

# Appendix

## Proof of Lemma 2

*Proof.* This lemma is a straightforward consequence of the second-order necessary and sufficient conditions for optimality [1]. Notice that in our case, the Hessian of the Lagrangge function  $\nabla_{\mathbf{x}\mathbf{x}}^2 \mathcal{L}(\mathbf{x}, \gamma) = \mathbf{A} - \gamma \mathbf{I}$  and the constraint  $\mathbf{x}^T \mathbf{x} - 1 = 0$  has the Jacobian  $\mathbf{J}(\mathbf{x}) = \mathbf{x}$ .

- **Necessary conditions.** If  $\mathbf{x}_*$  is a local minimum of problem (2), then it satisfies the stationary conditions in Lemma 1 and

$$\mathbf{y}^T (\mathbf{A} - \gamma \mathbf{I}) \mathbf{y} \geq 0 \quad \forall \mathbf{y} \text{ s.t. } \mathbf{y}^T \mathbf{x}_* = 0. \quad (1)$$

Since  $\mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{y} = \mathbf{y}$  for all  $\mathbf{y}$  orthogonal to  $\mathbf{x}_*$ , we have

$$\begin{aligned} \mathbf{y}^T (\mathbf{A} - \gamma \mathbf{I}) \mathbf{y} &= \mathbf{y}^T \mathbf{P}_{\mathbf{x}_*}^\perp (\mathbf{A} - \gamma \mathbf{I}) \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{y} \\ &= \mathbf{y}^T \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{A} \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{y} - \gamma \mathbf{y}^T \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{y} \\ &= \mathbf{y}^T (\mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{A} \mathbf{P}_{\mathbf{x}_*}^\perp - \gamma \mathbf{I}) \mathbf{y}. \end{aligned}$$

Thus, condition (1) also implies

$$\mathbf{y}^T (\mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{A} \mathbf{P}_{\mathbf{x}_*}^\perp - \gamma \mathbf{I}) \mathbf{y} \geq 0 \quad \forall \mathbf{y} \text{ s.t. } \mathbf{y}^T \mathbf{x}_* = 0.$$

- **Sufficient conditions.** Let  $\mathbf{x}_*$  be a stationary point of problem (2). By the same argument, we can also prove that  $\mathbf{x}_*$  is a strict local minimum if

$$\mathbf{y}^T (\mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{A} \mathbf{P}_{\mathbf{x}_*}^\perp - \gamma \mathbf{I}) \mathbf{y} > 0 \quad \forall \mathbf{y} \text{ s.t. } \mathbf{y}^T \mathbf{x}_* = 0. \quad (2)$$

Now it is sufficient to show that (2) is equivalent to  $\gamma < \lambda_{n-1}$ . In fact, this can be shown by the definition of  $\lambda_{n-1}$ :

$$\lambda_{n-1} = \min_{\substack{\mathbf{u} \in \mathcal{S}^{n-1} \\ \mathbf{u} \neq \mathbf{x}_*}} \mathbf{u}^T \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{A} \mathbf{P}_{\mathbf{x}_*}^\perp \mathbf{u}.$$

For the global minimizer result, we refer to Lemmas 2.4 and 2.8 in [2]. □

## Proof of Lemma 4

Since  $\frac{\partial}{\partial \mathbf{x}} \|\mathbf{x}\| = \frac{\mathbf{x}}{\|\mathbf{x}\|}$  and  $\frac{\partial^2}{\partial \mathbf{x} \partial \mathbf{x}^T} \|\mathbf{x}\| = \frac{1}{\|\mathbf{x}\|} \mathbf{I} - \frac{1}{\|\mathbf{x}\|^2} \frac{\mathbf{x}}{\|\mathbf{x}\|} \mathbf{x}^T$ , the Taylor series expansion of function  $f(\mathbf{x}) = \frac{\mathbf{x}}{\|\mathbf{x}\|}$  is given by

$$\begin{aligned} f(\mathbf{x} + \boldsymbol{\delta}) &= f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \boldsymbol{\delta} \rangle + O(\|\boldsymbol{\delta}\|^2) \\ &= f(\mathbf{x}) + \left( \frac{1}{\|\mathbf{x}\|} \mathbf{I} - \frac{1}{\|\mathbf{x}\|^2} \frac{\mathbf{x}}{\|\mathbf{x}\|} \mathbf{x}^T \right) \boldsymbol{\delta} + O(\|\boldsymbol{\delta}\|^2) \\ &= f(\mathbf{x}) + \frac{1}{\|\mathbf{x}\|} \left( \mathbf{I} - \frac{\mathbf{x} \mathbf{x}^T}{\|\mathbf{x}\|^2} \right) \boldsymbol{\delta} + O(\|\boldsymbol{\delta}\|^2). \end{aligned}$$

