



非线性半定规划的雅可比唯一性定理

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摘要: 提出了非线性半定规划的雅可比唯一性条件, 证明在这一条件下, 刻画 KKT 条件的映射在 KKT 点处导数是非奇异的. 在雅可比唯一性条件下, 证明了非线性半定规划的稳定性定理并建立了下层为非线性半定优化问题的一类特殊双层规划的必要性最优条件.

关键词: 半定规划; 雅可比唯一性条件; 稳定性; 双层规划

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0 引 言

最优化问题的扰动分析是非常重要的专题, 在数值算法实现的稳健性分析和双层规划的理论研究中起着非常重要的作用. 目前, 扰动分析的研究已经取得了丰富的进展, 比如近年来国际优化领域出版了关于变分分析、扰动分析、非光滑方程和互补与变分不等式的著名专著^[1-4], 在这些专著中最优化的扰动理论都不同程度地被给予关注. 文献[5]详细介绍了非线性规划的扰动分析结果, 文献[2]详细介绍了一般最优化问题的扰动分析结果.

追溯到扰动分析的早期工作, 讨论的问题非常特殊, 如讨论问题的函数是二次连续可微的, 扰动后的函数关于决策变量和扰动参数也是二次连续可微的, 在此情况下, 扰动问题解的存在性、连续性和微分性质. Fiacco 等^[6]在 1968 年对非线性规划在这种情况的扰动分析给出讨论, 提出了著名的雅可比唯一性条件 (Jacobian uniqueness conditions). 对非线性半定规划而言, 类似的雅可比唯一性条件是什么样的条件, 由此条件出发得到什么样的稳定性理论, 还没有文献涉及, 本文讨论这些问题.

1 雅可比唯一性定理

考虑非线性半定规划问题:

$$\begin{aligned} \min \quad & f(x) \\ \text{s. t.} \quad & G(x) \in S^p \\ & x \in R^n \end{aligned} \quad (1)$$

其中 $f: R^n \rightarrow R$ 与 $G: R^n \rightarrow S^p$ 是二次连续可微函数和映射. 式(1)的 Lagrange 函数定义为

$L(x, Y) = f(x) + \langle Y, G(x) \rangle; (x, Y) \in R^n \times S^p$
称 $(\bar{x}, \bar{Y})$ 为式(1)的稳定点, 如果

$$D_x L(\bar{x}, \bar{Y}) = 0; 0 \geq G(\bar{x}) \perp \bar{Y} \geq 0$$

式(1)在稳定点 $\bar{x}$ 处的临界锥 $C(\bar{x})$ 定义为

$$C(\bar{x}) = \{d \in R^n : Df(\bar{x})d \leq 0, DG(\bar{x})d \in T_{S^p}(G(\bar{x}))\}$$

设 $\bar{x}$ 是可行点, 所谓雅可比唯一性条件是指如下的 4 个条件成立:

(1) 存在 $\bar{Y} \in S^p$ 满足

$$D_x L(\bar{x}, \bar{Y}) = 0; 0 \geq G(\bar{x}) \perp \bar{Y} \geq 0$$

(2) 约束非退化条件在 $\bar{x}$ 处成立, 即

$$DG(\bar{x})R^n + \text{lin } T_{S^p}(G(\bar{x})) = S^p$$

(3) 严格互补条件成立, 即

$$\lambda_i(G(\bar{x}) + \bar{Y}) \neq 0; \forall i = 1, 2, \dots, p$$

(4) 二阶充分条件成立, 即

$$\sup_{y \in A(\bar{x})} \{D_{xx}^2 L(\bar{x}, \bar{Y})(d, d) + d^T H(\bar{x}, \bar{Y})d\} > 0;$$

$$\forall d \in C(\bar{x}) \setminus \{0\}$$

其中

$$H(\bar{x}, \bar{Y}) = \left(-2 \left\langle \bar{Y}, \frac{\partial G(\bar{x})}{\partial x_i} G(\bar{x})^\dagger \frac{\partial G(\bar{x})}{\partial x_j} \right\rangle \right)$$

$G(\bar{x})^\dagger$ 是矩阵 $G(\bar{x})$ 的广义逆, 集合 $\Lambda(\bar{x})$ 是在 $\bar{x}$ 处的 Lagrange 乘子集合:

$$\Lambda(\bar{x}) = \{Y \in S^p : D_x L(\bar{x}, Y) = 0, Y \in N_{S^p_+}(G(\bar{x}))\}$$

