

## LOCAL SOLUTIONS OF CONSTRAINED MINIMIZATION PROBLEMS AND CRITICAL POINTS OF LIPSCHITZ FUNCTIONS

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**Abstract.** In this paper we use the penalty approach in order to study two constrained nonconvex minimization problems with locally Lipschitzian objective and constraint functions in a Banach space. We show that a local minimizer of the constrained minimization problem which is not a critical point of the constraint function is also a local minimizer of a corresponding unconstrained penalized problem if a penalty coefficient is large enough.

### 1. INTRODUCTION AND THE MAIN RESULT

Penalty methods are an important and useful tool in constrained optimization. See, for example, [1, 2, 4] and the references mentioned there. In this paper we use the penalty approach in order to study two constrained nonconvex minimization problems with locally Lipschitzian objective and constraint functions in a Banach space. The first problem is an equality-constrained problem and the second one is an inequality-constrained problem. A penalty function is said to have the exact penalty property if there is a penalty coefficient for which a solution of an unconstrained penalized problem is a solution of the corresponding constrained problem. The notion of exact penalization was introduced by Eremin [5] and Zangwill [12] for use in the development of algorithms for nonlinear constrained optimization. Since that time exact penalty functions have continued to play a key role in the theory of mathematical programming [1-4, 6-10]. A local exactness of penalties was studied in [6, 8, 10]. For more discussions and various applications of exact penalization to various constrained optimization problems see [1, 2, 4, 10].

Usually the exact penalty property is related to calmness of the perturbed constraint function. In [14] we use an assumption of different nature which is not difficult to verify. In particular, we show in [14] that the problem  $f(x) \rightarrow \min$

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subject to  $g(x) = c$  possesses the exact penalty if the real number  $c$  is not a critical value of the function  $g$ . In other words the set  $g^{-1}(c)$  does not contain a critical point of the function  $g$ . Note that in [14] we used the notion of a critical point of a Lipschitz function introduced in [13]. The result of [14] was generalized in [15] for a constrained minimization problem with an arbitrary number of mixed constraints. Moreover, in [15] we do not assume that the set  $g^{-1}(c)$  does not contain a critical point of the function  $g$ . Instead of it we suppose that the set  $g^{-1}(c)$  does not contain a critical point of the function  $g$  which is a minimizer of the constrained minimization problem. In the present paper we make another development of the result of [14] and establish the existence of a local penalty. More precisely, we show that a local minimizer of the constrained minimization problem which is not a critical point of the constraint function is also a local minimizer of a corresponding unconstrained penalized problem if a penalty coefficient is large enough.

Let  $\mathbf{R}$  be the set of all real numbers,  $(X, \|\cdot\|)$  be a Banach space,  $(X^*, \|\cdot\|_*)$  its dual space and let  $\phi : X \rightarrow \mathbf{R}$  be a locally Lipschitzian function. For each  $x \in X$  let

$$\phi^0(x, h) = \limsup_{t \rightarrow 0^+, y \rightarrow x} [\phi(y + th) - \phi(y)]/t, \quad h \in X$$

be the Clarke generalized directional derivative of  $\phi$  at the point  $x$  [3], let

$$\partial\phi(x) = \{l \in X^* : \phi^0(x, h) \geq l(h) \text{ for all } h \in X\}$$

be Clarke's generalized gradient of  $\phi$  at  $x$  [3] and set

$$(1.1) \quad \Xi_\phi(x) = \inf\{\phi^0(x, h) : h \in X \text{ and } \|h\| \leq 1\}$$

(see [13, 14]).

A point  $x \in X$  is called a critical point of  $\phi$  if  $0 \in \partial\phi(x)$  [13, 14]. It is not difficult to see that  $x \in X$  is a critical point of  $\phi$  if and only if  $\Xi_\phi(x) \geq 0$ .

A real number  $c \in \mathbf{R}$  is called a critical value of  $\phi$  if there is a critical point  $x$  of  $\phi$  such that  $\phi(x) = c$ .

