

## OPTIMALITY CONDITIONS OF A CLASS OF SPECIAL NONSMOOTH PROGRAMMING <sup>\*1)</sup>

Song-bai Sheng

(Colleges of Science, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China)

Hui-fu Xu

(Australian Graduate School of Management, the University of New South Wales, Sydney, Australia)

### Abstract

In this paper, we investigate the optimality conditions of a class of special nonsmooth programming  $\min_{x \in R^n} F(x) = \sum_{i=1}^m |\max\{f_i(x), c_i\}|$  which arises from  $L_1$ -norm optimization, where  $c_i \in R$  is constant and  $f_i \in C^1, i = 1, 2, \dots, m$ . These conditions can easily be tested by computer.

*Key words:* Generalized gradient, Directional derivative, Optimality conditions, Nonsmooth programming.

### 1. Introduction

Consider a class of special nonsmooth programming

$$\min_{x \in R^n} F(x) = \sum_{i=1}^m |\max\{f_i(x), c_i\}| \quad (1.1)$$

where constant  $c_i \in R, f_i \in C^1, i = 1, 2, \dots, m$ , and in general there is at least one  $c_i < 0$ . The problem (1.1) arises from the  $L_1$  norm optimization. For example, the discrete  $L_1$  linear approximation[2], the  $L_1$  solution of an overdetermined linear systems[3], the censored discrete linear  $L_1$  approximation[7,8]

$$\min_{x \in R^n} F(x) = \sum_{i=1}^m |y_i - \max\{a_i^T x, z_i\}| \quad (1.2)$$

and from the  $L_1$  penalty function model of constrained programming[5,6]

$$\min_{x \in R^n} F(x) = f(x) + \lambda \sum_{i=1}^m \max\{g_i(x), 0\} \quad (1.3)$$

where  $\lambda > 0$  is a penalty coefficient.

The aim of this paper is to investigate the optimality conditions of the problem(1.1). It is well known that for the general nonsmooth function  $F(x)$ , i.e.,  $F(x)$  is locally Lipschitz continuous at any  $x$ , the necessary condition of a local minimizer  $x^*$  of  $F(x)$  is  $0 \in \partial F(x^*)$ . This condition is not easily tested by computer. For the special problem (1.1), we can obtain the necessary conditions and sufficient conditions of a local minimizer  $x^*$  of  $F(x)$ , which can easily be tested by computer.

---

\* Received July 31, 2001.

<sup>1)</sup> The project was supported by NNSFC(No. 19771047) and NSFJS (BK97059).

In the next section, we consider the differential properties of  $F(x)$  and establish a characterization of the generalized gradient  $\partial F(x)$ . In section 3, we discuss the descent direction of  $F(x)$  based on the gradient of  $f_i(x), i = 1, 2, \dots, m$ . Then we provide necessary conditions and sufficient conditions for a (strict) local minimizer of  $F(x)$ . In the last section, we provide the optimality conditions of problem(1.2) and (1.3).

### 2. Differential Properties

The nonlinear and nonconvex function  $F(x)$  defined by (1.1) can be written as the sum of smooth functions and nonsmooth functions. To do this, for any given  $x \in R^n$ , define the index sets  $\Gamma_j(x), j = 1, \dots, 5$ , by

$$\Gamma_1(x) = \{i \in [1 : m] | f_i(x) > c_i \geq 0 \text{ or } f_i(x) > c_i, c_i < 0 \text{ and } f_i(x) \neq 0\},$$

$$\Gamma_2(x) = \{i \in [1 : m] | f_i(x) < c_i\}, \quad \Gamma_3(x) = \{i \in [1 : m] | f_i(x) = c_i \geq 0\},$$

$$\Gamma_4(x) = \{i \in [1 : m] | f_i(x) = c_i < 0\}, \quad \Gamma_5(x) = \{i \in [1 : m] | f_i(x) = 0 \text{ and } c_i < 0\}.$$

The sets  $\{\Gamma_j(x), j = 1, \dots, 5\}$  form a disjoint partition of  $\{1, 2, \dots, m\}$ , that is

$$\bigcup_{j=1}^5 \Gamma_j(x) = \{1, 2, \dots, m\}, \quad \forall x \in R^n,$$

$$\Gamma_i(x) \cap \Gamma_j(x) = \phi, \quad \forall i \neq j \quad \forall x \in R^n.$$

For the simplicity, let  $\Gamma_{ijk} = \Gamma_i(x) \cup \Gamma_j(x) \cup \Gamma_k(x)$ , we have

$$F(x) = \sum_{i \in \Gamma_{12}} |\max\{f_i(x), c_i\}| + \sum_{i \in \Gamma_{345}} |\max\{f_i(x), c_i\}| \tag{2.1}$$

For  $i \in \Gamma_1$  the component function  $|\max\{f_i(x), c_i\}| = \text{sign}(f_i(x))f_i(x)$ , which is smooth in a neighborhood of  $x$  with gradient  $\text{sign}(f_i(x))\nabla f_i(x)$ . For  $i \in \Gamma_2$  the component function  $|\max\{f_i(x), c_i\}| = |c_i|$ , which is constant and hence smooth in a neighborhood of  $x$ . Thus the gradient of the smooth part of  $F(x)$  is

$$g(x) = \nabla \left( \sum_{i \in \Gamma_{12}} |\max\{f_i(x), c_i\}| \right) = \sum_{i \in \Gamma_1} \text{sign}(f_i(x))\nabla f_i(x) \tag{2.2}$$

A definition of the generalized gradient  $\partial f(x)$  [4] of a piecewise smooth function at a point  $x$  is

$$\partial f(x) = \text{co}\{v \in R^n | \exists \text{ a sequence } \{x_k\} \text{ such that } x_k \rightarrow x, \nabla f(x_k) \text{ exists } \forall k \text{ and } \nabla f(x_k) \rightarrow v \text{ as } k \rightarrow +\infty\} \tag{2.3}$$

where  $\text{co}$  denotes the convex hull. Furthermore,  $\partial f(x)$  is a nonempty compact convex set in  $R^n$ .

Now, for  $i \in \Gamma_{345}$  the corresponding component functions are piecewise smooth. According to (2.3) the generalized gradients are given by

$$\partial |\max\{f_i(x), c_i\}| = \begin{cases} \text{co}\{0, \nabla f_i(x)\} = \{v \in R^n | v = \lambda_i \nabla f_i(x), 0 \leq \lambda_i \leq 1\}, i \in \Gamma_3; \\ \text{co}\{0, -\nabla f_i(x)\} = \{v \in R^n | v = \lambda_i \nabla f_i(x), -1 \leq \lambda_i \leq 0\}, i \in \Gamma_4; \\ \text{co}\{\nabla f_i(x), -\nabla f_i(x)\} = \{v \in R^n | v = \lambda_i \nabla f_i(x), -1 \leq \lambda_i \leq 1\}, i \in \Gamma_5. \end{cases}$$