定理 1 设 $f: \mathbf{R}^n \rightarrow \mathbf{R}$ 与 $G: \mathbf{R}^n \rightarrow S^p$ 是二次连续可微函数和映射, Φ 是式(1)的可行集合, $\bar{x} \in \Phi$ 满足条件(1)~(4), 则映射

$$F(x, Y) = \begin{pmatrix} D_x L(x, Y) \\ \Pi_{S^p_+}(Y + G(x)) - Y \end{pmatrix}$$

在 $(\bar{x}, \bar{Y})$ 处的导数是非奇异的.

证明 由条件(3)可得矩阵 $\bar{A} = \bar{Y} + G(\bar{x})$ 是非奇异的, 因此有 $\Pi_{S^p_+}$ 在 $\bar{A}$ 处是可微的, F 在 $(\bar{x}, \bar{Y})$ 处是可微的. 设 $\bar{A}$ 具有如下的谱分解:

$$\bar{A} = P \Lambda P^T$$

其中 $\Lambda = \text{diag}\{\lambda_1, \dots, \lambda_p\}$, $\lambda_1 \geq \dots \geq \lambda_p$ 是 $\bar{A}$ 的 p 个特征值, $P \in \mathbf{R}^{p \times p}$ 是正交矩阵, $P = (q_1 \dots q_p)$, 则映射 $\Pi_{S^p_+}$ 在 $\bar{A}$ 处沿 $H \in S^p$ 的方向导数为

$$\Pi'_{S^p_+}(\bar{A}; H) = P(P^T H P \circ \Omega)P^T \quad (2)$$

其中 $\circ$ 为矩阵的 Hadamard 乘积运算, $\Omega \in S^p$ 的元素 Ω_{ij} 定义为

$$\Omega_{ij} = \frac{[\lambda_i]_{++} + [\lambda_j]_{++}}{|\lambda_i| + |\lambda_j|}; i, j = 1, 2, \dots, p \quad (3)$$

于是, 映射 F 在 $(\bar{x}, \bar{Y})$ 处沿 $(\Delta x, \Delta Y)$ 的方向导数为

$$DF(\bar{x}, \bar{Y})(\Delta x, \Delta Y) = \begin{pmatrix} D_{xx} L(\bar{x}, \bar{Y}) \Delta x + DG(\bar{x})^* \Delta Y \\ P(P^T(\Delta Y + DG(\bar{x}) \Delta x)P \circ \Omega)P^T - \Delta Y \end{pmatrix}$$

由 $DF(\bar{x}, \bar{Y})(\Delta x, \Delta Y) = 0$ 得

$$D_{xx} L(\bar{x}, \bar{Y}) \Delta x + DG(\bar{x})^* \Delta Y = 0 \quad (4)$$

$$P^T \Delta Y P \circ (1_p 1_p^T - \Omega) = P^T (DG(\bar{x}) \Delta x) P \circ \Omega \quad (5)$$

引入指标集合

$$\alpha = \{i: \lambda_i(\bar{A}) > 0\}, \gamma = \{i: \lambda_i(\bar{A}) < 0\}$$

则

$$G(\bar{x}) = P \begin{pmatrix} 0 & \\ & \Lambda_\gamma \end{pmatrix} P^T, \bar{Y} = P \begin{pmatrix} \Lambda_\alpha & \\ & 0 \end{pmatrix} P^T$$

记 $P_\alpha = (p_i: i \in \alpha)$, $P_\gamma = (p_i: i \in \gamma)$. 由于严格互

补条件成立, 临界锥 $C(\bar{x})$ 可以表示为

$$C(\bar{x}) = \{d \in \mathbf{R}^n : P_\alpha^T DG(\bar{x}) d P_\alpha = 0\} \quad (6)$$

把 Ω 表示为

$$\Omega = \begin{pmatrix} \Omega_{\alpha\alpha} & \Omega_{\alpha\gamma} \\ \Omega_{\gamma\alpha} & \Omega_{\gamma\gamma} \end{pmatrix} \quad (7)$$

则 $\Omega_{\alpha\alpha} = 1_{|\alpha|} 1_{|\alpha|}^T$, $\Omega_{\gamma\gamma} = 0_{|\gamma| \times |\gamma|}$,

$$\Omega_{ij} = \frac{\lambda_i}{\lambda_i + |\lambda_j|}; i \in \alpha, j \in \gamma \quad (8)$$