For each  $x \in X$  and each  $r > 0$  put

$$B(x, r) = \{y \in X : \|x - y\| \leq r\}.$$

Suppose that a function  $f : X \rightarrow \mathbf{R} \cup \{\infty\}$ , a function  $g : X \rightarrow \mathbf{R}$  is locally Lipschitzian and that a real number  $c$  is such that the set  $g^{-1}(c)$  is nonempty.

We consider the constrained problems

$$(P_e) \quad f(x) \rightarrow \min \text{ subject to } x \in g^{-1}(c)$$

and

$$(P_i) \quad f(x) \rightarrow \min \text{ subject to } x \in g^{-1}((-\infty, c]).$$

We associate with these two problems the corresponding families of unconstrained minimization problems

$$(P_{\lambda_e}) \quad f(x) + \lambda|g(x) - c| \rightarrow \min, \quad x \in X$$

and

$$(P_{\lambda_i}) \quad f(x) + \lambda \max\{g(x) - c, 0\} \rightarrow \min, \quad x \in X$$

where  $\lambda > 0$ .

The following theorem is our main result.

**Theorem 1.1.** *Assume that*

$$(1.2) \quad \bar{x} \in X \text{ satisfies } g(\bar{x}) = c,$$

*$\bar{x}$  is not a critical point of  $g$  and that there exists  $\bar{r} > 0$  such that the following properties hold: the function  $f$  is finite-valued and Lipschitzian on the set  $B(\bar{x}, \bar{r})$ ;*

$$(1.3) \quad f(x) \geq f(\bar{x}) \text{ for each } x \in B(\bar{x}, \bar{r}) \cap g^{-1}(c).$$

*Then there exist  $r_1 > 0$  and  $\Lambda_0 > 0$  such that if  $\lambda \geq \Lambda_0$  and if  $x \in B(\bar{x}, r_1)$  satisfies*

$$f(x) + \lambda|g(x) - c| \leq f(\bar{x}),$$

*then  $g(x) = c$ .*

**Corollary 1.1.** *Assume that all the assumptions of Theorem 1.1 hold and let  $r_1 > 0$  and  $\Lambda_0 > 0$  be as guaranteed by Theorem 1.1. Then if  $\lambda \geq \Lambda_0$  and if  $x \in B(\bar{x}, r_1)$  satisfies*

$$f(x) + \lambda \max\{g(x) - c, 0\} \leq f(\bar{x}),$$

*then  $g(x) \leq c$ . Denote by  $\text{co}(A)$  the convex hull of a set  $A \subset X^*$ .*

Theorem 1.1 implies the following result which establishes a necessary optimality condition for the problem  $(P_e)$ .

**Proposition 1.1.** *Assume that all the assumptions of Theorem 1.1 hold. Then there is  $\Lambda_0 > 0$  such that*

$$0 \in \partial f(\bar{x}) + \Lambda_0 \text{co}(\partial g(\bar{x}) \cup (-\partial g(\bar{x}))).$$

*Proof.* Let  $r_1 > 0$  and  $\Lambda_0 > 0$  be as guaranteed by Theorem 1.1. We may assume that  $r_1 < \bar{r}$ . Then for each  $x \in B(\bar{x}, r_1)$

$$f(\bar{x}) + \Lambda_0|g(\bar{x}) - c| = f(\bar{x}) \leq f(x) + \Lambda_0|g(x) - c|.$$

This implies that

$$0 \in \partial f(\bar{x}) + \Lambda_0 \partial(|g(\cdot) - c|)(\bar{x}) \subset \partial f(\bar{x}) + \Lambda_0 \text{co}(\partial g(\bar{x}) \cup (-\partial g(\bar{x}))).$$

Proposition 1.1 is proved. ■

Corollary 1.1 implies the following result which establishes a necessary optimality condition for the problem  $(P_i)$ .

