

Chapter 9

The Method of Multipliers

9.1 Introduction

In our study of exterior penalty functions in the previous section we found that there was a compromise between differentiability and exactness. That is given a penalty function

$$P_\alpha(x) = f_0(x) + \alpha\beta(x)$$

either the penalty term is differentiable in which case the penalty parameter α must tend to $+\infty$ or $\beta(x)$ is nondifferentiable in which case α need not tend to $+\infty$. In this section we consider a modification to the quadratic differentiable penalty term $\hat{\beta}_2$ which avoids the need to send α to $+\infty$.

Recall that in each step of the exterior penalty method applied to

$$P_\alpha(x) := f_0(x) + \alpha \left[\sum_{i=1}^s (f_i(x)_+)^2 + \sum_{i=s+1}^m (f_i(x))^2 \right]$$

one solves the unconstrained minimization problem

$$\min_{x \in \mathbb{R}^n} P_\alpha(x).$$

The solution x_α satisfies

$$(9.1.1) \quad 0 = \nabla P_\alpha(x_\alpha) = \nabla f_0(x_\alpha) + \sum_{i=1}^s \nabla f_i(x_\alpha)(\alpha f_i(x_\alpha)_+) + \sum_{i=s+1}^m \nabla f_i(x_\alpha)(\alpha f_i(x_\alpha)).$$

Setting

$$(u_\alpha)_i := \begin{cases} \alpha f_i(x_\alpha)_+ & \text{if } i = 1, \dots, s \\ \alpha f_i(x_\alpha) & \text{if } i = s+1, \dots, m \end{cases}$$

we can write (9.1.1) as

$$0 = \nabla_x L(x_\alpha, u_\alpha)$$

where $L(x, u) = f_0(x) + u^T f(x)$ is the Lagrangian for the problem \mathcal{P} .

$$\begin{aligned} \min \quad & f_0(x) \\ \text{subject to} \quad & f_0(x) \leq 0 \quad i = 1, \dots, s \\ & f_0(x) = 0 \quad i = s + 1, \dots, m \end{aligned}$$

Consequently, if $x_\alpha \rightarrow \bar{x}$ a local solution to \mathcal{P} , then every cluster point of $\{u_\alpha\}$ is a Kuhn-Tucker multiplier for \bar{x} . This indicates that we should think of the vectors u_α as multiplier approximates that are to be updated at each iteration. By doing so, we avoid the need to send the penalty parameter α to $+\infty$. The strategy is as follows: given $\alpha > 0$ and an estimate of the multipliers $u \in \mathbb{R}^m$, let $x_{\alpha, u}$ be the solution to the equation

$$0 = \nabla f_0(x) + \sum_{i=1}^s \nabla f_i(x)(\alpha f_i(x) + u_i)_+ + \sum_{i=s+1}^m \nabla f_i(x)(\alpha f_i(x) + u_i).$$

Then update the multiplier estimates u_i via the equations

$$u_i = (\alpha f_i(x_{\alpha, u}) + u_i)_+ \quad \text{for } i = 1, \dots, s$$

and

$$u_i = (\alpha f_i(x_{\alpha, u}) + u_i) \quad \text{for } i = s + 1, \dots, m.$$

This procedure describes the basic structure of an algorithm known as *the method of multipliers*. Before we provide a precise description of this algorithm let us first examine expression (9.1) more carefully.

9.2 The Augmented Lagrangian

Observe that expression (9.1) is a first order optimality condition for some function. In order to recover this function we can integrate the right hand side of (9.1) in the variable x . By adding in the appropriate constant term this integration yields the function

$$\begin{aligned} L(x, u, \alpha) &:= f_0(x) + \frac{1}{2\alpha} [\text{dist}_2^2[\alpha f(x) + u | K] - \|u\|_2^2] \\ &:= f_0(x) + \frac{1}{2\alpha} \sum_{i=1}^s ((\alpha f_i(x) + u_i)_+)^2 - u_i^2 \\ &\quad + \frac{\alpha}{2} \sum_{i=s+1}^m f_i(x)(f_i(x) + u_i). \end{aligned}$$

where $K := \mathbb{R}_-^s \times \{0\}_{\mathbb{R}^{m-s}}$. The function $L(x, u, \alpha)$ is called the augmented Lagrangian for \mathcal{P} . The name is derived from the fact that if $s = 0$, that is there are only equality constraints, then $L(x, u, \alpha)$ takes the form

$$L(x, u, \alpha) = L(x, u) + \frac{\alpha}{2} \|f(x)\|_2^2$$

where $L(x, u) = f_0(x) + u^T f(x)$ is the usual Lagrangian. Thus $L(x, u, \alpha)$ can be thought of as arising from the usual Lagrangian after one has incorporated a vehicle for penalizing constraint violation. The augmented Lagrangian possesses the following remarkable property.

THEOREM 9.2.1 *Let $\alpha > 0$, f_i , $i = 0, \dots, m$ differentiable at $x \in \mathbb{R}^n$. Then*

$$0 = \nabla_{x,u}L(x, u, \alpha)$$

if and only if (x, u) is a Kuhn-Tucker pair for \mathcal{P} .