由式(5)可得

$$q_i^T DG(\bar{x}) \Delta x q_j = 0, (i, j) \in \alpha \times \alpha;$$

$$q_i^T \Delta Y q_j = \frac{\Omega_{ij}}{1 - \Omega_{ij}} q_i^T DG(\bar{x}) \Delta x q_j = 0, (i, j) \in \alpha \times \gamma;$$

$$q_i^T \Delta Y q_j = \frac{\lambda_i}{|\lambda_j|} q_i^T DG(\bar{x}) \Delta x q_j, (i, j) \in \alpha \times \gamma;$$

$$q_i^T \Delta Y q_j = 0, (i, j) \in \gamma \times \gamma \quad (9)$$

用 Δx 与式(4)两边的向量做内积, 并由式(9)可得

$$\begin{aligned} 0 &= \langle \Delta x, D_{xx}^2 L(\bar{x}, \bar{Y}) \Delta x + DG(\bar{x})^* \Delta Y \rangle = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) + \langle DG(\bar{x}) \Delta x, \Delta Y \rangle = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) + \\ &= 2 \sum_{i \in \alpha, j \in \gamma} \frac{\lambda_i}{|\lambda_j|} [q_i^T (DG(\bar{x}) \Delta x) q_j]^2 = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) - \\ &= 2 \sum_{i \in \alpha, j \in \gamma} \frac{\lambda_i}{\lambda_j} [q_i^T (DG(\bar{x}) \Delta x) q_j]^2 = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) - 2 \sum_{i, j=1}^p (P^T Y P)_{ij} \times \\ &= (P^T G(\bar{x})^+ P)_{ij} (P^T (DG(\bar{x}) \Delta x) P)_{ij}^2 = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) - \\ &= 2 \sum_{s, t=1}^n \left\langle P^T \bar{Y} P, P^T \frac{\partial G(\bar{x})}{\partial x_s} P P^T G(\bar{x})^+ \times \right. \\ &= P P^T \frac{\partial G(\bar{x})}{\partial x_t} P^T \left. \right\rangle \Delta x_s \Delta x_t = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) - 2 \sum_{s, t=1}^n \left\langle \bar{Y}, \frac{\partial G(\bar{x})}{\partial x_s} \times \right. \\ &= G(\bar{x})^+ \frac{\partial G(\bar{x})}{\partial x_t} \left. \right\rangle \Delta x_s \Delta x_t = \\ &= D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) + \langle \Delta x, H(\bar{x}, \bar{Y}) \Delta x \rangle \end{aligned}$$

即

$$D_{xx}^2 L(\bar{x}, \bar{Y})(\Delta x, \Delta x) + \langle \Delta x, H(\bar{x}, \bar{Y}) \Delta x \rangle = 0 \quad (10)$$

根据在条件(3)成立的前提下临界锥的表达式(6),式(9)的第一式意味着 $\Delta x \in C(\bar{x})$, 因此由二阶条件和式(10)可推出 $\Delta x = 0$. 由式(4)可得

$$DG(\bar{x})^* \Delta Y = 0$$

由此结合 $P_a^T \Delta Y P_\gamma = 0$ 与 $P_\gamma^T \Delta Y P_\gamma = 0$ 以及约束非退化条件(2), 得到 $P_a^T \Delta Y P_a = 0$, 于是得到 $\Delta Y = 0$. 证毕.

在雅可比唯一性条件成立的前提下, 可以进行式(1)的稳定性分析.

命题 1 考虑如下的扰动问题:

$$\begin{aligned} \min \quad & \bar{f}(x, u) \\ \text{s. t.} \quad & \bar{G}(x, u) \in S^p \\ & x \in R^n \end{aligned} \quad (11)$$

其中 $\bar{f}: R^n \times R^m \rightarrow R$ 与 $\bar{G}: R^n \times R^m \rightarrow S^p$ 是二次连续可微函数和映射, $\bar{f}(x, 0) = f(x)$, $\bar{G}(x, 0) = G(x)$. 如果雅可比唯一性条件(1)~(4)成立, 则存在 $\epsilon > 0$ 与唯一的二次连续可微映射 $x: B(0, \epsilon) \rightarrow B(\bar{x}, \epsilon)$, 满足对任意的 $u \in B(0, \epsilon)$, $x(u)$ 是式(11)满足二阶增长条件的局部极小点, 其中 $B(\bar{x}, \epsilon)$ 表示以 $\bar{x}$ 为球心, ϵ 为半径的开球, $B(0, \epsilon)$ 也有类似的定义.

