

## Continuity of $\varepsilon$ -Approximate Solution Set

Kazunori Yokoyama (横山一憲) \*

### Abstract

In this note, we present the continuity of  $\varepsilon$ -approximate solutions set for the nonlinear programming problems. In [1], the similar continuity for the unconstrained problem was shown. We show another result. The continuity of the approximate solution set is estimated by using the  $\rho$ -distance.

## 1 Preliminaries

In this note, we consider the following nonlinear programming problem:

(P) minimize  $f(x)$

subject to  $g(x) \leq 0$

where  $g = (g_1, \dots, g_m)$ ,  $f$  and  $g_i (i = 1, \dots, m) : \mathbf{R}^n \rightarrow \mathbf{R}$ .

We denote the feasible set  $\{x \in \mathbf{R}^n \mid g(x) \leq 0\}$  by  $K$ .

We suppose that the following assumption is satisfied.

**Assumption.** Let  $f$  and  $g_i (i = 1, \dots, m)$  be convex and  $f$  be bounded from below. Let  $K \neq \emptyset$ . The parameter  $\varepsilon$  is positive.

For the problem (P), the  $\varepsilon$ -approximate solution is well known as follows.

**Definition 1.1.** An element  $\bar{x} \in K$  is said to be an  $\varepsilon$ -approximate solution for (P) if and only if  $\bar{x}$  satisfies that  $f(x) + \varepsilon \geq f(\bar{x})$  for any  $x \in K$ .

We set  $\inf_K f = \inf\{f(x) \mid x \in K\}$  and denote the  $\varepsilon$ -approximate solution set  $\{\bar{x} \in K \mid f(x) + \varepsilon \geq f(\bar{x})$  for any  $x \in K\}$  by  $A(\varepsilon)$ .

Clearly, we have  $A(\varepsilon) \neq \emptyset$  under the above assumption.

To estimate the approximate solution set, we define the  $\rho$ -distance and the Hausdorff distance:

---

\*Department of Management and Information Sciences, Niigata University of Management, Kamo, Niigata, 959-13, Japan, e-mail address:kazu@duck.niigataum.ac.jp

**Definition 1.2.** For  $C \subset \mathbf{R}^n$ ,

$$d(x, C) = \inf\{\|x - y\| \mid y \in C\}$$

denotes the distance from  $x$  to  $C$ . For any  $C, D \subset \mathbf{R}^n, \rho \geq 0$ , we set

$$C_\rho = C \cap \rho B$$

where  $B = \{x \in \mathbf{R}^n \mid \|x\| \leq 1\}$ : unit ball.

For,  $\rho \geq 0$ , the  $\rho$ -distance is defined to be

$$d_\rho(C, D) = \max\{e(C_\rho, D), e(D, C_\rho)\}$$

where  $e(C, D) = \sup_{x \in C} d(x, D)$ , and the Hausdorff distance between  $C$  and  $D$  is

$$\text{haus}(C, D) = \max\{e(C, D), e(D, C)\}.$$

## 2 The unconstrained case

In this section we introduce the result of [1]. In [1], Attouch and Wets investigated the Lipschitz continuity of the approximate solution set for the unconstrained programming problems. The problem is as follows:

minimize  $F(x)$  where  $F: \mathbf{R}^n \rightarrow \mathbf{R}$ .

For this problem, the approximate solution set is defined to be

$$\varepsilon - \text{argmin} F = \{\bar{x} \mid \inf F + \varepsilon \geq F(\bar{x})\}$$

where  $\inf F = \inf\{F(x) \mid x \in \mathbf{R}^n\}$ . Also, we denote level set of a function  $f$  by

$$\text{lev}_\alpha F = \{x \in \mathbf{R}^n \mid F(x) \leq \alpha\}.$$

To show the Lipschitz continuity, the important lemma was proved in [1].

**Lemma 2.1.** [1, Lemma4.1.] Suppose that there exists  $\rho_0 > 0$  such that

$$(\varepsilon - \text{argmin} F)_{\rho_0} \neq \emptyset \text{ for all } \varepsilon > 0.$$

Then, for all  $\alpha > \inf F$  and  $\eta \geq 0$ ,

$$\text{for all } \hat{x} \in \text{lev}_{(\alpha+\eta)} F, \quad d(\hat{x}, \text{lev}_\alpha F) \leq \eta \frac{\|\hat{x}\| + \rho_0}{(\eta + \alpha) - \inf F}$$

which in turn implies that for all  $\rho \geq \rho_0$ ,

$$d_\rho((\alpha + \eta) - \text{argmin} F, \alpha - \text{argmin} F) \leq \eta \frac{\rho_0 + \rho}{(\eta + \alpha) - \inf F}.$$

### 3 The constrained case

We apply lemma 2.1. to the constrained programming problems (P).

