ill-conditioned when there is an infimum gap

# The Infimum Gap



Occurrence of an infimum gap

# Link with Multiplier Abnormality

There is a relation between infimum gaps and abnormality of Lagrange multipliers.

Consider the finite dimensional optimization problem:

$$(P_1) \begin{cases} \text{Minimize } g(x) \\ \text{s.t. } h(x) < 0 \text{ and } x \in C \end{cases}$$

and its relaxation (replace  $\{x|h(x) < 0\}$  by closed set  $\{x|h(x) \leq 0\}$ ):

$$(R_1) \begin{cases} \text{Minimize } g(x) \\ \text{s.t. } h(x) \leq 0 \text{ and } x \in C \end{cases}$$

(Data:  $h(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $g(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R}$ , Lipschitz functions)

# Finite Dimensional Case

**Fact:** Suppose there exists  $\delta > 0$ ,  $\epsilon > 0$  and  $\bar{x}$  such that  $\bar{x}$  is feasible for  $(R_1)$  and

$$g(\bar{x}) \leq \inf\{g(x) \mid h(x) < 0 \text{ and } x \in C\}.$$

Then

$$0 \in 0 \cdot \partial g(\bar{x}) + \partial h(\bar{x}) + N_C(\bar{x})$$

i.e. **infimum gap implies abnormal multiplier rule**

# Proof

' $\bar{x}$  has cost strictly less than infimum cost over unrelaxed points  $x$ ' implies

(S): If  $x_i \rightarrow \bar{x}$  and  $h(x_i) < 0$  for all  $i$ , then

$x_i \notin C$  for all  $i$  sufficiently large.

Take  $\epsilon_i \rightarrow 0$  and consider:

( $P_i$ ) Minimize  $\{J_i(x) := (h(x + \epsilon_i))d_C(x) \mid x \in \mathbb{R}\}$ .

For each  $i$ ,  $\bar{x}$  is a minimizer. So by Ekeland's Theorem there exists  $x_i$  such that:

1)  $\bar{x}$  minimizes  $\rightarrow J_i(x) + \epsilon^{1/2}|x - x_i|$ , and

2)  $|x - x_i| \leq \epsilon^{1/2}$

But, by (S),  $'h(x_i) + \epsilon_i \leq 0' \implies 'd_C(x_i) > 0'$

for  $i$  sufficiently large. Use this to show

$$0 \in 0 \cdot \partial g(x_i) + \partial h(x_i) + N_C(\bar{x}) + \text{'error term'}$$

Pass to limit . .

# Necessary Conditions of Optimality

It is possible to reformulate  $(P)$  as a **generalized problem in the Calculus of Variations**:

$$\begin{cases} \text{Minimize } \int_0^1 L(t, x(t), \dot{x}(t)) dt + g(x(0), x(1)) \\ \text{over } x(\cdot) \in W^{1,1} \text{ s.t. } (x(0), x(1)) \in C, \end{cases}$$

where

$$L(t, x, v) := \begin{cases} 0 & \text{if } v \in F(t, x) \\ +\infty & \text{if } v \notin F(t, x). \end{cases}$$

Write Hamiltonian:

$$H(t, x, p) = \sup\{e \cdot p \mid e \in F(t, x)\}$$

Nonsmooth analysis approaches have validated generalization of the classical necessary conditions:

$$(\rho(t), \dot{\rho}(t)) = \nabla_{x,p} L(t, x(t), \rho(t)) \text{ (The Euler Lagrange condition)}$$

and

$$(-\dot{\rho}(t), \bar{x}(t)) = \nabla_{x,p} H(t, \bar{x}(t), \rho(t)) \text{ (Hamilton's condition)}$$

# Generalized Euler Lagrange Condition

## Theorem (Euler Lagrange Inclusion, Ioffe/Rockafellar 1996)

Let  $\bar{x}$  be a strong local minimizer. Assume (H1) and (H2).

Then there exists  $p(\cdot) \in W^{1,1}$  and  $\lambda \geq 0$  such that

$$(p(\cdot), \lambda) \neq 0$$

$$\dot{p}(t) \in \text{co} \{q \mid (q, p(t)) \in N_{\text{Gr}F(t, \cdot)}(\bar{x}(t), \dot{\bar{x}}(t))\} \text{ a.e.}$$

$$p(t) \cdot \dot{\bar{x}}(t) = \sup \{p(t) \cdot e \mid e \in F(t, \bar{x})(t)\} \text{ a.e.}$$

$$(p(0), -p(1)) \in \lambda \partial g(\bar{x}(0), \bar{x}(1)) + N_C(\bar{x}(0), \bar{x}(1)).$$

# Generalized Hamiltonian Inclusion

## Theorem (Generalized Hamiltonian Inclusion, Clarke 1973)

Let  $\bar{x}$  be a strong local minimizer. Assume (H1) and (H2) and

$F(t, x)$  is convex for all  $(t, x)$

Then there exists  $p(\cdot) \in W^{1,1}$  and  $\lambda \geq 0$  such that

$$(p(\cdot), \lambda) \neq 0$$

$$(-\dot{p}(t), \dot{\bar{x}}(t)) \in \text{co} \partial H(t, \bar{x}(t), p(t)(t), \lambda) \text{ a.e.}$$

$$(p(0), -p(1)) \in \lambda \partial g(\bar{x}(0), \bar{x}(1)) + N_C(\bar{x}(0), \bar{x}(1)).$$

