

First- and Second-Order Necessary Conditions via Lower-order Exact Penalty Functions

Xiaoqi Yang

Department of Applied Mathematics
The Hong Kong Polytechnic University

Joint with Zhangyou Chen (SWJTU), Kaiwen Meng (SWJTU), Zhiqing Meng (ZJUTCEM).

April 1, 2019

Outline

- 1 Introduction
- 2 KKT conditions of (NLP)
 - by Dini-directional derivative
 - by contingent derivative
 - by subderivative
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)
 - Max-Type and Integral-Type Penalty Functions
 - Optimality Conditions of (SIP)
 - Optimality Conditions of (GSIP)
- 6 Conclusions
- 7 References

- 1 Introduction
- 2 KKT conditions of (NLP)
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)
- 6 Conclusions
- 7 References

Consider the nonlinear programming problem (NLP):

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & g_i(x) \leq 0, \quad i \in I := \{1, \dots, m\}, \\ & h_j(x) = 0, \quad j \in J := \{m+1, \dots, m+q\}, \end{aligned}$$

where $f, g_i, h_j : R^n \rightarrow R$ are assumed to be smooth functions.

KKT conditions, originated with [?] and [?], are the well-known first-order necessary conditions for local minima of (NLP).

KKT conditions are useful in the design of optimal algorithms as one can compute a KKT point at most.

We denote by C the feasible set and by \bar{S} the set of optimal solutions of (NLP).

(NLP) has a local minimum at \bar{x} } \implies the following KKT condition a
 plus a constraint qualification

$$\nabla f(\bar{x}) + \sum_{i \in I(\bar{x})} \mu_i \nabla g_i(\bar{x}) + \sum_{j \in J} \eta_j \nabla h_j(\bar{x}) = 0 \quad (\mu_i \geq 0).$$

Constraint qualifications include:

- LICQ [?]
- MFCQ [?]
- ACQ [?]
- GCQ (weakest CQ) [?]

Literature review

Another approach to study optimality conditions is by virtue of exact penalty functions. [?] and [?] used l_1 exact penalty functions to derive KKT necessary optimality conditions.

On the other hand, [?] and [?] used $l_p(p \in [0, 1])$ exact penalty functions (see [?]) to derive KKT necessary optimality conditions together with some nonpositivity condition on the second-order directional derivative of the constraints.

Let $0 \leq p \leq 1$, $0^0 := 0$ and $g_{i+}(x) = \max\{g_i(x), 0\}$. A particular penalty term associated with (NLP) is of the form

$$S^p(x) = \sum_{i \in I} g_{i+}^p(x) + \sum_{j \in J} |h_j(x)|^p \quad \forall x \in R^n,$$

while the l_p penalty function associated with (NLP) is of the form

$$\mathcal{F}_p(x) := f(x) + \mu S^p(x).$$

- $p = 1$, the classical l_1 penalty function, see [?] and [?].
- $p < 1$, referred to as the lower order l_p penalty function, first introduced in [?] for the study of MPEC and was rediscovered from a unified augmented Lagrangian scheme by [?] and [?].

A penalty function is said to be exact if any optimal solution of (NLP) is also one for the penalty problem.

By definition, \mathcal{F}_0 is exact at any local minimum of (NLP). It was shown in [?] that \mathcal{F}_p with $0 < p \leq 1$ is exact if and only if the following generalized calmness-type condition holds:

$$\liminf_{u \rightarrow 0} \frac{\beta(u) - \beta(0)}{\|u\|^p} > -\infty,$$

where $\beta(u)$ is the optimal value of the optimization problem

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & g_i(x) \leq u_i, \quad i \in I, \quad h_j(x) = u_j, \quad j \in J. \end{aligned}$$

When $p = 1$, this result was established in [?] and [?].

Let f be locally Lipschitz. If the following error bound condition holds

$$\tau d(x, \bar{S}) \leq S^P(x), \quad x \in X$$

then $\mathcal{F}_p(x)$ is an exact penalty function.

The exact penalty function plays a key role in deriving KKT conditions.

- 1 Introduction
- 2 KKT conditions of (NLP)**
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)
- 6 Conclusions
- 7 References

$$I(\bar{x}) := \{i \in I \mid g_i(\bar{x}) = 0\}.$$

$$I(\bar{x}, w) := \{i \in I \mid g_i(\bar{x}) = 0, \langle \nabla g_i(\bar{x}), w \rangle = 0\}.$$

The first-order linearized tangent cone to C at \bar{x} is

$$L_C(\bar{x}) := \left\{ w \in \mathbb{R}^n \mid \begin{array}{l} \langle \nabla g_i(\bar{x}), w \rangle \leq 0 \quad \forall i \in I(\bar{x}) \\ \langle \nabla h_j(\bar{x}), w \rangle = 0 \quad \forall j \in J \end{array} \right\}.$$

The Dini upper directional derivative of a function $\phi : \mathbb{R}^n \rightarrow \mathbb{R}$ at $x \in \mathbb{R}^n$ in the direction $u \in \mathbb{R}^n$ is defined by

$$D_+ \phi(x; u) = \limsup_{t \rightarrow 0^+} \frac{\phi(x + tu) - \phi(x)}{t}.$$

The generalized Clarke second-order directional derivative of a $C^{1,1}$ function is

$$g^{\circ\circ}(x; w) = \limsup_{y \rightarrow x, t \rightarrow 0^+} \frac{\nabla g(y + tu)^T w - \nabla g(y)^T w}{t}.$$

If $F_p(x) = f(x) + \mu \sum_{i \in I} g_{i+}^p(x)$ is exact at \bar{x} , then

$$D_+ F_p(\bar{x}; u) \geq 0, \quad \forall u \in R^n.$$

Thus

$$\nabla f(\bar{x})^\top u + \mu \sum_{i \in I} D_+ g_{i+}^p(\bar{x}; u) \geq 0, \quad \forall u \in R^n.$$

Then,

$$\sum_{i \in I} D_+ g_{i+}^p(\bar{x}; u) \leq 0 \implies \nabla f(\bar{x})^\top u \geq 0, \quad \forall u \in R^n.$$

By Farkas lemma, which says that exactly one of the following two systems has a solution:

$$\text{System 1} \quad Au \leq 0, \quad c^\top u > 0, \quad \text{for some } u,$$

$$\text{System 2} \quad A^\top \mu = c, \quad \mu \geq 0, \quad \text{for some } \mu,$$

we establish that the following KKT condition holds:

$$\nabla f(\bar{x}) + \sum_{i \in I(\bar{x})} \mu_i \nabla g_i(\bar{x}) = 0 \quad (\mu_i \geq 0).$$

The case $p \in (0, 1)$.