证明 定义映射

$$H(x, u, Y) = \begin{pmatrix} D_x L_0(x, u, Y) \\ \Pi_{S^p_+}(Y + \bar{G}(x, u)) - Y \end{pmatrix}$$

其中

$$L_0(x, u, Y) = \bar{f}(x, u) + \langle Y, \bar{G}(x, u) \rangle$$

是式(11)的 Lagrange 函数, 显然有 $H(\bar{x}, 0, \bar{Y}) = 0$, $D_{x,Y} H(\bar{x}, 0, \bar{Y}) = DF(\bar{x}, \bar{Y})$ 是映上的. 根据隐函数定理, 则存在 $\epsilon > 0$ 与唯一的二次连续可微映射 $(x, Y): B(0, \epsilon) \rightarrow B(\bar{x}, \epsilon) \times B(\bar{Y}, \epsilon)$, 满足 $(x(0), Y(0)) = (\bar{x}, \bar{Y})$. 对任意的 $u \in B(0, \epsilon)$, $H(x(u), u, Y(u)) = 0$, 这表明 $(x(u), Y(u))$ 是式(11)的 KKT 点, 即

$$D_x L_0(x(u), u, Y(u)) = 0; \quad 0 \geq \bar{G}(x(u)) \perp Y(u) \geq 0$$

由 $(x(\cdot), Y(\cdot))$ 的连续性, 对 $u \in B(0, \epsilon)$, 式(11)在 $x(u)$ 处的约束非退化条件成立, 严格互补条件 $\lambda_i (\bar{G}(x(u), u) + Y(u)) \neq 0, \forall i$ 成立.

由于 $C(\bar{x}) = \{d: \langle \bar{Y}, DG(\bar{x})d \rangle = 0\}$,

$$C(x(u)) = \{d: \langle Y(u), D\bar{G}(x(u), u)d \rangle = 0\}$$

在 $u = 0$ 处连续(在变分分析的集值映射连续的意义下)以及

$$H(x(u), Y(u)) = \left(-2 \left\langle Y(u), \frac{\partial \bar{G}(x(u), u)}{\partial x_i} \times \bar{G}(x(u), u) + \frac{\partial \bar{G}(x(u), u)}{\partial x_j} \right\rangle \right)$$

在 $u = 0$ 处的连续性, 对充分小的 $\epsilon > 0, u \in B(0, \epsilon)$ 时,

$$\sup_{Y \in A(x(u))} \{D_{xx}^2 L_0(x(u), u, Y(u))(d, d) +$$

$$d^T H(x(u), Y(u))d\} > 0;$$

$$\forall d \in C(x(u)) \setminus \{0\}$$

即在 $(x(u), Y(u))$ 处, 式(11)的二阶充分最优性条件成立, 因此 $x(u)$ 是式(11)满足二阶增长条件的局部极小点.

作为命题 1 的应用, 考虑扰动问题:

$$\begin{aligned} \min \quad & f(x) \\ \text{s. t.} \quad & G(x) + Z \in S^p \\ & x \in R^n \end{aligned} \quad (12)$$

其中 $Z \in S^p$. 式(12)的最优值函数被称为扰动函数, 记为 $v(Z)$.

定理 2 设 $f: R^n \rightarrow R$ 与 $G: R^n \rightarrow S^p$ 是二次连续可微函数和映射, $\bar{x} \in \Phi$ 满足条件(1)~(4), 则

$$Dv(0)H = -\langle \bar{Y}, H \rangle; \quad \forall H \in S^p \quad (13)$$

证明 由命题 1, 存在 $\epsilon > 0$, 唯一的连续可微映射 $(x, Y): B(0, \epsilon) \rightarrow B(\bar{x}, \epsilon) \times B(\bar{Y}, \epsilon)$, 满足对任意的 $Z \in B(0, \epsilon)$, $(x(Z), Y(Z))$ 满足式(12)的 KKT 条件, 即

$$\begin{aligned} D_x L_0(x(Z), Z, Y(Z)) &= 0 \\ \Pi_{S^p_+}(Y(Z) + G(x(Z)) + Z) - Y(Z) &= 0 \end{aligned} \quad (14)$$