The Generalized Hamiltonian Inclusion condition is valid also for non-convex  $F(\cdot, \cdot)$ 's (Clarke, 2005)



# Partially Convexified Hamiltonian Inclusion

## Theorem (Euler Lagrange Inclusion, Loewen/Rockafellar 1996)

Let  $\bar{x}$  be a strong local minimizer. Assume (H1) and (H2), and

(C)  $f(t, x)$  is convex

Then there exists  $p(\cdot) \in W^{1,1}$  and  $\lambda \geq 0$  such that

$$(p(\cdot), \lambda) \neq 0$$

$$-\dot{p}(t) \in \text{co} \{q \mid (q, \dot{\bar{x}}(t)) \in \partial_{x,p} H(t, \bar{x}(t), \dot{\bar{x}}(t))\} \text{ a.e.}$$

$$(p(0), -p(1)) \in \lambda \partial g(\bar{x}(0), \bar{x}(1)) + N_C(\bar{x}(0), \bar{x}(1)).$$

Open question: True without hypothesis (C)?

# Conditions for an Infimum Gap (1)

## Theorem A, Palladino/Vinter

Let  $\bar{x}(\cdot)$  be a strong local minimizer. Assume (H1) and (H2). Assume also that, for each  $\epsilon > 0$ , there exists a feasible relaxed trajectory  $x(\cdot)$  such that

$$g(x(0), x(1)) < g(\bar{x}(0), \bar{x}(1)) \text{ and } \|x(\cdot) - \bar{x}(\cdot)\|_{L^\infty} \leq \epsilon$$

Then there exists  $p(\cdot) \in W^{1,1}$  and such that

$$p(\cdot) \neq 0$$

$$(-\dot{p}(t), \dot{\bar{x}}(t)) \in \text{co } \partial H(t, \bar{x}(t)), p(t)(t), \} \text{ a.e.}$$

$$(p(0), -p(1)) \in 0 \cdot \partial g(\bar{x}(0), \bar{x}(1)) + N_C(\bar{x}(0), \bar{x}(1)).$$

“a strong local minimizer which is not also a strong local relaxed minimizer is an abnormal extremal (w.r.t. the Hamiltonian Inclusion)”

(loffe 1996 proved related theorem for a  $W^{1,1}$  infimum gap - stronger hypotheses.)

# Conditions for an Infimum Gap (2)

## Theorem B, Palladino/Vinter

Let  $\bar{x}(\cdot)$  be a feasible relaxed trajectory. Assume (H1) and (H2).

Suppose that there exist  $\delta > 0$  and  $\epsilon > 0$  such that

$$g(\bar{x}(0), \bar{x}(1)) < \inf\{g(x(0), x(1)) \mid x(\cdot) \text{ is feasible and } \|x(\cdot) - \bar{x}(\cdot)\|_{L^\infty} \leq \epsilon\}$$

Then there exists  $p(\cdot) \in W^{1,1}$  and such that

$$p(\cdot) \neq 0$$

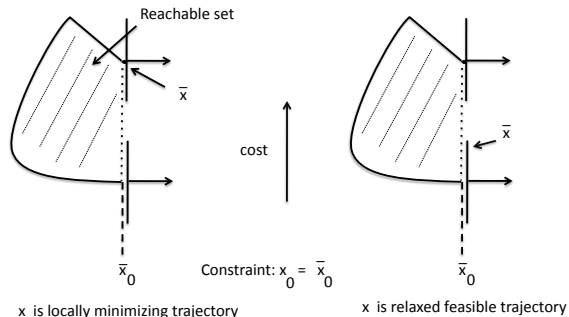
$$(-\dot{p}(t), \dot{\bar{x}}(t)) \in \text{co } \partial H(t, \bar{x}(t), p(t)(t)), \} \text{ a.e.}$$

$$(p(0), -p(1)) \in 0 \cdot \partial g(\bar{x}(0), \bar{x}(1)) + N_C(\bar{x}(0), \bar{x}(1)).$$

“a feasible relaxed trajectory which has cost strictly less than that of any  $L^\infty$ -neighbouring trajectory is an abnormal extremal (w.r.t. Hamiltonian Inclusion)”

(Warga 1972 proved a related theorem for controlled differential equations)

# Type A and Type B Theorems



Type A Theorem

Type B Theorem

# Concluding Comments/Open Questions

Links between abnormality and infimum gap first investigated by Warga

Take a minimizer  $\bar{x}$

loffe:

' $\bar{x}$  is not a  $W^{1,1}$  local relaxed minimizer'  $\implies$  'E-L conditions are abnormal'

Now we know:

' $\bar{x}$  is not a strong local relaxed minimizer'  $\implies$  'Hamiltonian inclusion abnormal'

-Theory readily adapts to allow for state constraints

Open questions:

- Conditions for **all** multipliers to be abnormal item[-] Counter-examples distinguishing differ conditions
- Relaxation theorems with extra constraint  $\|x(\cdot) - \bar{x}(\cdot)\|_{W^{1,1}} \leq \epsilon$