

## Chapter 6

# Constrained Optimization Algorithmic Methods

In this chapter we discuss how we can solve certain constrained problems by applying the algorithmic methods developed for unconstrained problems.

### 6.1 Exterior Penalty Methods

In exterior penalty methods we replace the constrained problem by a sequence of unconstrained problems. The solutions of the unconstrained problems generally violate the constraints of the original problem while giving the penalized functional a lower value than the constrained functional. The idea is that the sequence of solutions of the unconstrained problems converge to the solution of the constrained problem.

Consider the constrained problem

$$\begin{aligned} & \min f(x) \\ & \text{subject to} \\ & g(x) \leq 0 \\ & h(x) = 0 \\ & x \in X \end{aligned} \tag{P_1}$$

where  $X$  is a nonempty open subset of  $\mathbb{R}^n$ ,  $g(x) = (g_1(x), \dots, g_m(x))^T$ ,  $h(x) = (h_1(x), \dots, h_k(x))^T$ .

Define  $\phi, \psi : \mathbb{R} \rightarrow \mathbb{R}$  as follows:

$$\begin{cases} \phi(t) = 0 & \text{if } t \leq 0 \\ \phi(t) > 0 & \text{if } t > 0 \end{cases}$$
$$\begin{cases} \psi(t) = 0 & \text{if } t = 0 \\ \psi(t) > 0 & \text{if } t \neq 0 \end{cases}$$

Corresponding to  $(P_1)$  and  $\mu \geq 0$  we consider the unconstrained penalized problem  $(P_{1\mu})$

$$(P_{1\mu}) = \min \{f(x) + \mu \alpha(x)\}$$

where

$$\alpha(x) = \sum_{i=1}^m \phi(g_i(x)) + \sum_{i=1}^k \psi(h_i(x))$$

We make the standing assumptions that  $f, g, h, \phi$  and  $\psi$  are continuous.

We solve  $(P_{1\mu})$  for increasing values of  $\mu \geq 0$  and consider the convergence property of  $\{x_\mu\}_{\mu \geq 0}$  as  $\mu \nearrow \infty$ , where  $x_\mu$  is a solution of  $(P_{1\mu})$ . The function  $f(x) + \mu \alpha(x)$  is called a penalized functional and  $\phi(g_i(x))$  and  $\psi(h_i(x))$  are called penalty terms.

**Lemma 6.1.1** *Let  $\theta(\mu) = \inf \{f(x) + \mu \alpha(x) \mid x \in X\}$  and  $x_\mu \in X$  be such that  $\theta(x_\mu) = f(x_\mu) + \mu \alpha(x_\mu)$ . Then,*

- (i)  $\inf \{f(x) \mid x \in X, g(x) \leq 0, h(x) = 0\} \geq \sup_{\mu \geq 0} \theta(\mu)$
- (ii) *The function  $\mu \mapsto f(x_\mu)$  and  $\mu \mapsto \theta(\mu)$  are nondecreasing while the function  $\mu \mapsto \alpha(x_\mu)$  is nonincreasing.*

*Proof:* For any  $x \in X$  such that  $g(x) \leq 0$ ,  $h(x) = 0$ , and any  $\mu \geq 0$  we have

$$f(x) = f(x) + \mu \alpha(x) \geq \inf \{f(x) + \mu \alpha(x) \mid x \in X\} = \theta(\mu)$$

Thus,

$$\begin{aligned} \theta(\mu) &\leq f(x), & \mu &\geq 0 \\ \sup_{\mu} \theta(\mu) &\leq f(x) \\ \mu &\geq 0 \end{aligned}$$

Thus,

$$\sup_{\mu \geq 0} \theta(\mu) \leq \inf \{f(x) \mid x \in X, g(x) \leq 0, h(x) = 0\}$$

proving (i).

