

The use of Lagrange multipliers in optimization and variational problems is discussed extensively in Chapter 50.

Least squares methods and Lagrange multipliers are used to tackle many problems in computer graphics and computer vision; see Trucco and Verri [178], Metaxas [124], Jain, Katsuri, and Schunck [100], Faugeras [59], and Foley, van Dam, Feiner, and Hughes [63].

## 42.2 Quadratic Optimization: The General Case

In this section we complete the study initiated in Section 42.1 and give necessary and sufficient conditions for the quadratic function  $\frac{1}{2}x^\top Ax - x^\top b$  to have a global minimum. We begin with the following simple fact:

**Proposition 42.4.** *If  $A$  is an invertible symmetric matrix, then the function*

$$f(x) = \frac{1}{2}x^\top Ax - x^\top b$$

*has a minimum value iff  $A \succeq 0$ , in which case this optimal value is obtained for a unique value of  $x$ , namely  $x^* = A^{-1}b$ , and with*

$$f(A^{-1}b) = -\frac{1}{2}b^\top A^{-1}b.$$

*Proof.* Observe that

$$\frac{1}{2}(x - A^{-1}b)^\top A(x - A^{-1}b) = \frac{1}{2}x^\top Ax - x^\top b + \frac{1}{2}b^\top A^{-1}b.$$

Thus,

$$f(x) = \frac{1}{2}x^\top Ax - x^\top b = \frac{1}{2}(x - A^{-1}b)^\top A(x - A^{-1}b) - \frac{1}{2}b^\top A^{-1}b.$$

If  $A$  has some negative eigenvalue, say  $-\lambda$  (with  $\lambda > 0$ ), if we pick any eigenvector  $u$  of  $A$  associated with  $\lambda$ , then for any  $\alpha \in \mathbb{R}$  with  $\alpha \neq 0$ , if we let  $x = \alpha u + A^{-1}b$ , then since  $Au = -\lambda u$ , we get

$$\begin{aligned} f(x) &= \frac{1}{2}(x - A^{-1}b)^\top A(x - A^{-1}b) - \frac{1}{2}b^\top A^{-1}b \\ &= \frac{1}{2}\alpha u^\top A\alpha u - \frac{1}{2}b^\top A^{-1}b \\ &= -\frac{1}{2}\alpha^2\lambda \|u\|_2^2 - \frac{1}{2}b^\top A^{-1}b, \end{aligned}$$

and since  $\alpha$  can be made as large as we want and  $\lambda > 0$ , we see that  $f$  has no minimum. Consequently, in order for  $f$  to have a minimum, we must have  $A \succeq 0$ . If  $A \succeq 0$ , since  $A$  is invertible, it is positive definite, so  $(x - A^{-1}b)^\top A(x - A^{-1}b) > 0$  iff  $x - A^{-1}b \neq 0$ , and it is clear that the minimum value of  $f$  is achieved when  $x - A^{-1}b = 0$ , that is,  $x = A^{-1}b$ .  $\square$