Lemma

[?]. Let $\bar{h}(x) = (\max\{h(x), 0\})^p$ with $p \in (0, 1)$ and h be continuously differentiable at x .

- (i) If $h(x) < 0$, then $D_+\bar{h}(x; d) = 0$;
- (ii) If $h(x) = 0$ and $\langle \nabla h(x), d \rangle < 0$, then $D_+\bar{h}(x; d) = 0$;
- (iii) If $p \in (0.5, 1)$, $h(x) = 0$, $\langle \nabla h(x), d \rangle = 0$ and $h^{\circ\circ}(x; d)$ is finite, then $D_+\bar{h}(x; d) = 0$;
- (iv) If $p = 0.5$, $h(x) = 0$ and $\langle \nabla h(x), d \rangle = 0$, then
$$D_+\bar{h}(x; d) \leq \sqrt{\max\{\frac{1}{2}h^{\circ\circ}(x; d), 0\}};$$
- (v) If $p \in (0, 0.5)$, $h(x) = 0$, $\langle \nabla h(x), d \rangle = 0$ and $h^{\circ\circ}(x; d) < 0$, then $D_+\bar{h}(x; d) = 0$.

By estimating the upper Dini-directional derivative of $\mathcal{F}_p(x)$, we have

Theorem

[?] If $F_p(x)$ is exact at \bar{x} and in addition, one of the following conditions is satisfied:

- (i) $p \in (\frac{1}{2}, 1]$, $g_i (i \in I)$ and $h_j (j \in J)$ are $C^{1,1}$,
- (ii) $p = \frac{1}{2}$ and, for every $w \in L_C(\bar{x})$, it follows that

$$g_i^{\circ\circ}(\bar{x}; w) \leq 0, \quad \forall i \in I(\bar{x}, w),$$

$$h_j^{\circ\circ}(\bar{x}; w) = 0, \quad \forall j \in J,$$
- (iii) $p \in [0, 1/2)$, $q = 0$ (i.e., there is no equality constraint) and, for every $w \in L_C(\bar{x})$ with $w \neq 0$, it follows that

$$g_i^{\circ\circ}(\bar{x}; w) < 0, \quad \forall i \in I(\bar{x}, w),$$

then $\text{KKT}(\bar{x}) \neq \emptyset$.

Let $M : R^n \rightrightarrows R^s$ be a set-valued map and $(x, y) \in \text{gph}M$. The contingent derivative of M at (x, y) is defined by the set-valued map $DM(x, y) : R^n \rightrightarrows R^s$ such that

$$\text{gph}(DM(x, y)) = T_{\text{gph}M}(x, y).$$

In particular, when M is single-valued at x , i.e., $M(x) = \{y\}$, we use $DM(x)$ to denote $DM(x, y)$ for simplicity, and define the kernel of $DM(x)$ by

$$\text{Ker}DM(x) = \{u \in R^n \mid 0 \in DM(x)(u)\}.$$

Now, define an optimality indication set of (NLP) with respect to C and \bar{x} as follows:

$$\Pi(C, \bar{x}) := \{p \in [0, 1] \mid \text{Ker}DS^p(\bar{x})^* \subset \text{Ker}DS(\bar{x})^*\}.$$

By estimating the contingent derivative of $\mathcal{F}_p(x)$, we have

Theorem

[?] If there exists $p \in \Pi(C, \bar{x})$ such that the l_p penalty function \mathcal{F}_p is exact at \bar{x} , then $\text{KKT}(\bar{x}) \neq \emptyset$.

In what follows,

- we distinguish a point $\bar{x} \in C$ for consideration;
- let $\phi : R^n \rightarrow R_+ \cup \{+\infty\}$ be a lower semicontinuous function such that

$$C = \{x \in R^n \mid \phi(x) = 0\}.$$

- ϕ is called a **penalty term** associated with (NLP)
- The function of the form

$$f + \mu\phi$$

is called a **penalty function** associated with (NLP), where μ , a positive number, is often referred to as the **penalty parameter**.

Definition

We say that the penalty term ϕ is of **KKT-type at \bar{x}** if the KKT condition holds at \bar{x} whenever the penalty function $f + \mu\phi$ is exact at \bar{x} .

Theorem

Consider the following conditions:

- (i) $[\ker d\phi(\bar{x})]^* \subset L_C(\bar{x})^*$.
- (ii) $\widehat{\partial}\phi(\bar{x}) \subset L_C(\bar{x})^*$.
- (iii) The penalty term ϕ is of KKT-type at \bar{x} .

Then (i) \implies (ii) \iff (iii).

Theorem

Let $0 \leq p < 1$. Consider the following conditions:

- (i) $[\ker dS^p(\bar{x})]^* = L_C(\bar{x})^*$.
- (ii) $\widehat{\partial}S^p(\bar{x}) = L_C(\bar{x})^*$.
- (iii) S^p is a KKT-type penalty term at \bar{x} .

Then (i) \implies (ii) \iff (iii).

- 1 Introduction
- 2 KKT conditions of (NLP)
- 3 KKT-type Penalty Terms and Their Characterizations**
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)
- 6 Conclusions
- 7 References

In what follows,

- we distinguish a point $\bar{x} \in C$ for consideration;
- let $\phi : R^n \rightarrow R_+ \cup \{+\infty\}$ be a lower semicontinuous function such that

$$C = \{x \in R^n \mid \phi(x) = 0\}.$$

- ϕ is called a **penalty term** associated with (NLP)
- The function of the form

$$f + \mu\phi$$

is called a **penalty function** associated with (NLP), where μ , a positive number, is often referred to as the **penalty parameter**.