Next, we suppose  $0 \leq \mu < \lambda$ , and

$$\theta(\lambda) = f(x_\lambda) + \lambda \alpha(x_\lambda) = \min \{f(x) + \lambda \alpha(x) \mid x \in X\} \quad (6.1)$$

$$\theta(\mu) = f(x_\mu) + \mu \alpha(x_\mu) = \min \{f(x) + \mu \alpha(x) \mid x \in X\} \quad (6.2)$$

We have

$$\theta(\mu) = f(x_\mu) + \mu \alpha(x_\mu) \leq f(x_\lambda) + \mu \alpha(x_\lambda) \leq f(x_\lambda) + \lambda \alpha(x_\lambda) = \theta(\lambda)$$

Thus,  $\mu \mapsto \theta(\mu)$  is nondecreasing.

$$f(x_\lambda) + \lambda \alpha(x_\lambda) \leq f(x_\mu) + \lambda \alpha(x_\mu) \quad (6.3)$$

$$f(x_\mu) + \mu \alpha(x_\lambda) \leq f(x_\lambda) + \mu \alpha(x_\lambda) \quad (6.4)$$

$$(6.5)$$

From (6.3) we have

$$\lambda [\alpha(x_\lambda) - \alpha(x_\mu)] \leq f(x_\mu) - f(x_\lambda) \quad (6.6)$$

From (6.4) we have

$$f(x_\mu) - f(x_\lambda) \leq \mu [\alpha(x_\lambda) - \alpha(x_\mu)] \quad (6.7)$$

From (6.7) we have

$$-\mu [\alpha(x_\lambda) - \alpha(x_\mu)] \leq f(x_\lambda) - f(x_\mu) \quad (6.8)$$

Adding inequalities (6.6) and (6.8) we have

$$(\lambda - \mu) [\alpha(x_\lambda) - \alpha(x_\mu)] \leq 0 \quad (6.9)$$

Since  $\lambda - \mu > 0$  we have

$$\begin{aligned} \alpha(x_\lambda) - \alpha(x_\mu) &\leq 0 \\ \alpha(x_\lambda) &\leq \alpha(x_\mu). \end{aligned}$$

Thus,  $\mu \mapsto \alpha(x_\mu)$  is nonincreasing.

From (6.4) we have

$$f(x_\mu) - f(x_\lambda) \leq \mu [\alpha(x_\lambda) - \alpha(x_\mu)] \quad (6.10)$$

Since  $\mu \geq 0$  and  $\alpha(x_\lambda) - \alpha(x_\mu) \leq 0$ , (6.10) gives

$$f(x_\mu) - f(x_\lambda) \leq 0.$$

Thus,

$$f(x_\mu) \leq f(x_\lambda)$$

showing that  $\mu \mapsto \alpha(x_\mu)$  is nondecreasing.  $\square$

**Theorem 6.1.1** *Suppose that the feasible set for  $(\mathcal{P}_1)$  is nonempty. Assume that there exists  $x_\mu \in X$  such that  $\theta(\mu) = f(x_\mu) + \mu \alpha(x_\mu)$  for each  $\mu \geq 0$ . Assume that  $\{x_\mu | \mu \geq 0\}$  is a compact subset of  $X$ . Then, there exists  $x^* \in X$  such that*

$$\begin{aligned} & \inf \{f(x) | x \in X, g(x) \leq 0, h(x) = 0\} \\ &= \min \{f(x) | x \in X, g(x) \leq 0, h(x) = 0\} \\ &= f(x^*) \\ &= \sup_{\mu \geq 0} \theta(\mu) = \lim_{\mu \rightarrow \infty} \theta(\mu) \end{aligned}$$

*Proof:* Let  $\Lambda = \sup_{\mu \geq 0} \theta(\mu)$ . By Lemma 4.1.1  $\theta$  is a nondecreasing function of  $\mu \geq 0$ . Thus,

$$\lim_{\mu \rightarrow \infty} \theta(\mu) = \Lambda.$$

We must show that  $\alpha(x_\mu) \rightarrow 0$  as  $\mu \rightarrow \infty$ . Suppose  $\inf_{\mu \geq 0} \alpha(x_\mu) = \delta > 0$ . Then,

$$\begin{aligned} & \inf \{f(x) | x \in X, g(x) \leq 0, h(x) = 0\} \\ &\geq \theta(\mu) = f(x_\mu) + \mu \alpha(x_\mu) \\ &\geq f(x_\mu) + \mu \delta \end{aligned}$$

