

ECE 68000: MODERN AUTOMATIC CONTROL

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Minimization subject to inequality constraints

Problem statement

- Find a point $\mathbf{x} \in \mathbb{R}^N$ that minimizes $f(\mathbf{x})$ subject to inequality constraints,

$$\left. \begin{array}{rcl} g_1(\mathbf{x}) & \leq & 0 \\ g_2(\mathbf{x}) & \leq & 0 \\ & \vdots & \\ g_P(\mathbf{x}) & \leq & 0 \end{array} \right\}$$

- Write the above inequality constraints in a compact form as

$$\mathbf{g}(\mathbf{x}) \leq \mathbf{0},$$

where $\mathbf{h} : \mathbb{R}^N \rightarrow \mathbb{R}^P$.

- Let \mathbf{x}^* be a point satisfying the constraints, that is,
 $\mathbf{g}(\mathbf{x}^*) \leq \mathbf{0}$
- Let J be the set of indices j for which $g_j(\mathbf{x}^*) = 0$

Regular point of the constraints

- The point \mathbf{x}^* is said to be a regular point of the constraints $\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$ if the gradient vectors,

$$\nabla g_j(\mathbf{x}^*), \quad j \in J,$$

are linearly independent

- A constraint $g_j(\mathbf{x}) \leq 0$ is active at \mathbf{x}^* if $g_j(\mathbf{x}^*) = 0$
- The index set J , defined above, contains indices of active constraints

The first-order necessary condition (FONC) for function minimization subject to inequality constraints

Theorem

Let \mathbf{x}^* be a regular point and a local minimizer of f subject to $\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$. Then there exists a vector $\boldsymbol{\mu}^* \in \mathbb{R}^P$ such that

- 1 $\boldsymbol{\mu}^* \geq \mathbf{0}$,
- 2 $\nabla f(\mathbf{x}^*) + \left[\nabla g_1(\mathbf{x}^*) \quad \cdots \quad \nabla g_P(\mathbf{x}^*) \right] \boldsymbol{\mu}^* = \mathbf{0}$,
- 3 $\boldsymbol{\mu}^{*\top} \mathbf{g}(\mathbf{x}^*) = 0$

Proof of FONC

- Since \mathbf{x}^* is a relative minimizer over the constraint set $\{\mathbf{x} : \mathbf{g}(\mathbf{x}) \leq \mathbf{0}\}$, it is also a minimizer over a subset of the constraint set obtained by setting the active constraints to zero
- Therefore, for the resulting equality constrained problem

$$\nabla f(\mathbf{x}^*) + \begin{bmatrix} \nabla g_1(\mathbf{x}^*) & \cdots & \nabla g_P(\mathbf{x}^*) \end{bmatrix} \boldsymbol{\mu}^* = \mathbf{0},$$

where $\mu_j^* = 0$ if $g_j(\mathbf{x}^*) < 0$

- This means that $\boldsymbol{\mu}^{*\top} \mathbf{g}(\mathbf{x}^*) = 0$
- Thus μ_i may be non-zero only if the corresponding constraint is active, that is, $g_i(\mathbf{x}^*) = 0$

Proving that $\mu^* \geq 0$

- It remains to show that $\mu^* \geq 0$
- By contraposition: suppose that for some $k \in J$, we have $\mu_k^* < 0$
- Consider a surface formed by all other active constraints, that is, the surface

$$\{\mathbf{x} : g_j(\mathbf{x}) = 0, j \in J, j \neq k\}.$$

- Also consider

$$\nabla g_k(\mathbf{x}^*)^\top \mathbf{y} < 0$$

- Let $\mathbf{x}(t)$, $t \in [-a, a]$, $a > 0$, be a curve on the surface such that

$$\dot{\mathbf{x}}(0) = \mathbf{y}$$

- Note that for small t , the curve $\mathbf{x}(t)$ is feasible

Minimality of $f(\mathbf{x}^*)$

- Apply the transposition operator to get

$$\nabla f(\mathbf{x}^*)^\top + \sum_{i=1}^P \mu_i^* \nabla g_i(\mathbf{x}^*)^\top = \mathbf{0}^\top$$

- Post-multiplying the above by \mathbf{y} and taking into account the fact that \mathbf{y} belongs to the tangent space to the surface gives

$$\begin{aligned} \nabla f(\mathbf{x}^*)^\top \mathbf{y} &= -\mu_k^* \nabla g_k(\mathbf{x}^*)^\top \mathbf{y} \\ &< 0 \end{aligned}$$

Finish of the proof of FONC

- Suppose, without loss of generality, that $\|\mathbf{y}\|_2 = 1$. Then,

$$\begin{aligned}\frac{df(\mathbf{x}(t))}{dt} &= \nabla f(\mathbf{x}^*)^\top \mathbf{y} \\ &< 0,\end{aligned}$$

that is, the rate of increase of f at \mathbf{x}^* in the direction \mathbf{y} is negative

- This would mean that we could decrease the value of f moving just slightly away from \mathbf{x}^* along \mathbf{y} while, at the same time, preserving feasibility
- But this contradicts the minimality of $f(\mathbf{x}^*)$
- In sum, if \mathbf{x}^* is a relative minimizer then we also have the components of $\boldsymbol{\mu}^*$ all non-negative □
- The vector $\boldsymbol{\mu}^*$ is called the vector of the Karush-Kuhn-Tucker (KKT) multipliers