**Proposition 1.2.** *Assume that all the assumptions of Theorem 1.1 hold and that*

$$f(x) \geq f(\bar{x}) \text{ for each } x \in B(\bar{x}, \bar{r}) \cap g^{-1}((-\infty, c]).$$

*Then there is  $\Lambda_0 > 0$  such that*

$$0 \in \partial f(\bar{x}) + \Lambda_0 \text{co}(\partial g(\bar{x}) \cup \{0\}).$$

*Proof.* Let  $r_1 > 0$  and  $\Lambda_0 > 0$  be as guaranteed by Theorem 1.1. We may assume that  $r_1 < \bar{r}$ . Corollary 1.1 implies that for each  $x \in B(\bar{x}, r_1)$

$$f(\bar{x}) + \Lambda_0 \max\{g(\bar{x}) - c, 0\} = f(\bar{x}) \leq f(x) + \Lambda_0 \max\{g(x) - c, 0\}.$$

This implies that

$$0 \in \partial f(\bar{x}) + \Lambda_0 \partial(\max\{g(\cdot) - c, 0\})(\bar{x}) \subset \partial f(\bar{x}) + \Lambda_0 \text{co}(\partial g(\bar{x}) \cup \{0\}).$$

Proposition 1.2 is proved. ■

## 2. AN AUXILIARY RESULT

Let  $(Y, \|\cdot\|)$  and  $(Z, \|\cdot\|)$  be Banach spaces,  $A \subset Y$  and  $B \subset Z$ . We say that  $h : A \rightarrow B$  is an  $\mathcal{L}$ -mapping if for each  $x \in A$  there exists  $r > 0$  such that the restriction  $h : A \cap B(x, r) \rightarrow B$  is Lipschitz.

Assume that  $g : X \rightarrow \mathbf{R}$  is a locally Lipschitz function. In the sequel we use the following auxiliary result obtained in [16].

**Lemma 2.1.** *Assume that  $x_0 \in X$ ,  $\delta > 0$  and that  $\Xi_g(x_0) < -\delta$ . Then there exist  $r > 0$  and an  $\mathcal{L}$ -mapping  $V : X \rightarrow X$  such that*

$$\begin{aligned} \|V(x)\| &\leq 2 \text{ for all } x \in X, \\ g^0(x, V(x)) &\leq 0 \text{ for all } x \in X, \\ g^0(x, V(x)) &\leq -\delta \text{ for all } x \in B(x_0, r). \end{aligned}$$

3. PROOF OF THEOREM 1.1

There exists  $M_0 > 0$  such that

$$(3.1) \quad |f(z)| \leq M_0 \text{ for all } z \in B(\bar{x}, \bar{r})$$

and

$$(3.2) \quad |f(z_1) - f(z_2)| \leq M_0 \|z_1 - z_2\| \text{ for all } z_1, z_2 \in B(\bar{x}, \bar{r}).$$

Since  $\bar{x}$  is not a critical point of  $g$  there is  $\delta > 0$  such that

$$(3.3) \quad \Xi_g(\bar{x}) < -\delta.$$

By Lemma 2.1 and (3.3) there exist  $r_0 > 0$  and an  $\mathcal{L}$ -mapping  $V : X \rightarrow X$  such that

$$(3.4) \quad \|V(x)\| \leq 2 \text{ for all } x \in X,$$

$$(3.5) \quad g^0(x, V(x)) \leq 0 \text{ for all } x \in X$$

and

$$(3.6) \quad g^0(x, V(x)) \leq -\delta \text{ for all } x \in B(\bar{x}, r_0).$$

We may assume without loss of generality that

$$(3.7) \quad r_0 < \bar{r}.$$

It was shown in [11] that the mapping  $V$  generates a flow  $\sigma : \mathbf{R} \times X \rightarrow X$  such that the mapping  $\sigma$  is continuous and that

$$(3.8) \quad (d/dt)\sigma(t, x) = V(\sigma(t, x)) \text{ for all } x \in X \text{ and all } t \in \mathbf{R}.$$

Assume that

$$(3.9) \quad x \in X, t_1, t_2 \in \mathbf{R}, \text{ and } t_1 < t_2.$$

By the properties of the Clarke generalized directional derivative [3]

$$(3.10) \quad g(\sigma(t_2, x)) - g(\sigma(t_1, x)) \leq (t_2 - t_1)l((d\sigma/dt)(\sigma(s, x))),$$

where

$$(3.11) \quad s \in [t_1, t_2] \text{ and } l \in \partial g(\sigma(s, x)).$$

By (3.10), (3.11), (3.8), (3.9) and (3.5),

$$(3.12) \quad g(\sigma(t_2, x)) - g(\sigma(t_1, x)) = l(V(\sigma(s, x)))(t_2 - t_1) \leq 0.$$