其中

$$L_0(x, Z, Y) = f(x) + \langle Y, G(x) + Z \rangle$$

由式(14)的第二式得

$$\Pi'_{S^p_+}(DY(0)H + DG(x(0))H + H) - DY(0)H = 0$$

即

$$P^T DG(\bar{x}) D_x(0) H P \circ \Omega - P^T DY(0) H P \circ (1_p 1_p^T - \Omega) + P^T H P \circ \Omega = 0 \quad (15)$$

由于 $(1_p 1_p^T - \Omega)_{aa} = 0_{|a| \times |a|}$, $\Omega_{aa} = 1_{|a|} 1_{|a|}^T$, 由式

(15) 得

$$(\mathbf{P}^T \mathbf{D}\mathbf{G}(\bar{\mathbf{x}}) \mathbf{D}\mathbf{x}(\mathbf{0}) \mathbf{H}\mathbf{P})_{aa} = (\mathbf{P}^T \mathbf{H}\mathbf{P})_{aa} \quad (16)$$

根据

$$\nabla f(\bar{\mathbf{x}}) = -\mathbf{D}\mathbf{G}(\bar{\mathbf{x}})^* \bar{\mathbf{Y}}$$

和式(16) 得

$$\begin{aligned} \mathbf{D}\mathbf{v}(\mathbf{0})\mathbf{H} &= \nabla f(\mathbf{x}(\mathbf{0}))^T \mathbf{D}\mathbf{x}(\mathbf{0})\mathbf{H} = \\ &= -(\mathbf{D}\mathbf{G}(\bar{\mathbf{x}})^* \bar{\mathbf{Y}})^T \mathbf{D}\mathbf{x}(\mathbf{0})\mathbf{H} = \\ &= -\langle \bar{\mathbf{Y}}, \mathbf{D}\mathbf{G}(\bar{\mathbf{x}}) \mathbf{D}\mathbf{x}(\mathbf{0})\mathbf{H} \rangle = \\ &= -\langle \mathbf{P}^T \bar{\mathbf{Y}}\mathbf{P}, \mathbf{P}^T \mathbf{D}\mathbf{G}(\bar{\mathbf{x}}) \mathbf{D}\mathbf{x}(\mathbf{0}) \mathbf{H}\mathbf{P}^T \rangle = \\ &= -\langle \mathbf{A}_{aa}, (\mathbf{P}^T \mathbf{D}\mathbf{G}(\bar{\mathbf{x}}) \mathbf{D}\mathbf{x}(\mathbf{0}) \mathbf{H}\mathbf{P}^T)_{aa} \rangle = \\ &= -\langle \mathbf{A}_{aa}, (\mathbf{P}^T \mathbf{H}\mathbf{P})_{aa} \rangle = \\ &= -\langle \mathbf{P}^T \bar{\mathbf{Y}}\mathbf{P}, \mathbf{P}^T \mathbf{H}\mathbf{P} \rangle = \\ &= -\langle \bar{\mathbf{Y}}, \mathbf{H} \rangle \end{aligned}$$

得到结论.

2 一类双层规划的最优性条件

考虑如下的双层优化问题, 上层优化问题定义为

$$\begin{aligned} \min \quad & \theta(\mathbf{x}, \mathbf{u}) \\ \text{s. t.} \quad & \mathbf{x} \in \text{Sol P}(\mathbf{u}) \\ & \mathbf{u} \in \mathbf{U}_{ad} \end{aligned} \quad (17)$$

下层为问题 $\text{P}(\mathbf{u})$, 定义如下:

$$\begin{aligned} \min \quad & f(\mathbf{x}) \\ \text{s. t.} \quad & \mathbf{G}(\mathbf{x}) + \mathbf{B}\mathbf{u} \in \mathbf{S}^p \\ & \mathbf{x} \in \mathbf{R}^n \end{aligned} \quad (18)$$

其中 $\theta: \mathbf{R}^n \times \mathbf{R}^m \rightarrow \mathbf{R}$ 是连续可微函数, $\mathbf{U}_{ad} \subset \mathbf{R}^m$ 是非空闭凸集合, $\text{Sol P}(\mathbf{u})$ 表示问题 $\text{P}(\mathbf{u})$ 的最优解集合, $\mathbf{B}: \mathbf{R}^m \rightarrow \mathbf{S}^p$ 是一连续的线性算子.