Definition

We say that the penalty function $f + \mu\phi$ is **exact at \bar{x}** if, $f + \mu\phi$ admits a local minimum at \bar{x} with some **finite penalty parameter**.

[exactness of penalty function at $\bar{x} \implies \bar{x}$ being a local minimum of (NLP)]

It is well-known that ¹

\mathcal{F}_p with $p = 1$ is exact at $\bar{x} \implies$ KKT condition at \bar{x} .

But in general,

\mathcal{F}_p with $0 < p < 1$ is exact at $\bar{x} \not\implies$ KKT condition at \bar{x} .

¹See Theorem 4.8 of [?].

Definition

We say that the penalty term ϕ is of **KKT-type at \bar{x}** if the KKT condition holds at \bar{x} whenever the penalty function $f + \mu\phi$ is exact at \bar{x} .

We will employ the tools from Variational Analysis, see [?].

For any $f : R^n \rightarrow \bar{R}$ and a point \bar{x} with $f(\bar{x})$ finite,

- The vector $v \in R^n$ is a regular subgradient of f at \bar{x} , written $v \in \widehat{\partial}f(\bar{x})$, if

$$f(x) \geq f(\bar{x}) + \langle v, x - \bar{x} \rangle + o(\|x - \bar{x}\|).$$

- For any $w \in R^n$, the subderivative (or Hadamard directional derivative) of f at \bar{x} for w is defined by

$$df(\bar{x})(w) := \liminf_{\tau \rightarrow 0+, w' \rightarrow w} \frac{f(\bar{x} + \tau w') - f(\bar{x})}{\tau}.$$

-

$$\widehat{\partial}f(\bar{x}) = \{v \in R^n \mid \langle v, w \rangle \leq df(\bar{x})(w) \forall w \in \text{dom}df(\bar{x})\}.$$

Lemma

Suppose that the function $\psi : R^n \rightarrow \bar{R}$ has a local minimum at \bar{x} with $\psi(\bar{x})$ finite. Then we have

$$[\text{dom}d\psi(\bar{x})]^* \subset \widehat{\partial}\psi(\bar{x}) \subset [\text{ker}d\psi(\bar{x})]^*. \quad (1)$$

Moreover,

- The first inclusion in (1) is an equality if and only if the regular subdifferential $\widehat{\partial}\psi(\bar{x})$ is a cone;
- The second inclusion in (1) is an equality if and only if $[\text{dom}d\psi(\bar{x})]^* = [\text{ker}d\psi(\bar{x})]^*$;
- If the subderivative $d\psi(\bar{x})$ is a sublinear function as is true when ψ is regular at \bar{x} (see Definition 7.25 of [?]), then

$$\text{clpos}(\widehat{\partial}\psi(\bar{x})) = [\text{ker}d\psi(\bar{x})]^*. \quad (2)$$

We recall the **variational description of regular subgradients**:

Lemma

([?], Proposition 8.5). A vector v belongs to $\widehat{\partial}f(\bar{x})$ if and only if, on some neighborhood of \bar{x} , there is a function $h \leq f$ with $h(\bar{x}) = f(\bar{x})$ such that h is differentiable at \bar{x} with $\nabla h(\bar{x}) = v$. Moreover h can be taken to be continuously differentiable with $h(x) < f(x)$ for all $x \neq \bar{x}$ near \bar{x} .

Remark

This variational description is a contribution to the basics of variational analysis, as pointed out on p.347 of [?].

We can obtain from Lemmas 9 and 10 the following.

Theorem

Consider the following conditions:

- (i) $[\ker d\phi(\bar{x})]^* \subset L_C(\bar{x})^*$.
- (ii) $\widehat{\partial}\phi(\bar{x}) \subset L_C(\bar{x})^*$.
- (iii) *The penalty term ϕ is of KKT-type at \bar{x} .*

Then (i) \implies (ii) \iff (iii).

Theorem

Let $0 \leq p < 1$. Consider the following conditions:

- (i) $[\ker dS^p(\bar{x})]^* = L_C(\bar{x})^*$.
- (ii) $\widehat{\partial}S^p(\bar{x}) = L_C(\bar{x})^*$.
- (iii) S^p is a KKT-type penalty term at \bar{x} .

Then (i) \implies (ii) \iff (iii).

Remark

In the case of $p = 0$, (i) and (ii) are equivalent, and moreover Theorem 12 recovers a well-known result that the GCQ $[T_C(\bar{x})^* = L_C(\bar{x})^*]$ is the weakest one ensuring KKT conditions.

Remark

In the case of $0 < p < 1$, we are not aware of the equivalence of (i) and (ii), although they are the same in many situations.

By a direct calculation using the chain rule for second subderivatives of piecewise linear-quadratic functions ², we have

$$dS^{\frac{1}{2}}(\bar{x})(w) = +\infty \quad \forall w \notin L_C(\bar{x}),$$

and if $w \in L_C(\bar{x})$, we have $dS^{\frac{1}{2}}(\bar{x})(w)$

$$= \frac{\sqrt{2}}{2} \sqrt{\max_{\rho \in \text{KKT}_0(\bar{x}), \|\rho\|_\infty=1} \left\langle \left[\sum_{i \in I} \rho_i \nabla^2 g_i(\bar{x}) + \sum_{j \in J} \rho_j \nabla^2 h_j(\bar{x}) \right] w, w \right\rangle},$$

where

$$\text{KKT}_0(\bar{x}) := \left\{ \rho \mid \begin{array}{l} \sum_{i \in I} \rho_i \nabla g_i(\bar{x}) + \sum_{j \in J} \rho_j \nabla h_j(\bar{x}) = 0 \\ \rho_i \geq 0 \quad \forall i \in I(\bar{x}), \rho_i = 0 \quad \forall i \in I \setminus I(\bar{x}) \end{array} \right\}$$

denotes the degenerate KKT multiplier set at \bar{x} .