Since  $\mu \mapsto f(x_\mu)$  is nondecreasing  $f(x_\mu) + \mu \delta \mapsto \infty$ . Thus, since

$$\inf \{f(x) | x \in X, g(x) \leq 0, h(x) = 0\} < \infty$$

due to the fact that the feasible set is nonempty it follows that  $\inf_{\mu \geq 0} \alpha(x_\mu) = 0$ . Since  $\mu \mapsto \alpha(x_\mu)$  is nonincreasing, we must conclude  $\lim_{\mu \rightarrow \infty} \alpha(x_\mu) = 0$ .

Since  $\{x_\mu | \mu \geq 0\}$  is a compact subset of  $X$  there exist  $\mu_1 < \mu_2 < \dots < \mu_n < \dots$  and  $x^* \in X$  such that

$$\lim_{n \rightarrow \infty} x_{\mu_n} = x^*.$$

By continuity of  $\alpha$  we have  $\alpha(x^*) = 0$ . Thus,  $x^*$  is feasible. Since  $f, g, h, \phi, \psi$  are continuous

$$\lim_{n \rightarrow \infty} \theta(\mu_n) = \Lambda,$$

and

$$\inf \{f(x) | x \in X, g(x) \leq 0, h(x) = 0\} \geq \sup_{\mu \geq 0} \theta(\mu) = \lim_{n \rightarrow \infty} \theta(\mu_n) = f(x^*).$$

Since  $x^*$  is feasible it follows that

$$\inf \{f(x) | x \in X, g(x) \leq 0, h(x) = 0\} = f(x^*).$$

$\square$

**Remark 6.1.1** *Trying to find  $x_\mu$  can be computationally difficult. To illustrate this point we assume that the auxiliary function  $f_\mu(x)$  is twice continuously differentiable. In the case we have only equality constraints*

$$f_\mu'' = f''(x) + \sum_{i=1}^k \mu \psi'(h_i(x)) h_i''(x) + \mu \sum_{i=1}^k \mu \psi''(h_i(x)) h_i'(x) h_i^T(x).$$

*The Hessian can be ill conditioned as  $\mu \rightarrow \infty$ .*

**Example 6.1.1**

Consider the problem

$$\begin{aligned} \min \quad & f(x) = x_1^2 + x_2^2 \\ \text{subject to} \quad & h(x) = x_1 + x_2 - 1 = 0 \end{aligned}$$

Set

$$f_\mu(x) = f(x) + \mu (h(x))^2$$

Then,

$$\begin{aligned} \frac{\partial}{\partial x_1} f_\mu(x) &= 2(1+\mu)x_1 + 2\mu(x_2 - 1) \\ \frac{\partial}{\partial x_2} f_\mu(x) &= 2(1+\mu)x_2 + 2\mu(x_1 - 1) \\ \frac{\partial^2}{\partial x_1^2} f_\mu(x) &= \frac{\partial^2}{\partial x_2^2} f_\mu(x) = 2(1+\mu) \\ \frac{\partial^2}{\partial x_2 \partial x_1} f_\mu(x) &= 2\mu \end{aligned}$$

$$f''_\mu(x) = 2 \begin{pmatrix} 1+\mu & \mu \\ \mu & 1+\mu \end{pmatrix}$$

Thus, the hessian of  $f_\mu$  is  $2(1+\mu) > 0$ . We note the system

$$\begin{aligned} \frac{\partial}{\partial x_1} f_\mu(x) &= 0 \\ \frac{\partial}{\partial x_2} f_\mu(x) &= 0 \end{aligned}$$

has a solution

$$x_1(\mu) = x_2(\mu) = \frac{\mu}{1+2\mu}.$$

We note  $x_1(\mu)$  and  $x_2(\mu)$  converge to  $\frac{1}{2}$  as  $\mu \rightarrow \infty$ .