对任何 $\mathbf{u} \in \mathbf{R}^m$, 设在 $(\mathbf{x}(\mathbf{u}), \mathbf{Y}(\mathbf{u}))$ 处问题 $\text{P}(\mathbf{u})$ 的雅可比唯一性条件成立, 由命题 1 得, $(\mathbf{x}(\mathbf{u}), \mathbf{Y}(\mathbf{u}))$ 是二次连续可微映射, 满足

$$\begin{aligned} \nabla_{\mathbf{x}} L_0(\mathbf{x}, \mathbf{u}, \mathbf{Y}) &= \mathbf{0} \\ \Pi_{\mathbf{S}_+^p}(\mathbf{Y} + \mathbf{G}(\mathbf{x}) + \mathbf{B}\mathbf{u}) - \mathbf{Y} &= \mathbf{0} \end{aligned} \quad (19)$$

其中

$$L_0(\mathbf{x}, \mathbf{u}, \mathbf{Y}) = f(\mathbf{x}) + \langle \mathbf{Y}, \mathbf{G}(\mathbf{x}) + \mathbf{B}\mathbf{u} \rangle$$

令 $\mathbf{V}(\mathbf{u}) = \mathbf{D}\Pi_{\mathbf{S}_+^p}(\mathbf{Y}(\mathbf{u}) + \mathbf{G}(\mathbf{x}(\mathbf{u})) + \mathbf{B}\mathbf{u}): \mathbf{R}^m \rightarrow \mathbf{S}^p$, 可得到下述的最优性必要条件.

命题 2 设 $f: \mathbf{R}^n \rightarrow \mathbf{R}$ 与 $\mathbf{G}: \mathbf{R}^n \rightarrow \mathbf{S}^p$ 是二次连续可微函数和映射, 对每一 $\mathbf{u} \in \mathbf{R}^m$, $(\mathbf{x}(\mathbf{u}),$

$\mathbf{Y}(\mathbf{u}))$ 处问题 $\text{P}(\mathbf{u})$ 的雅可比唯一性条件成立. 如果 $\mathbf{u}^* \in \mathbf{U}_{ad}$ 是式(17) 的局部极小点, 则

$$\langle -\mathbf{B}^*(\mathbf{V}(\mathbf{u}^*)\mathbf{P}_2) + \nabla_{\mathbf{u}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle \geq 0; \quad \forall \mathbf{u} \in \mathbf{U}_{ad} \quad (20)$$

其中 $(\mathbf{P}_1, \mathbf{P}_2) \in \mathbf{R}^n \times \mathbf{S}^p$ 满足如下的伴随方程:

$$\begin{pmatrix} \nabla_{\mathbf{x}}^2 L(\mathbf{x}(\mathbf{u}^*), \mathbf{Y}(\mathbf{u}^*)) & \mathbf{D}\mathbf{G}(\mathbf{x}(\mathbf{u}^*))^* \\ \mathbf{V}(\mathbf{u}^*)\mathbf{D}\mathbf{G}(\mathbf{x}(\mathbf{u}^*)) & \mathbf{V}(\mathbf{u}^*) - \mathbf{I} \end{pmatrix}^* \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \end{pmatrix} = \begin{pmatrix} \nabla_{\mathbf{x}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*) \\ \mathbf{0} \end{pmatrix} \quad (21)$$

证明 定义 $\theta_0(\mathbf{u}) = \theta(\mathbf{x}(\mathbf{u}), \mathbf{u})$. 如果 $\mathbf{u}^* \in \mathbf{U}_{ad}$ 是式(17) 的局部极小点, 则

$$\langle \nabla \theta_0(\mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle \geq 0; \quad \forall \mathbf{u} \in \mathbf{U}_{ad} \quad (22)$$

令

$$\mathbf{M}(\mathbf{u}) = \begin{pmatrix} \nabla_{\mathbf{x}}^2 L(\mathbf{x}(\mathbf{u}), \mathbf{Y}(\mathbf{u})) & \mathbf{D}\mathbf{G}(\mathbf{x}(\mathbf{u}))^* \\ \mathbf{V}(\mathbf{u})\mathbf{D}\mathbf{G}(\mathbf{x}(\mathbf{u})) & \mathbf{V}(\mathbf{u}) - \mathbf{I} \end{pmatrix}$$