But we have no idea the explicit formula of $\widehat{\partial} S^p(\bar{x})$, though we are sure that

$$\widehat{\partial} S^{\frac{1}{2}}(\bar{x}) = \{v \mid \langle v, w \rangle \leq dS^{\frac{1}{2}}(\bar{x})(w) \quad \forall w\}.$$

²See Chapter 12 of [2]

Proposition

$S^{\frac{1}{2}}$ is of KKT-type at \bar{x} if one of the following conditions is satisfied:

(i) For every $w \in L_C(\bar{x})$, it follows that

$$\langle w, \nabla^2 g_i(\bar{x})w \rangle \leq 0 \quad \forall i \in I(\bar{x}, w), \quad \langle w, \nabla^2 h_j(\bar{x})w \rangle = 0 \quad \forall j \in J. \quad (3)$$

(ii) For every $w \in L_C(\bar{x})$, there exists some $z \in R^n$ such that

$$\begin{aligned} \langle \nabla g_i(\bar{x}), z \rangle + \langle w, \nabla^2 g_i(\bar{x})w \rangle &\leq 0 \quad \forall i \in I(\bar{x}, w), \\ \langle \nabla h_j(\bar{x}), z \rangle + \langle w, \nabla^2 h_j(\bar{x})w \rangle &= 0 \quad \forall j \in J. \end{aligned}$$

(iii) For every $w \in L_C(\bar{x})$, it follows that

$$\max_{\lambda \in \text{KKT}_0(\bar{x})} \left\{ \sum_{i \in I} \lambda_i \langle w, \nabla^2 g_i(\bar{x})w \rangle + \sum_{j \in J} \lambda_j \langle w, \nabla^2 h_j(\bar{x})w \rangle \right\} = 0. \quad (4)$$

- Condition (3) was originally given in [?]. In general, we have
 - LICQ $\not\Rightarrow$ (3). Consider $x_2^2 - x_1 \leq 0$ and $\bar{x} = (0, 0)$.
 - (3) $\not\Rightarrow$ LICQ. Consider $x^3 \leq 0$ and $\bar{x} = 0$.
- Condition (4) is newly obtained, and we have

$$\text{MFCQ} \implies (4),$$

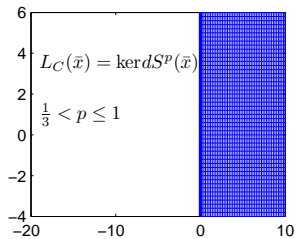
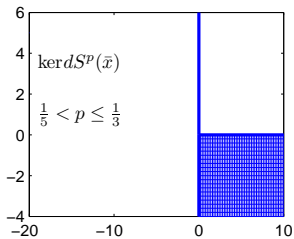
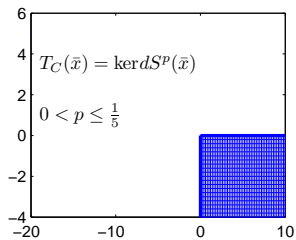
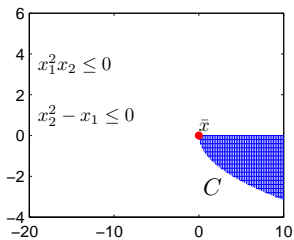
because the MFCQ at $\bar{x} \iff \text{KKT}_0(\bar{x}) = \{0\}$.

Example

Let $\bar{x} = (0, 0)$ and let

$$C = \left\{ x \in R^n \mid \begin{array}{l} x_1^2 x_2 \leq 0 \\ x_2^2 - x_1 \leq 0 \end{array} \right\}.$$

- Neither the GCQ nor (3) is satisfied at \bar{x} .
- (4) holds and $\text{KKT}_0(\bar{x}) = R_+ \times \{0\}$.



$T_C(\bar{x}) = R_+ \times (-R_+)$, $L_C(\bar{x}) = R_+ \times R$, and

$$\ker dS^p(\bar{x}) = \begin{cases} R_+ \times (-R_+) & \text{if } 0 < p \leq \frac{1}{5}, \\ R_+ \times (-R_+) \cup \{0\} \times R_+ & \text{if } \frac{1}{5} < p \leq \frac{1}{3}, \\ R_+ \times R & \text{if } \frac{1}{3} < p \leq 1. \end{cases}$$

- 1 Introduction
- 2 KKT conditions of (NLP)
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions**
- 5 KKT conditions of (SIP) and (GSIP)
- 6 Conclusions
- 7 References

Denote the set of all KKT multipliers at \bar{x} by $\text{KKT}(\bar{x})$ and the critical cone at \bar{x} by

$$\mathcal{V}(\bar{x}) := \left\{ w \in R^n \left| \begin{array}{l} \langle \nabla f(\bar{x}), w \rangle \leq 0 \\ \langle \nabla g_i(\bar{x}), w \rangle \leq 0 \quad \forall i \in I \text{ with } g_i(\bar{x}) = 0 \\ \langle \nabla h_j(\bar{x}), w \rangle = 0 \quad \forall j \in J \end{array} \right. \right\}.$$

The second-order necessary condition (for short, SON), originated with [?], holds at a local minimum \bar{x} of (NLP) if

$$\sup_{\lambda \in \text{KKT}(\bar{x})} \langle w, \nabla_{xx}^2 L(\bar{x}, \lambda) w \rangle \geq 0 \quad \forall w \in \mathcal{V}(\bar{x}),$$

where the convention $\sup \emptyset := -\infty$ is used.

- l_1 exactness \implies (SON). See Corollary 4.5 of [?].