PROOF: Note that $0 = \nabla_{x,u}L(x, u, \alpha)$ if and only if

$$\begin{aligned} 0 &= \nabla f_0(x) + \sum_{i=1}^s (\alpha f_i(x) + u_i)_+ \nabla f_i(x) + \sum_{i=s+1}^m (\alpha f_i(x) + u_i) \nabla f_i(x) \\ u_i &= (\alpha f_i(x) + u_i)_+ \quad i = 1, \dots, s \\ 0 &= f_i(x) \quad i = s + 1, \dots, m. \end{aligned}$$

Hence the result will be established once we have shown that

$$[(a - b)_+ - a = 0 \iff a \geq 0, b \geq 0, ab = 0].$$

Case 1: $a - b \geq 0$

If $a - b \geq 0$, then $(a - b)_+ = a - b$ so that $b = 0$. Consequently, $a \geq 0$, $b \geq 0$, $ab = 0$.

Case 2: $a - b \leq 0$

If $(a - b) \leq 0$, then $(a - b)_+ = 0$ so that $a = 0$. Consequently, $a \geq 0$, $b \geq 0$ and $ab = 0$.

The converse is trivial. \blacksquare

Thus it would seem that we need only find the roots of the equation $0 = \nabla_{x,u}L(x, u, \alpha)$ in order to locate Kuhn-Tucker points for the problem \mathcal{P} . This is precisely what the method of multipliers attempts to do.

In order to investigate the rate of convergence for these methods we require the nonsingularity of the hessian

$$\nabla_{x,u}^2L(x, u, \alpha).$$

Unfortunately, $\nabla_{x,u}^2L(x, u, \alpha)$ does not always exist since $(\alpha f_i(x) + u_i)_+$ is not everywhere differentiable. A sufficient condition under which $\nabla_{x,u}^2L(x, u, \alpha)$ does exist near a Kuhn-Tucker point (\bar{x}, \bar{u}) for \mathcal{P} is *strict complementary slackness*.

DEFINITION 9.2.1 *Let (\bar{x}, \bar{u}) be a Kuhn-Tucker pair for \mathcal{P} . We say that the strict complementary slackness condition (SCSC) is satisfied at (\bar{x}, \bar{u}) if $\bar{u}_i > 0$ whenever $f_i(\bar{x}) < 0$ $i = 1, \dots, s$.*

Observe that if the SCSC is satisfied at the K-T pair (\bar{x}, \bar{u}) then

$$(\alpha f_i(x) + u_i)_+ = 0$$

for all (x, u) near (\bar{x}, \bar{u}) for each $i \notin A(\bar{x}) = \{i : f_i(\bar{x}) = 0\}$, and

$$(\alpha f_i(x) + u_i)_+ = (\alpha f_i(x) + u_i)$$

for all (x, u) near (\bar{x}, \bar{u}) for each $i \in A(\bar{x})$. Consequently, $\nabla_{x,u}^2 L(x, u, \alpha)$ exists near (\bar{x}, \bar{u}) and is given by

$$\nabla_{x,u}^2 L(x, u, \alpha) = \begin{bmatrix} \nabla_{x,x} L(x, u, \alpha) & f'_E(x)^T & f'_A(x) & 0 \\ f'_E(x) & 0 & 0 & 0 \\ f'_A(x) & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{\alpha} I_N \end{bmatrix}.$$

Here we have reordered the components of the vector u into the multipliers associated with the equality constraints u_E with $E = \{s+1, \dots, m\}$, the multipliers associated with the active inequality constraints u_A with $A = A(\bar{x})$, and the multipliers associated with the inactive inequality constraints u_N with $N = \{1, \dots, s\} \setminus A(x)$. Also for any matrix $M \in \mathbb{R}^{m \times n}$ and index set $J \subset \{1, \dots, m\}$, M_J represents that matrix whose rows are those of M with index in J . Finally,

$$\begin{aligned} \nabla_{xx} L(x, u, \alpha) &= \nabla^2 f_0(x) + \sum_{i \in A} \alpha \nabla f_i(x) \nabla f_i(x)^T + (\alpha f_i(x) + u_i) \nabla^2 f_i(x) \\ &\quad + \sum_{i=s+1}^m \alpha \nabla f_i(x) \nabla f_i(x)^T + (\alpha f_i(x) + u_i) \nabla^2 f_i(x) \\ &= \nabla_{xx}^2 L(x, u) + \alpha \sum_{i \in A \cup \{s+1, \dots, m\}} \nabla f_i(x) \nabla f_i(x)^T + f_i(x) \nabla^2 f_i(x) \end{aligned}$$

In order to establish the nonsingularity of $\nabla^2 L(x, u, \alpha)$ we need the following three facts from linear algebra whose proof are left as an exercise.