$$h(x_1(\mu), x_2(\mu)) = -\frac{1}{1+2\mu} < 0$$

Thus,  $x_1(\mu)$  and  $x_2(\mu)$  are infeasible and

$$h^2(x_1(\mu), x_2(\mu)) = \frac{1}{(1+2\mu)^2} \rightarrow 0 \quad \text{as } \mu \rightarrow \infty.$$

Next,

$$f_\mu(x_\mu) = \frac{\mu}{1+2\mu} < \frac{1}{2}$$

and

$$\lim_{\mu \rightarrow \infty} f_\mu(x_\mu) = \frac{1}{2}$$

We note that  $f_\mu(x_\mu)$  increases to  $\frac{1}{2}$  as  $\mu \rightarrow \infty$ . We can verify that  $x_1 = x_2 = \frac{1}{2}$  provides the solution to the problem.

## 6.2 Methods of Feasible Directions

### 6.2.1 Zoutendijk's Method

Consider the problem

$$\begin{array}{ll} \min & f(x) \\ \text{subject to} & g(x) \leq 0 \end{array}$$

#### Algorithm

- (i) Start with an initial feasible point  $x_1$ , and small numbers  $\varepsilon_1, \varepsilon_2, \dots$  for convergence criteria. Evaluate  $f(x_1), g_j(x_1), \quad j = 1, \dots, m$ . Set the iteration number  $i = 1$ .
- (ii) If  $g_j(x_i) < 0, \quad j = 1, \dots, m$  set the current search direction as  $S_i = -\nabla f(x_i)$ . Normalize  $S_i$  in a suitable manner, and go to step (v). If at least one  $g_j(x_i) = 0$ , go to step (iii).
- (iii) Find a feasible direction  $S$  by solving the problem:

$$\begin{array}{ll} \min & \alpha \\ \text{subject to} & \\ & S^T \nabla g_j(x_i) + \theta \alpha \leq 0, \quad j = 1, 2, \dots, p \\ & S^T \nabla f(x_i) + \alpha \leq 0 \\ & -1 \leq S_i \leq 1, \quad i = 1, 2, \dots, m \end{array}$$

where  $S_i$  is the  $i$ th component of  $S$ , and where the first  $p$  of the  $m$  constraints are assumed to be active at the point  $x_i$ . The  $\theta_j$ 's can be taken to be 1.

- (iv) If the value of  $\alpha$  found in step (iii) is nearly equal to zero, i.e.,  $\alpha \leq \varepsilon_i$  terminate the iteration and set  $x_{opt} = x_i$ . If  $\alpha > \varepsilon_i$  go to step (v) by taking  $S_i = S$ .
- (v) Find a suitable step length  $\lambda_i$  along the direction  $S_i$  and obtain a new point  $x_{i+1}$  as

$$x_{i+1} = x_i + \lambda_i S_i$$

- (vi) Evaluate the objective function  $f(x_{i+1})$ .
- (vii) Test for the convergence of the method. If

$$\left| \frac{f(x_i) - f(x_{i+1})}{f(x_i)} \right| \leq \varepsilon_2 \quad \text{and} \quad \|x_i - x_{i+1}\| \leq \varepsilon_3$$

terminate the iteration process taking  $x_{opt} = x_{i+1}$ . Otherwise, go to step (viii).

- (viii) Set the new iteration number as  $i = i + 1$ , and repeat from step (ii) onwards.