For any w and z , let

$$I(\bar{x}, w) := \{i \in I(\bar{x}) \mid \langle w, \nabla g_i(\bar{x}) \rangle = 0\},$$

$$I(\bar{x}, w, z) := \{i \in I(\bar{x}, w) \mid \langle z, \nabla g_i(\bar{x}) \rangle + \langle w, \nabla^2 g_i(\bar{x}) w \rangle = 0\},$$

and let the second-order linearized tangent set to C at \bar{x} in the direction $w \in L_C(\bar{x})$ be given by

$$L_C^2(\bar{x} \mid w) := \left\{ z \mid \begin{array}{l} \langle \nabla g_i(\bar{x}), z \rangle + \langle w, \nabla^2 g_i(\bar{x}) w \rangle \leq 0 \quad \forall i \in I(\bar{x}, w) \\ \langle \nabla h_j(\bar{x}), z \rangle + \langle w, \nabla^2 h_j(\bar{x}) w \rangle = 0 \quad \forall j \in J \end{array} \right.$$

The parabolic subderivative of f at \bar{x} for w with respect to z is defined by, see [?]

$$d^2f(\bar{x})(w | z) := \liminf_{\tau \rightarrow 0+, z' \rightarrow z} \frac{f(\bar{x} + \tau w + \frac{1}{2}\tau^2 z') - f(\bar{x}) - \tau df(\bar{x})(w)}{\frac{1}{2}\tau^2}.$$

Theorem

Let \bar{x} be a local minimum of (NLP). Suppose that the penalty function $f + \mu\phi$ is exact at \bar{x} . If

$$L_C^2(\bar{x} | w) \subset \text{clconv}[\ker d^2\phi(\bar{x})(w | \cdot)] \quad \forall w \in \mathcal{V}(\bar{x}), \quad (5)$$

then the SON condition holds, and in particular when $L_C^2(\bar{x} | w) = \emptyset$, the supremum in the SON condition is $+\infty$.

Let $\bar{x} \in C$ and let $\phi = S^P$.

We shall give sufficient conditions in terms of the original data for the inclusion

$$L_C^2(\bar{x} \mid w) \subset \ker d^2 S^P(\bar{x})(w \mid \cdot) \quad \forall w \in L_C(\bar{x}) \quad (6)$$

to hold, which is slightly stronger than (5) since in general $\ker d^2 S^P(\bar{x})(w \mid \cdot)$ is not a closed and convex set and $\mathcal{V}(\bar{x}) \subsetneq L_C(\bar{x})$.

Theorem

Let \bar{x} be a local minimum of (NLP). Suppose that the l_p penalty function is exact at \bar{x} . If, in addition, one of the following conditions is satisfied:

- (i) $p \in (\frac{2}{3}, 1]$,
- (ii) $p = \frac{2}{3}$ and, for every $z \in L_C^2(\bar{x} | w)$, it follows that

$$\begin{cases} \langle w, \nabla^2 g_i(\bar{x})z \rangle + \frac{1}{3}g_i^{(3)}(\bar{x})(w, w, w) \leq 0 & \forall i \in I(\bar{x}, w, z), \\ \langle w, \nabla^2 h_j(\bar{x})z \rangle + \frac{1}{3}h_j^{(3)}(\bar{x})(w, w, w) = 0 & \forall j \in J, \end{cases} \quad (7)$$

- (iii) $p \in [0, \frac{2}{3})$, $q = 0$ (i.e., there is no equality constraint) and, for every $z \in L_C^2(\bar{x} | w)$ with $(w, z) \neq 0$, it follows that

$$\langle w, \nabla^2 g_i(\bar{x})z \rangle + \frac{1}{3}g_i^{(3)}(\bar{x})(w, w, w) < 0 \quad \forall i \in I(\bar{x}, w, z),$$

Remark

- (a) *Let $p = 1$. By applying the second-order Taylor expansion we have*

$$L_C^2(\bar{x} | w) = \ker d^2 S(\bar{x})(w | \cdot) \quad \forall w \in L_C(\bar{x}), \quad (8)$$

which implies that condition (6) holds. This recovers a well-known result that the (SON) condition holds at \bar{x} when the l_1 penalty function is exact at \bar{x} , see [?].

(b) Let $0 \leq p < 1$. It can be shown that

$$\ker d^2 S^p(\bar{x})(w \mid \cdot) \subset L_C^2(\bar{x} \mid w) \quad \forall w \in \ker dS^p(\bar{x}). \quad (9)$$

Thus, condition (5) holds if and only if

$$L_C^2(\bar{x} \mid w) = \text{clconv}[\ker d^2 S^p(\bar{x})(w \mid \cdot)] \quad \forall w \in \mathcal{V}(\bar{x}). \quad (10)$$

Moreover, it is clear that

$$T_C^2(\bar{x} \mid w) = \ker d^2 S^0(\bar{x})(w \mid \cdot), \quad \forall w \in T_C(\bar{x}).$$

Condition (10) with $p = 0$ reduces to the so-called SGCQ, originated with [?], which holds at \bar{x} if by definition

$$L_C^2(\bar{x} \mid w) = \text{clconv}[T_C^2(\bar{x} \mid w)] \quad \forall w \in \mathcal{V}(\bar{x}).$$

- (c) *It was shown by [?] that if the linear independent constraint qualification (for short, LICQ) holds at \bar{x} , then*

$$L_C^2(\bar{x} | w) = T_C^2(\bar{x} | w) \quad \forall w \in L_C(\bar{x}),$$

and hence (6) holds for any $p \in [0, 1]$.

Simple example can be given to demonstrate that condition (7) may not hold even if the LICQ holds at \bar{x} .

- 1 Introduction
- 2 KKT conditions of (NLP)
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)**
- 6 Conclusions
- 7 References

Consider the following semi-infinite program, denoted as (SIP):

$$\min f(x) \quad \text{s.t. } g(x, t) \leq 0, t \in \Omega,$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $g : \mathbb{R}^n \times \Omega \rightarrow \mathbb{R}$ are smooth functions, and Ω is a nonempty and compact set of parameters in \mathbb{R}^m .