则

$$\mathbf{M}(\mathbf{u}^*) \begin{pmatrix} \mathbf{J}\mathbf{x}(\mathbf{u}^*)(\mathbf{u} - \mathbf{u}^*) \\ \mathbf{D}\mathbf{Y}(\mathbf{u}^*)(\mathbf{u} - \mathbf{u}^*) \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ -\mathbf{V}(\mathbf{u}^*)\mathbf{B}(\mathbf{u} - \mathbf{u}^*) \end{pmatrix}$$

注意到式(21) 可以表示为

$$\mathbf{M}(\mathbf{u}^*)^* \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \end{pmatrix} = \begin{pmatrix} \nabla_{\mathbf{x}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*) \\ \mathbf{0} \end{pmatrix}$$

得到对 $\mathbf{u} \in \mathbf{U}_{ad}$,

$$\begin{aligned} 0 &\leq \langle \nabla \theta_0(\mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle = \\ &= \langle \mathbf{J}\mathbf{x}(\mathbf{u}^*)^T \nabla_{\mathbf{x}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*) + \\ &\quad \nabla_{\mathbf{u}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle = \\ &= \left\langle \begin{pmatrix} \nabla_{\mathbf{x}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*) \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \mathbf{J}\mathbf{x}(\mathbf{u}^*)(\mathbf{u} - \mathbf{u}^*) \\ \mathbf{D}\mathbf{Y}(\mathbf{u}^*)(\mathbf{u} - \mathbf{u}^*) \end{pmatrix} \right\rangle + \\ &= \langle \nabla_{\mathbf{u}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle = \\ &= \left\langle [\mathbf{M}(\mathbf{u}^*)^{-1}]^* \begin{pmatrix} \nabla_{\mathbf{x}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*) \\ \mathbf{0} \end{pmatrix}, \right. \\ &\quad \left. \mathbf{M}(\mathbf{u}^*) \begin{pmatrix} \mathbf{J}\mathbf{x}(\mathbf{u}^*)(\mathbf{u} - \mathbf{u}^*) \\ \mathbf{D}\mathbf{Y}(\mathbf{u}^*)(\mathbf{u} - \mathbf{u}^*) \end{pmatrix} \right\rangle + \\ &= \langle \nabla_{\mathbf{u}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle = \\ &= \left\langle \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \end{pmatrix}, \begin{pmatrix} \mathbf{0} \\ -\mathbf{V}(\mathbf{u}^*)\mathbf{B}(\mathbf{u} - \mathbf{u}^*) \end{pmatrix} \right\rangle + \\ &= \langle \nabla_{\mathbf{u}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*), \mathbf{u} - \mathbf{u}^* \rangle = \\ &= \langle -\mathbf{B}^*(\mathbf{V}(\mathbf{u}^*)\mathbf{P}_2) + \nabla_{\mathbf{u}}\theta(\mathbf{x}(\mathbf{u}^*), \mathbf{u}^*), \\ &\quad \mathbf{u} - \mathbf{u}^* \rangle \end{aligned}$$

即式(20)成立.

3 结 语

本文证明了非线性半定规划的雅可比唯一性定理,扰动问题的函数是决策变量与扰动参数的二次连续可微函数时的扰动解的连续可微性质,扰动函数的导数,以及一类下层为非线性半定规划的特殊双层规划的最优性条件. 在雅可比唯一性条件中,严格互补条件是至关重要的,如果这一条件不成立,非线性半定规划的扰动性分析需要用到正半定矩阵锥的非光滑分析. 非线性系统的强正则性和映射的 Lipschitz 同胚,与约束非退化条件和强二阶充分性最优条件等详见文献[7].

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Jacobian uniqueness theorem for nonlinear semidefinite programming

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Abstract: Jacobian uniqueness conditions for nonlinear semidefinite programming are presented, under which, the mapping characterizing the KKT conditions is demonstrated to have a nonsingular derivative at the KKT point. Under the Jacobian uniqueness conditions, stability theorem for nonlinear semidefinite programming is proved and the necessary optimality conditions for a special bi-level program, whose lower level problem is a nonlinear semidefinite optimization problem, are established.

Key words: semidefinite programming; Jacobian uniqueness conditions; stability; bi-level program