**Remark 6.2.1**

$$\begin{array}{ll} \min & -\alpha \\ \text{subject to} & \\ & S^T \nabla g_j(x_i) + \theta_j \alpha \leq 0, \quad j = 1, 2, \dots, p \\ & S^T \nabla f(x_i) + \alpha \leq 0 \\ & -1 \leq S_i \leq 1, \quad i = 1, 2, \dots, n \end{array}$$

is a linear programming problem. To put it in standard form we may proceed as follows:

$$\begin{aligned}
 -1 \leq S_i \leq 1 &\implies 0 \leq S_i + 1 \leq 2 \\
 S^T \nabla g_j(x_i) &= (S_1, \dots, S_n) \cdot \begin{pmatrix} \partial_1 g_j(x_i) \\ \partial_2 g_j(x_i) \\ \vdots \\ \partial_n g_j(x_i) \end{pmatrix} \\
 &= (S_1 + 1, \dots, S_n + 1) \cdot \begin{pmatrix} \partial_1 g_j(x_i) \\ \partial_2 g_j(x_i) \\ \vdots \\ \partial_n g_j(x_i) \end{pmatrix} - (1, \dots, 1) \cdot \begin{pmatrix} \partial_1 g_j(x_i) \\ \partial_2 g_j(x_i) \\ \vdots \\ \partial_n g_j(x_i) \end{pmatrix}
 \end{aligned}$$

Thus, if we set  $t_i = S_{i+1}$ , then  $0 \leq t_i \leq 2$ , and

$$S^T \nabla g_j(x_i) = t_i \partial_1 g_j(x_1) + \dots + t_n \partial_n g_j(x_i) - \sum_{k=1}^n \partial_k g_j(x_i).$$

Thus, the above linear programming problem can be written as

$$\begin{aligned}
 &\min -\alpha \\
 &\text{subject to} \\
 &\sum_{k=1}^n t_k \partial_k g_j(x_i) + \theta_j \alpha \leq \sum_{k=1}^n \partial_k g_j(x_i) \\
 &\sum_{k=1}^n t_k \partial_k f(x_i) + \alpha \leq \sum_{k=1}^n \partial_k f(x_i), \quad 0 \leq t_i \leq 2
 \end{aligned}$$

Finally,

$$\begin{aligned}
 &\min -\alpha \\
 &\text{subject to} \\
 &\sum_{k=1}^n t_k \partial_k g_j(x_i) + \theta_j \alpha + y_j = \sum_{k=1}^n \partial_k g_j(x_i) \\
 &\sum_{k=1}^n t_k \partial_k f(x_i) + \alpha + y_{p+1} = \sum_{k=1}^n \partial_k f(x_i) \\
 &t_1 + y_{p+2} = 2 \\
 &t_2 + y_{p+3} = 2 \\
 &\vdots \\
 &t_1 + y_{p+n+1} = 2 \\
 &t_1 \geq 0 \\
 &t_2 \geq 0 \\
 &\vdots \\
 &t_n \geq 0 \\
 &y_1 \geq 0 \\
 &\vdots \\
 &y_{p+n+1} \geq 0 \\
 &\alpha \geq 0
 \end{aligned}$$

## 6.3 Barrier Methods

Barrier methods generate a sequence of strictly feasible iterates that converge to a solution of the problem from the interior of the feasible region. For this reason they are called interior point methods. They are not appropriate for equality constraints.

Consider the nonlinear inequality constrained problem

$$(P_2) \quad \begin{cases} \min f(x) \\ \text{subject to} \\ g_i(x) \geq 0, \quad i = 1, \dots, m \end{cases}$$

Assume that  $f, g_i, i = 1, \dots, m$  are continuous, and the set

$$\{x \in \mathbb{R}^n \mid g_i(x) > 0, i = 1, \dots, m\} \text{ is not empty.}$$

Let

$$\varphi_1(x) = -\sum_{i=1}^m \ln(g_i(x)).$$

Note that if  $g_i(x) \rightarrow 0^+$  then  $\varphi_1(x) \rightarrow \infty$ .

Next, let

$$\varphi_2(x) = \sum_{i=1}^m \frac{1}{g_i(x)}$$

If  $g_i(x) \rightarrow 0^+$  then  $\varphi_2(x) \rightarrow \infty$ .