Thus

$$g(\sigma(t_2, x)) - g(\sigma(t_1, x)) \leq 0$$

$$(3.13) \quad \text{for all } x \in X, \text{ each } t \in \mathbf{R} \text{ and each } t_2 > t_1.$$

There are

$$(3.14) \quad \tau_1 \in (0, 1), \quad r_1 \in (0, r_0)$$

such that

$$(3.15) \quad \begin{aligned} & \|\sigma(t, x) - \bar{x}\| < r_0 \\ & \text{for each } t \in [-\tau_1, \tau_1] \text{ and each } x \in B(\bar{x}, r_1). \end{aligned}$$

Assume now that

$$(3.16) \quad x \in B(\bar{x}, r_1), \quad t_1, t_2 \in [-\tau_1, \tau_1] \text{ and } t_1 < t_2.$$

By the properties of the Clarke generalized directional derivative [3], (3.8) and (3.16),

$$(3.17) \quad g(\sigma(t_2, x)) - g(\sigma(t_1, x)) = l(d\sigma/dt(\sigma(s, x)))(t_2 - t_1),$$

where

$$(3.18) \quad s \in [t_1, t_2] \text{ and } l \in \partial g(\sigma(s, x)).$$

By (3.17) and (3.8),

$$(3.19) \quad g(\sigma(t_2, x)) - g(\sigma(t_1, x)) = l(V(\sigma(s, x)))(t_2 - t_1).$$

In view of (3.18), (3.16) and (3.15),

$$(3.20) \quad \sigma(s, x) \in B(\bar{x}, r_0).$$

By (3.20) and (3.6),

$$(3.21) \quad g^0(\sigma(s, x), V(\sigma(s, x))) \leq -\delta.$$

It follows from (3.19), (3.18) and (3.21) that

$$(3.22) \quad g(\sigma(t_2, x)) - g(\sigma(t_1, x)) \leq -\delta(t_2 - t_1)$$

for each  $x \in B(\bar{x}, r_1)$  and each  $t_1, t_2 \in [-\tau_1, \tau_1]$  satisfying  $t_1 < t_2$ . By (3.22) for each  $x \in B(\bar{x}, r_1)$ ,

$$g(\sigma(\tau_1, x)) \leq g(x) - \delta\tau_1$$

and

$$(3.23) \quad g(\sigma(-\tau_1, x)) \geq g(x) + \delta\tau_1.$$

Choose a positive number  $\Lambda_0$  such that

$$(3.24) \quad \Lambda_0 > 2M_0\delta^{-1}\tau_1^{-1}.$$

Assume that

$$(3.25) \quad \lambda \geq \Lambda_0, \quad x \in B(\bar{x}, r_1)$$

and

$$(3.26) \quad f(x) + \lambda|g(x) - c| \leq f(\bar{x}).$$

We show that  $g(x) = c$ . Assume the contrary. Then

$$(3.27) \quad g(x) \neq c.$$

By (3.25), (3.26), (3.14), (3.7) and (3.1),

$$\Lambda_0|g(x) - c| \leq f(\bar{x}) + M_0 \leq 2M_0$$

and

$$(3.28) \quad |g(x) - c| \leq 2M_0\Lambda_0^{-1}.$$

In view of (3.23), (3.25), (3.28) and (3.24),

$$g(\sigma(\tau_1, x)) \leq g(x) - \delta\tau_1 \leq c + 2M_0\Lambda_0^{-1} - \delta\tau_1 < c$$

and

$$g(\sigma(-\tau_1, x)) \geq \delta\tau_1 + g(x) \geq \delta\tau_1 + c - 2M_0\Lambda_0^{-1} > c.$$