**Lemma 3.1.** Suppose that there exists  $\rho_0 > 0$  such that

$$A(\varepsilon)_{\rho_0} \neq \emptyset \text{ for all } \varepsilon > 0.$$

Then, for all  $\inf_K f + \varepsilon > \inf_K f$ ,

$$\text{for all } \hat{x} \in A(\varepsilon_2), d(\hat{x}, A(\varepsilon_1)) \leq (\varepsilon_2 - \varepsilon_1) \frac{\|\hat{x}\| + \rho_0}{\varepsilon_1}$$

which in turn implies that for all  $\rho \geq \rho_0$ ,

$$d_\rho(A(\varepsilon_2), A(\varepsilon_1)) \leq (\varepsilon_2 - \varepsilon_1) \frac{\rho_0 + \rho}{\varepsilon_1}.$$

However the above assumption does not hold in the following easy example.

**Example 3.1.** Let  $f(x_1, x_2) = 2^{x_1+x_2}$ :convex and  $g(x_1, x_2) = (x_1, x_2)$ :convex. Then, we have

$$A(0) = \emptyset \text{ and } A(\varepsilon) = \{x \mid x \leq 0 \text{ and } 2^{x_1+x_2} \leq \varepsilon\}.$$

So, it holds

$$\|\bar{x}\| \rightarrow +\infty \text{ where } \bar{x} \in A(\varepsilon) \text{ as } \varepsilon \rightarrow 0.$$

We would like to change the assumption and show the similar result.

**Proposition 3.1.** We suppose that the strong Slater condition is satisfied i.e. there are  $x_s \in \mathbf{R}^n, \delta > 0$  such that

$$\delta \tilde{B} \subset H(x_s) + \mathbf{R}_+^{(m+1)}.$$

where  $H(x) = (g(x), f(x) - \inf_K f - \varepsilon_1), \tilde{B} \subset \mathbf{R}_+^{(m+1)}$ : unitball.

Also, suppose there exists  $C > 0$  such that

$$\sup_{x_0 \in A(\varepsilon_2) \setminus A(\varepsilon_1)} \|x_0 - x_s\| \leq C.$$

Then, we have

$$(A(\varepsilon_2), A(\varepsilon_1)) \leq \frac{(\varepsilon_2 - \varepsilon_1)C}{\delta}.$$

**Remark.** The assumption of proposition 3.1. is satisfied in example 3.1. Let  $\varepsilon_2 = 0.5, \varepsilon_1 = 0.25$ . So, there exist  $x_s = (-2, -2)$  and  $\delta = 0.125$  such that the strong Slater condition is satisfied. Since  $A(\varepsilon_2) = \{x \mid x \leq 0, x_2 \leq -x_1 - 1\}, A(\varepsilon_1) = \{x \mid x \leq 0, x_2 \leq -x_1 - 2\}$ , we have

$$\sup_{x_0 \in A(\varepsilon_2) \setminus A(\varepsilon_1)} \|x_0 - x_s\| \leq \|(-1, 0) - (-2, -2)\| = \sqrt{5} \text{ and } \text{haus}(A(0.5), A(0.25)) \leq \frac{(0.5-0.25)\sqrt{5}}{0.125}.$$

The above strong Slater condition is equivalent to the ordinary one.

**Proposition 3.2.** [9] The strong Slater condition is satisfied if and only if the Slater condition be done.

## References

- [1] H.Attouch and R.J.-B.Wets, Quantitative Stability of Variational Systems : 3,  $\varepsilon$ -Approximate Solutions, Math. Program., Vol.61, pp.197-214, 1993
- [2] D.P.Bertsekas and S.K.Mitter, A Descent Numerical Method for Optimization Problems with Nondifferential Cost Functionals, SIAM J.Control, Vol.11, pp.637-652, 1973
- [3] A.M.Geoffrion, Objective function approximations in mathematical programming, Maht. Program., Vol.13, pp.233-37, 1977
- [4] 伊藤輝生, 非線形計画問題の罰関数法による数値解の誤差範囲, 計測自動制御学会論文集 13-2, pp.142-147, 1977
- [5] C.Lemaréchal, Nondifferentiable Optimizaiton, in G.L.Nemhauser et al. eds., *Handbooks in OR and MS, Vol.1* (Elsevier), pp.529-572, 1989
- [6] S.M.Robinson, An application of error bound for convex programming problems in linear space, SIAM J. Control, Vol.12, pp.271-273, 1975
- [7] S.M.Robinson, Regularity and stability for convex multivalued functions, Maht. Oper. Res., Vol.1, No.2, pp.130-143, 1976
- [8] K.Yokoyama,  $\varepsilon$ -Optimality Criteria for Convex Programming Problems via Exact Penalty Functions, Math. Program., Vol.56, pp.233-243, 1992
- [9] K.Yokoyama, 非線形計画問題の近似最適解, RIMS Kokyuroku, Vol.945, pp.27-29, 1996