LEMMA 9.2.1 *Let $A \in \mathbb{R}^{m \times n}$, $B \in \mathbb{R}^{n \times n}$ and $D \in \mathbb{R}^{n \times n}$. If*

1. *the rows of D are linearly independent,*
2. *$Dx = 0, x \neq 0 \implies x^T Bx > 0$, and*
3. *$\mu \geq 0$,*

then the matrix $\begin{bmatrix} B + \mu A^T A & D^T \\ D & 0 \end{bmatrix}$ is nonsingular

THEOREM 9.2.2 [Finsler's Theorem] *Let $B, C \in \mathbb{R}^{n \times n}$ with C positive semi-definite. Then $x^T Bx > 0$ for every $x \in \mathbb{R}^n, x \neq 0$ such that $x^T Cx = 0$ if and only if $B + \mu C$ is positive definite for all $\mu \geq \bar{\mu}$ for some $\bar{\mu}$.*

THEOREM 9.2.3 [Debreu's Theorem] *Let $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times n}$. Then $x^T Bx > 0$ for every $x \in \mathbb{R}^n$ with $x \neq 0$ such that $Ax = 0$ if and only if $B + \mu A^T A$ is positive definite for all $\mu \geq \bar{\mu}$ for some $\bar{\mu}$.*

The following result is an easy consequence of these linear algebraic results.

THEOREM 9.2.4 (*The positive definiteness of $\nabla_{xx}^2 L(\bar{x}, \bar{u}, \alpha)$ and the nonsingularity of $\nabla^2 L(\bar{x}, \bar{u}, \alpha)$*)

1. Let (\bar{x}, \bar{u}) be a Kuhn-Tucker point for \mathcal{P} and suppose that

(a) (*Strict Complementary Slackness*)

$$\bar{u}_i > 0 \text{ whenever } f_i(x) < 0 \quad i = 1, \dots, s.$$

and

(b) (*Second-Order Sufficiency*)

$$\nabla f_i(\bar{x})^T d = 0 \quad i \in A(\bar{x}) \cup \{s+1, \dots, m\} \implies d^T \nabla_{11} L(\bar{x}, \bar{u}) d > 0.$$

Then $\nabla_{xx} L(\bar{x}, \bar{u}, \alpha)$ is positive definite for all $\alpha \geq \bar{\alpha}$ for some $\bar{\alpha} > 0$.

2. If in addition to the hypotheses in (1) we assume that

(c) (*The LI Condition*) the gradients $\{\nabla f_i(\bar{x}) : i \in A(\bar{x}) \cup \{s+1, \dots, m\}\}$ are linearly independent ,

Then $\nabla^2 L(\bar{x}, \bar{u}, \alpha)$ is non-singular for all $\alpha > 0$.

PROOF: (i) We have that

$$\nabla_{xx}^2 L(\bar{x}, \bar{u}, \alpha) = \nabla_{xx}^2 L(\bar{x}, \bar{u}) + \alpha f_I'(\bar{x}) f_I'(\bar{x})^T$$

where $I = A(\bar{x}) \cup \{s+1, \dots, m\}$. Consequently, the result follows from Debreu's Theorem 9.2.3.

(ii) This just follows from Lemma 9.2.1. ■

We now formally state the method of multipliers.

9.2.1 Algorithm: The Method of Multipliers

Let $(x^0, u^0, \alpha^0) \in \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}_+$ stop if $|\nabla L(x^i, u^i, \alpha^i)| < \epsilon$. Having (x^i, u^i, α^i) determine $(x^{i+1}, u^{i+1}, \alpha^{i+1})$ as follows

1. Let x^{i+1} solve

$$L(x^{i+1}, u^i, \alpha^i) = \min_{x \in \mathbb{R}^n} L(x, u^i, \alpha^i)$$

or

$$\nabla_x L(x^{i+1}, u^i, \alpha^i) = 0.$$

2. Set $u^{i+1} = u^i + \alpha^i \nabla_u L(x^{i+1}, u^i, \alpha^i)$ or equivalently

$$u_j^{i+1} = (\alpha^i f_j(x^{i+1}) + u^i)_+ \quad \text{for } j = 1, \dots, s$$

and

$$u_j^{i+1} = (\alpha^i f_j(x^{i+1}) + u^i) \quad \text{for } j = s+1, \dots, m.$$

3. Set

$$\alpha^{i+1} := \begin{cases} \alpha^i & \text{if } \|u^{i+1} - u^i\|_\infty \leq \frac{1}{4}\|u^i - u^{i-1}\|_\infty \\ 10\alpha^i & \text{else} \end{cases}$$

In the following theorem we provide a sample of the type of convergence result that can be obtained for this method.

THEOREM 9.2.5 *Let the assumptions (a), (b), and (c) of Theorem 9.2.4 hold and let $\alpha \geq \bar{\alpha}$. Let f_0 and f be C^2 near the Kuhn-Tucker point \bar{x} . Then for α sufficiently large, but finite, there is an open neighborhood V_α of \bar{u} such that for $u^0 \in V_\alpha$ there is an x^0 such that $\nabla_x L(x^0, u^0, \alpha) = 0$ and the iterates (x^i, u^i) generated by algorithm 9.2.1 exist and converge to (\bar{x}, \bar{u}) at the linear root rate*

$$\|x^i - \bar{x}, u^i - \bar{u}\| \leq \delta(\epsilon/\alpha)^i$$

for some positive constants ϵ and δ .