Let

$$S^\circ = \{x \mid g_i(x) > 0, i = 1, \dots, m\}$$

Assume that  $S^\circ \neq \emptyset$ .

$$S^{\bar{c}irc} = \{x \mid g_i(x) \geq 0, \quad i = 1, \dots, m\}.$$

Then, to solve the problem  $(P_2)$  we consider barrier functions. For example, we consider

$$f_\mu(x) = f(x) + \mu \varphi_1(x), \quad \mu > 0$$

or

$$f_\mu(x) = f(x) + \mu \varphi_2(x)$$

for  $\mu$  values tending to zero. These two barrier functions are widely used. The parameter  $\mu$  is called the barrier parameter of the function  $f_\mu$ .

The barrier method solves a sequence of unconstrained problems

$$\min_x f_{\mu_k}(x)$$

where  $\mu_1 > \mu_2 > \mu_3 > \dots \searrow 0$ .

**Theorem 6.3.1** *Consider the problem*

$$(P_2) \quad \begin{cases} \min f(x) \\ \text{subject to} \\ g_i(x) \geq 0, \quad i = 1, \dots, m \end{cases}$$

Let

$$S^\circ = \{x \mid g_i(x) > 0, i = 1, \dots, m\}$$

$$S = \{x \mid g_i(x) \geq 0, i = 1, \dots, m\}$$

Assume

(i)  $f, g_i, i = 1, \dots, m$  are continuous on  $\mathbb{R}^n$ .

(ii) *The set  $\{x : x \in S, f(x) \leq \alpha\}$  is bounded for every  $\alpha > 0$ .*

(iii)  $S^\circ \neq \emptyset$

(iv)  $\bar{S}^\circ = S$

*Suppose  $x_\mu \in S^\circ$  is such that*

$$f_\mu(x(\mu)) = \min \{f(x) + \mu \varphi(x)\}$$

*Then,*

(a)  $f_{\mu_{k+1}}(x_{\mu_{k+1}}) \leq f_{\mu_k}(x_{\mu_k})$

(b)  $\varphi(x_{\mu_{k+1}}) > \varphi(x_{\mu_k})$

(c)  $\{x_{\mu_k}\}$  *has a convergent subsequence  $\{\mu_{k_\ell}\}$*

(c) *If  $\{\mu_{k_\ell}\} \rightarrow x^*$  then  $x^*$  is a solution of problem  $(P_2)$*

*Proof :*

$$f(x_{\mu_{n+1}}) + \mu_{n+1}\varphi(x_{\mu_{n+1}}) \leq f(x_{\mu_n}) + \mu_{n+1}\varphi(x_{\mu_n}) \quad (6.11)$$

$$f(x_{\mu_n}) + \mu_n\varphi(x_{\mu_n}) \leq f(x_{\mu_{n+1}}) + \mu_n\varphi(x_{\mu_{n+1}}) \quad (6.12)$$

Multiply inequality (6.11) by  $\mu_n$  and inequality (6.12) by  $\mu_{n+1}$  to obtain

$$\mu_n f(x_{\mu_{n+1}}) + \mu_n \mu_{n+1}\varphi(x_{\mu_{n+1}}) \leq \mu_n f(x_{\mu_n}) + \mu_n \mu_{n+1}\varphi(x_{\mu_n}) \quad (6.13)$$

$$\mu_{n+1} f(x_{\mu_n}) + \mu_{n+1} \mu_n\varphi(x_{\mu_n}) \leq \mu_{n+1} f(x_{\mu_{n+1}}) + \mu_{n+1} \mu_n\varphi(x_{\mu_{n+1}}) \quad (6.14)$$

Adding inequalities (6.13) and (6.14) we obtain

$$\mu_n f(x_{\mu_{n+1}}) + \mu_{n+1} f(x_{\mu_n}) + \mu_n \mu_{n+1}[\varphi(x_{\mu_{n+1}}) + \varphi(x_{\mu_n})] \leq \mu_n f(x_{\mu_n}) + \mu_{n+1} f(x_{\mu_{n+1}}) + \mu_n \mu_{n+1}[\varphi(x_{\mu_n}) + \varphi(x_{\mu_{n+1}})] \quad (6.15)$$

Then, from (3.6) it follows that

$$(\mu_{n+1} - \mu_n) f(x_{\mu_n}) \leq (\mu_{n+1} - \mu_n) f(x_{\mu_{n+1}}) \quad (6.16)$$

Thus, since  $\mu_{n+1} - \mu_n < 0$ ,

$$f(x_{\mu_{n+1}}) \leq f(x_{\mu_n}) \quad (6.17)$$

That is,

$$\{f(x_{\mu_k})\}_{n=1}^\infty$$

is a nonincreasing sequence.