Let x^* be a locally optimal solution of (SIP),

$$X := \{x \in \mathbb{R}^n : g(x, t) \leq 0, t \in \Omega\}$$

be the feasible set and, for $x \in X$, let

$$\Omega_x := \{t \in \Omega : g(x, t) = 0\}.$$

Literature review

Three types of optimality conditions for (SIP):

$$0 \in \text{conv}\{\nabla f(x^*), \nabla_x g(x^*, t) \ (t \in \Omega_{x^*})\},$$

(see Fritz John (1948), Pschenichnyi (1971), Hettich and Jongen (1978), and Borwein (1981),)

$$0 \in \nabla f(x^*) + \text{cl cone}\{\nabla_x g(x^*, t) \ (t \in \Omega_{x^*})\},$$

(see [?], Li, et al (2000),)

$$0 \in \nabla f(x^*) + \text{cone}\{\nabla_x g(x^*, t) \ (t \in \Omega_{x^*})\},$$

(see Pschenichnyi (1971), Lopez and Vercher (1983), Hettich and Kortanek (1993), Zheng and Yang (2007).)

Literature review

By a Farkas lemma, see [?],

$$0 \in \nabla f(x^*) + \text{cl cone}\{\nabla_x g(x^*, t) \mid t \in \Omega_{x^*}\}, \quad (11)$$

is equivalent to

$$\langle \nabla f(x^*), d \rangle \geq 0, \quad \forall d \in D(x^*), \quad (12)$$

where $D(x) = \{0 \neq d \in R^n : \langle \nabla_x g(x, t), d \rangle \leq 0 \forall t \in \Omega_x\}$.

In this talk, we will study (11) but using the form of (12).

Literature review

[?] introduced the following l_1 integral penalty function

$$f(x) + \rho \int_{\Omega(x)} g(x, t) d\mu(t),$$

where $\Omega(x) := \{t \in \Omega : g(x, t) > 0\}$, but too weak penalty for infeasibility.

Let $\rho > 0$. For (SIP), [?] also introduced the following l_p integral penalty function

$$f(x) + \rho \int_{\Omega} g_+^p(x, t) d\mu(t)$$

and established the convergence of the solution sequence of the penalty problems to an optimal solution of (SIP).

[?] established the exact l_1 integral penalty function

$$f(x) + \rho \int_{\Omega(x)} g(x, t) d\mu(t) \Big/ \int_{\Omega(x)} d\mu(t).$$

Penalty Functions

A p th-order max-type penalty function for SIP is defined as,

$$F_{max}^p(x) = f(x) + \rho \max_{t \in \Omega} g_+^p(x, t).$$

Let μ be a non-negative regular Borel measure defined on Ω with the support of μ being equal to Ω , that is $\text{supp}(\mu) = \Omega$, where the support of μ is defined as the set of the points $t \in \Omega$ such that any open neighbourhood V of t has a positive measure:

$$\text{supp}(\mu) := \{t \in \Omega : \mu(V) > 0, \text{ for any open neighbourhood } V \text{ of } t\}.$$

Two p th-order integral-type penalty functions for SIP are defined by

$$\begin{aligned} F_{int}^p(x) &= f(x) + \rho \int_{\Omega} g_+^p(x, t) d\mu(t), \\ \bar{F}_{int}^p(x) &= f(x) + \rho \left(\int_{\Omega} g_+(x, t) d\mu(t) \right)^p. \end{aligned}$$

Exactness of $F_{int}^p(x) \implies$ that of $\bar{F}_{int}^p(x) \implies$ that of $F_{max}^p(x)$.

The case $p = 1$.

(SIP) can be rewritten as

$$\min f(x) \text{ s.t. } \max_{t \in \Omega} g(x, t) \leq 0. \quad (13)$$

The exactness of F_{max}^1 is equivalent to saying that problem (13) has an l_1 exact penalty function in the usual sense, see Clarke (1983). Thus, if F_{max}^1 is exact, then the KKT-type optimality condition (12).

The case $p \in (0, 1)$.

Let $h : \mathbb{R}^n \rightarrow \mathbb{R}$. The upper Dini-directional derivative of h at a point x in the direction $d \in \mathbb{R}^n$ is defined by

$$D_+ h(x; d) = \limsup_{\lambda \downarrow 0} \frac{h(x + \lambda d) - h(x)}{\lambda}.$$

The generalized upper second-order directional derivatives of a $C^{1,1}$ function h at x in the direction $d \in \mathbb{R}^n$ is defined by

$$h^{\circ\circ}(x; d) = \limsup_{y \rightarrow x, \lambda \downarrow 0} \frac{\langle \nabla h(y + \lambda d), d \rangle - \langle \nabla h(y), d \rangle}{\lambda}.$$

Let $D(x) = \{0 \neq d \in \mathbb{R}^n : \langle \nabla_x g(x, t), d \rangle \leq 0 \ \forall t \in \Omega_x\}$ and let

$$\Omega_x^=(d) := \{t \in \Omega_x : \langle \nabla_x g(x, t), d \rangle = 0\},$$

$$\Omega_x^<(d) := \{t \in \Omega_x : \langle \nabla_x g(x, t), d \rangle < 0\},$$

The case $p \in (0, 1)$.

Lemma

[?] Let $\bar{h}(x) = (\max\{h(x), 0\})^p$ with $p \in]0, 1[$ and h be continuously differentiable at x .

- (i) If $h(x) < 0$, then $D_+\bar{h}(x; d) = 0$;
- (ii) If $h(x) = 0$ and $\langle \nabla h(x), d \rangle < 0$, then $D_+\bar{h}(x; d) = 0$;
- (iii) If $p \in (0.5, 1)$, $h(x) = 0$, $\langle \nabla h(x), d \rangle = 0$ and $h^{\circ\circ}(x; d)$ is finite, then $D_+\bar{h}(x; d) = 0$;
- (iv) If $p = 0.5$, $h(x) = 0$ and $\langle \nabla h(x), d \rangle = 0$, then
$$D_+\bar{h}(x; d) \leq \sqrt{\max\{\frac{1}{2}h^{\circ\circ}(x; d), 0\}};$$
- (v) If $p \in (0, 0.5)$, $h(x) = 0$, $\langle \nabla h(x), d \rangle = 0$ and $h^{\circ\circ}(x; d) < 0$, then $D_+\bar{h}(x; d) = 0$.