## Proof of Lemma 5

We have

$$\alpha_* = \underset{\substack{\alpha > 0 \\ \alpha(\lambda_1 + \gamma) < 2}}{\operatorname{argmin}} \max_{1 \leq i \leq n-1} \frac{|1 - \alpha \lambda_i|}{1 - \alpha \gamma} \quad (3)$$

For  $\gamma < \lambda$ , the function  $\frac{1-\alpha\lambda}{1-\alpha\gamma}$  is monotonically decreasing. Denote  $f(\alpha) = \max_{1 \leq i \leq n-1} \frac{|1-\alpha\lambda_i|}{1-\alpha\gamma}$ . Consider the following three cases:

- If  $1 - \alpha\lambda_{n-1} \geq 1 - \alpha\lambda_1 \geq 0$ , then (3) becomes

$$\begin{aligned} \min_{\alpha} f(\alpha) &= \min_{\alpha\lambda_1 \leq 1} \frac{1 - \alpha\lambda_{n-1}}{1 - \alpha\gamma} \\ &= \begin{cases} f(\frac{1}{\lambda_1}) = \frac{\lambda_1 - \lambda_{n-1}}{\lambda_1 - \gamma} & \text{if } \lambda_1 > 0 \\ f(\infty) = \frac{\lambda_{n-1}}{\gamma} & \text{otherwise} \end{cases} \end{aligned}$$

- If  $1 - \alpha\lambda_1 \leq 1 - \alpha\lambda_{n-1} \leq 0$ , then (3) becomes

$$\min_{\alpha} f(\alpha) = \min_{\alpha\lambda_{n-1} \geq 1} \frac{\alpha\lambda_1 - 1}{1 - \alpha\gamma} = f\left(\frac{1}{\lambda_{n-1}}\right) = \frac{\lambda_1 - \lambda_{n-1}}{\lambda_{n-1} - \gamma}$$

- If  $\begin{cases} 1 - \alpha\lambda_1 \leq 0 \\ 1 - \alpha\lambda_{n-1} \geq 0 \end{cases}$ , then (3) becomes

$$\begin{aligned} \min_{\alpha} f(\alpha) &= \min_{\alpha(\lambda_1 + \lambda_{n-1}) \leq 2} \left\{ \frac{\alpha\lambda_1 - 1}{1 - \alpha\gamma}, \frac{1 - \alpha\lambda_{n-1}}{1 - \alpha\gamma} \right\} \\ &= \begin{cases} f(\frac{2}{\lambda_1 + \lambda_{n-1}}) = \frac{\lambda_1 - \lambda_{n-1}}{\lambda_1 + \lambda_{n-1} - 2\gamma} & \text{if } \alpha(\lambda_1 + \lambda_{n-1}) < 2 \\ f(\infty) = \frac{\lambda_{n-1}}{\gamma} & \text{otherwise} \end{cases} \end{aligned}$$

In summary, we have

- If  $\lambda_1 + \lambda_{n-1} \leq 0$ , then

$$\min_{\alpha} f(\alpha) = \min \left\{ f\left(\frac{1}{\lambda_1}\right), f(\infty) \right\} = f(\infty)$$

- If  $\lambda_1 + \lambda_{n-1} > 0$ , then

$$\begin{aligned} \min_{\alpha} f(\alpha) &= \min \left\{ f\left(\frac{1}{\lambda_1}\right), f\left(\frac{1}{\lambda_{n-1}}\right), f\left(\frac{2}{\lambda_1 + \lambda_{n-1}}\right) \right\} \\ &= f\left(\frac{2}{\lambda_1 + \lambda_{n-1}}\right). \end{aligned}$$

## References

- [1] D. P. Bertsekas, *Nonlinear programming*, Athena Scientific optimization and computation series. Athena Scientific, 1999.
- [2] Danny C Sorensen, “Newton’s method with a model trust region modification,” *SIAM Journal on Numerical Analysis*, vol. 19, no. 2, pp. 409–426, 1982.