From (6.12) we have

$$\varphi(x_{\mu_n}) \leq \varphi(x_{\mu_{n+1}}) \quad (6.18)$$

Thus, the sequence  $\{\varphi(x_{\mu_n})\}_{n=1}^\infty$  is a nondecreasing sequence.

By assumption (ii)  $\{x_{\mu_n}\}$  has a subsequence  $\{x_{\mu_{k_\ell}}\}$  which is convergent. Thus, there exist  $x^*$  feasible such that

$$\lim_{\ell \rightarrow \infty} x_{\mu_{k_\ell}} = x^*.$$

since  $f$  is continuous  $f(x_{\mu_{k_\ell}}) \rightarrow f(x^*)$ . Next,

$$\begin{aligned} f(x_{\mu_{k+1}}) + \mu_{k+1}\varphi(x_{\mu_{k+1}}) &\leq f(x_{\mu_k}) + \mu_{k+1}\varphi(x_{\mu_k}) \\ &\leq f(x_{\mu_k}) + \mu_k\varphi(x_{\mu_k}) \end{aligned}$$

Thus, the sequence  $\{f(x_{\mu_{k+1}}) + \mu_{k+1}\varphi(x_{\mu_{k+1}})\}_{k=1}^\infty$  is a nonincreasing sequence, and

$$\lim_{\ell \rightarrow \infty} [f(x_{\mu_{k_\ell}}) + \mu_{k_\ell}\varphi(x_{\mu_{k_\ell}})] = f(x^*) + \lim_{\ell \rightarrow \infty} \mu_{k_\ell}\varphi(x_{\mu_{k_\ell}}) \geq f(x^*)$$



**Suppose  $\hat{x}$  is a solution to  $(P_2)$ . Then, for every  $\varepsilon > 0$ , there exists  $x_\varepsilon$  such that  $|\hat{x} - x_\varepsilon| < \varepsilon$  and  $g_i(x_\varepsilon) > 0$ ,  $i = 1, \dots, m$ . Then, there exists  $k_0$  such that for  $k \geq k_0$**

$$f(x_{\mu_k}) + \mu_k \varphi(x_{\mu_k}) \leq f(x_\varepsilon) + \mu_k \varphi(x_\varepsilon) \quad (6.19)$$

**Thus,**

$$\begin{aligned} f(x^*) &\leq \lim_{\ell \rightarrow \infty} [f(x_{\mu_{k_\ell}}) + \mu_{k_\ell} \varphi(x_{\mu_{k_\ell}})] \\ &\leq \lim_{\ell \rightarrow \infty} [f(x_\varepsilon) + \mu_{k_\ell} \varphi(x_\varepsilon)] \\ &= f(x_\varepsilon) \end{aligned}$$

**Thus,**

$$f(x^*) \leq f(\hat{x}).$$

**Since**

$$f(\hat{x}) \leq f(x^*),$$

**we have**

$$\begin{aligned} f(x^*) &\leq \lim_{\ell \rightarrow \infty} [f(x_{\mu_{k_\ell}}) + \mu_{k_\ell} \varphi(x_{\mu_{k_\ell}})] \\ &\leq f(\hat{x}) \\ &\leq f(x^*) \end{aligned}$$

**Thus,  $x^*$  is a solution to  $(P_2)$  and**

$$\lim_{\ell \rightarrow \infty} \mu_{k_\ell} \varphi(x_{\mu_{k_\ell}}) = 0.$$

□