The case $p \in (0, 1)$.

Now we establish a necessary optimality condition for SIP by virtue of the exact penalty function F_{int}^p .

Theorem

Let $p \in (0, 1)$ and F_{int}^p be exact at x^* . Under any one of the three assumptions below,

- (i) $p \in (0.5, 1)$ and $g(\cdot, t)$ is $C^{1,1}$, for all $t \in \Omega_{x^*}^-(d)$,
 - (ii) $p = 0.5$ and $g^{\circ\circ}(x^*, t; d) \leq 0$ for all $t \in \Omega_{x^*}^-(d)$ and $d \in D(x^*)$, and
 - (iii) $p \in (0, 0.5)$ and $g^{\circ\circ}(x^*, t; d) < 0$, for all $t \in \Omega_{x^*}^-(d)$ and $d \in D(x^*)$,
- we have

$$\langle \nabla f(x^*), d \rangle \geq 0, \forall d \in D(x^*).$$

The case $p \in (0, 1)$.

Next we employ the exactness of $\bar{F}_{int}(p \in (0, 1))$ to develop the optimality condition (12) of (SIP).

Theorem

Let $p \in (0, 1)$ and \bar{F}_{int}^p be exact at x^* . Under any one of the three assumptions below,

- (i) $p \in (0.5, 1)$ and $g(\cdot, t)$ is $C^{1,1}$, for all $t \in \Omega_{x^*}^-(d)$,
 - (ii) $p = 0.5$ and $g^{\circ\circ}(x^*, t; d) \leq 0$ for all $t \in \Omega_{x^*}^-(d)$ and $d \in D(x^*)$, and
 - (iii) $p \in (0, 0.5)$ and $g^{\circ\circ}(x^*, t; d) < 0$, for all $t \in \Omega_{x^*}^-(d)$ and $d \in D(x^*)$,
- we have

$$\langle \nabla f(x^*), d \rangle \geq 0, \forall d \in D(x^*).$$

The case $p \in (0, 1)$.

We need the following lemma in the proof of the above theorem.

Proposition

Let $g: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ be a non-negative function, $f: \mathbb{R}_+ \rightarrow \mathbb{R}$ be a continuous and strictly increasing function and $\lambda_0 \in \mathbb{R}_+$. Then

$$\limsup_{\lambda \rightarrow \lambda_0} f(g(\lambda)) \leq f(\limsup_{\lambda \rightarrow \lambda_0} g(\lambda)).$$

We will also consider the following generalized semi-infinite program, denoted as (GSIP),

$$\min f(x) \quad \text{s.t. } g(x, t) \leq 0, t \in \Omega \cap \Omega(x),$$

where Ω is a compact subset of \mathbb{R}^m ,

$$\Omega(x) := \{t \in \mathbb{R}^m : v_i(x, t) \leq 0, i = 1, \dots, l\}$$

and the functions $f: \mathbb{R}^n \rightarrow \mathbb{R}$, $g: \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$, and $v_i: \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R} (i = 1, \dots, l)$ are smooth.

[?] associated (GSIP) with an (SIP) problem via augmented Lagrangians of the lower level problem.

The lower level problem associated with (GSIP) is

$$Q(x) \quad \max_{t \in \Omega} g(x, t) \quad \text{s.t.} \quad v_i(x, t) \leq 0, i = 1, \dots, l.$$

Let $\text{val}Q(x)$ be the optimal value of the problem $Q(x)$. It is clear that

$$x \in X_{(\text{GSIP})} \quad \text{iff} \quad \text{val}Q(x) \leq 0.$$

Let $\bar{f}(x, \mu, c) = f(x)$ and, for $(x, \mu, c) \in \mathbb{R}^n \times \mathbb{R}^l \times \mathbb{R}_{++}$,

$$\bar{g}(x, t, \mu, c) = g(x, t) - \frac{1}{2c} \sum_{i=1}^l \{([cv_i(x, t) + \mu_i]_+)^2 - \mu_i^2\}.$$

Then \bar{g} is of $C^{1,1}$, see Hiriart-Urruty et al (1984).

Next we recall some concepts from [?].

Problem $Q(x)$ is said to satisfy the *quadratic growth condition* iff there is a $c \geq 0$ such that $\bar{g}(x, t, 0, c)$ is bounded above as a function of $t \in \Omega$.

Problem $Q(x)$ is said to be *stable of degree 2* iff there is a neighbourhood U of the origin in \mathbb{R}^l and a C^2 function $\pi_x : U \rightarrow \mathbb{R}$ such that

$$\nu(x, u) \leq \pi_x(u), \forall u \in U, \text{ and } \nu(x, 0) = \pi_x(0).$$

Let $\bar{H}(x, \mu, c) := \max_{t \in \Omega} \bar{g}(x, t, \mu, c)$.

Lemma

[?] Under the quadratic growth condition of $Q(x)$, we have

$$\text{val } Q(x) = \min_{(\mu, c) \in \mathbb{R}^l \times \mathbb{R}_{++}} \bar{H}(x, \mu, c)$$

iff the problem $Q(x)$ is stable of degree 2.