It follows from the inequality above, (3.22) and (3.25) that there is a unique

$$(3.29) \quad s \in [-\tau_1, \tau_1]$$

such that

$$(3.30) \quad g(\sigma(s, x)) = c.$$

In view of (3.30), (3.29), (3.22) and (3.25),

$$(3.31) \quad |c - g(x)| = |g(\sigma(s, x)) - g(\sigma(0, x))| \geq \delta|s|.$$

By (3.8) and (3.5),

$$(3.32) \quad \begin{aligned} \|x - \sigma(s, x)\| &= \|\sigma(0, x) - \sigma(s, x)\| \\ &\leq \left| \int_0^s \|V(\sigma(t, x))\| dt \right| \leq 2|s|. \end{aligned}$$

By (3.25), (3.29), (3.14) (3.15), (3.7), (3.2) and (3.32),

$$(3.33) \quad |f(x) - f(\sigma(s, x))| \leq M_0 \|x - \sigma(s, x)\| \leq 2M_0 |s|.$$

It follows from (3.30), (3.33), (3.31), (3.27) and (3.14) that

$$\begin{aligned} & f(\sigma(s, x)) + \lambda |g(\sigma(s, x)) - c| \\ &= f(\sigma(s, x)) \leq f(x) + 2M_0 |s| \\ &\leq f(x) + 2M_0 \delta^{-1} |c - g(x)| < f(x) + \Lambda_0 |c - g(x)|. \end{aligned}$$

Together with (1.3), (3.30), (3.29), (3.25), (3.15) and (3.7) this implies that

$$f(\bar{x}) \leq f(\sigma(s, x)) < f(x) + \lambda |g(x) - c|.$$

This contradicts (3.26). The contraction we have reached proves that  $g(x) = c$ . Theorem 1.1 is proved.

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#### REFERENCES

1. D. Boukari and A. V. Fiacco, Survey of penalty, exact-penalty and multiplier methods from 1968 to 1993, *Optimization*, **32** (1995), 301-334.
2. J. V. Burke, An exact penalization viewpoint of constrained optimization, *SIAM J. Control Optim.*, **29** (1991), 968-998.
3. F. H. Clarke, *Optimization and Nonsmooth Analysis*, Willey Interscience, 1983.
4. G. Di Pillo and L. Grippo, Exact penalty functions in constrained optimization, *SIAM J. Control Optim.*, **27** (1989), 1333-1360.
5. I. I. Eremin, The penalty method in convex programming, *Soviet Math. Dokl.*, **8** (1966), 459-462.
6. S.-P. Han and O. L. Mangasarian, Exact penalty function in nonlinear programming, *Math. Programming*, **17** (1979), 251-269.
7. J.-B. Hiriart-Urruty and C. Lemarechal, *Convex Analysis and Minimization Algorithms*, Springer, Berlin, 1993,
8. A. D. Ioffe, Necessary and sufficient conditions for a local minimum. I. A reduction theorem and first order conditions, *SIAM J. Control Optim.*, **17** (1979), 245-250.
9. B. S. Mordukhovich, Penalty functions and necessary conditions for the extremum in nonsmooth and nonconvex optimization problems, *Uspekhi Math. Nauk*, **36** (1981), 215-216.



10. B. S. Mordukhovich, *Variational Analysis and Generalized Differentiation, I: Basic Theory, II: Applications*, Springer, Berlin, 2006.
11. R. Palais, Lusternik-Schnirelman theory of Banach manifolds, *Topology*, **5** (1966), 115-132.
12. W. I. Zangwill, Nonlinear programming via penalty functions, *Management Sci.*, **13** (1967), 344-358.
13. A. J. Zaslavski, On critical points of Lipschitz functions on smooth manifolds, *Siberian Math. J.*, **22** (1981), 63-68.
14. A. J. Zaslavski, A sufficient condition for exact penalty in constrained optimization, *SIAM Journal on Optimization*, **16** (2005), 250-262.
15. A. J. Zaslavski, Existence of exact penalty for optimization problems with mixed constraints in Banach spaces, *J. Math. Anal. Appl.*, **324** (2006), 669-681.
16. A. J. Zaslavski, Stability of exact penalty for classes of constrained minimization problems in Banach spaces, *Taiwanese J. Math.*, **12** (2008), 1493-1510.

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