Consider the following (SIP) problem, denoted as (SIPg),

$$\min_{(x, \mu, c) \in \mathbb{R}^n \times \mathbb{R}^l \times \mathbb{R}_{++}} \bar{f}(x, \mu, c) \quad \text{s.t.} \quad \bar{g}(x, t, \mu, c) \leq 0, t \in \Omega.$$

Therefore we have

Proposition

Assume that, for all $x \in \mathbb{R}^n$, $Q(x)$ satisfies the quadratic growth condition and is stable of degree 2. Then problems (GSIP) and (SIPg) have the same optimal value, i.e., $\text{val}(\text{GSIP}) = \text{val}(\text{SIPg})$, and furthermore,

- (i) *if \hat{x} is a locally optimal solution of (GSIP), then there exists $(\hat{\mu}, \hat{c}) \in \mathbb{R}^l \times \mathbb{R}_{++}$ such that $(\hat{x}, \hat{\mu}, \hat{c})$ is a locally optimal solution of (SIPg);*
- (ii) *if $(\hat{x}, \hat{\mu}, \hat{c})$ is a locally optimal solution of (SIPg), then \hat{x} is a locally optimal solution of (GSIP).*

For $p \in (0, 1)$, let

$$G_{int}^p(x, \mu, c) := \bar{f}(x, \mu, c) + \rho \int_{\Omega} \bar{g}_+^p(x, t, \mu, c) d\mu(t).$$

By applying previous Theorem for SIP, we have.

Theorem

Let the assumptions of the previous Proposition hold. Let \hat{x} be a locally optimal solution of (GSIP) and G_{int}^p be exact at the point $(\hat{x}, \hat{\mu}, \hat{c})$. Then, under one of the following assumptions,

(i) $p \in (0.5, 1)$,

(ii) $p = 0.5$ and $\bar{g}_{(x,\mu,c)}^{\circ\circ}(\hat{x}, t, \hat{\mu}, \hat{c}; d) \leq 0$ for all $d \in D(\hat{x}, \hat{\mu}, \hat{c})$ and $t \in \Omega_{(\hat{x}, \hat{\mu}, \hat{c})}$ with $\langle \nabla_{(x,\mu,c)} \bar{g}(\hat{x}, t, \hat{\mu}, \hat{c}), d \rangle = 0$, and

(iii) $p \in (0, 0.5)$ and $\bar{g}_{(x,\mu,c)}^{\circ\circ}(\hat{x}, t, \hat{\mu}, \hat{c}; d) < 0$ for all $d \in D(\hat{x}, \hat{\mu}, \hat{c})$ and $t \in \Omega_{(\hat{x}, \hat{\mu}, \hat{c})}$ with $\langle \nabla_{(x,\mu,c)} \bar{g}(\hat{x}, t, \hat{\mu}, \hat{c}), d \rangle = 0$, we have

$$\langle \nabla f(\hat{x}), d_1 \rangle \geq 0,$$

for all $d_1 \in \mathbb{R}^n$ satisfying $\langle \nabla_x g(\hat{x}, t) - \nabla_x^T v(\hat{x}, t) \hat{\mu}, d_1 \rangle \leq 0, t \in \Omega_{(\hat{x}, \hat{\mu}, \hat{c})}$.

We now compute the generalized second-order directional derivative $\bar{g}_{(x,\mu,c)}^{\circ\circ}(\hat{x}, t, \hat{\mu}, \hat{c}; d)$ for $d \in D(\hat{x}, \hat{\mu}, \hat{c})$ and $t \in \Omega(\hat{x}, \hat{\mu}, \hat{c})$.

Lemma

Let $d \in D(\hat{x}, \hat{\mu}, \hat{c})$ and $t \in \Omega(\hat{x}, \hat{\mu}, \hat{c})$. Then the following formula holds:

$$\begin{aligned} \bar{g}_{(x,\mu,c)}^{\circ\circ}(\hat{x}, t, \hat{\mu}, \hat{c}; d) &= d_1^T [\nabla_{xx}^2 g(\hat{x}, t) - \sum_{i=1}^l \hat{\mu}_i \nabla_{xx}^2 v_i(\hat{x}, t)] d_1 \\ &\quad - \sum_{i \in \hat{I}_{(\hat{x}, \hat{\mu}, \hat{c})}^+(t)} (\sqrt{\hat{c}} d_1^T \nabla_x v_i(\hat{x}, t) + \frac{d_{2i}}{\sqrt{\hat{c}}})^2 + \sum_{i=1}^l \frac{d_{2i}^2}{\hat{c}}, \end{aligned}$$

where $\hat{I}_{(\hat{x}, \hat{\mu}, \hat{c})}^+(t) = \{i \in \{1, \dots, l\} : \hat{c} v_i(\hat{x}, t) + \hat{\mu}_i > 0\}$.

We have the following corollary.

Corollary

Assume that the following conditions hold:

- (i) $G_{int}^{\frac{1}{2}}(x, \mu, c)$ is exact at $(\hat{x}, \hat{\mu}, \hat{c})$;
- (ii) $g(\cdot, t)$ and $-v_i(\cdot, t)$ ($i = 1, \dots, l$) are concave for each $t \in \Omega$; and
- (iii) $\hat{I}_{(\hat{x}, \hat{\mu}, \hat{c})}^+(t) = \{1, \dots, l\}$ and $\langle \nabla_x v_i(\hat{x}, t), d_1 \rangle = 0$ for $d \in D(\hat{x}, \hat{\mu}, \hat{c})$, $t \in \Omega(\hat{x}, \hat{\mu}, \hat{c})$ and $i \in \hat{I}^+(t)$. Then we have

$$\langle \nabla f(\hat{x}), d_1 \rangle \geq 0,$$

for all $d_1 \in \mathbb{R}^n$ satisfying $\langle \nabla_x g(\hat{x}, t) - \nabla_x^T v(\hat{x}, t) \hat{\mu}, d_1 \rangle \leq 0$, $t \in \Omega(\hat{x}, \hat{\mu}, \hat{c})$.

- 1 Introduction
- 2 KKT conditions of (NLP)
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)
- 6 Conclusions**
- 7 References

- For (NLP), we discussed the first-order optimality conditions by Dini-directional derivative, contingent directional derivative and subderivative respectively.
- For (SIP) and (GSIP), we investigated the first-order optimality conditions by Dini-directional derivative.

- 1 Introduction
- 2 KKT conditions of (NLP)
- 3 KKT-type Penalty Terms and Their Characterizations
- 4 Second-order Necessary Conditions via Exact Penalty Functions
- 5 KKT conditions of (SIP) and (GSIP)
- 6 Conclusions
- 7 References**

