

## Chapter 19

# Stability Region of Dynamic System

Consider a dynamic system. The stability region of a stable equilibrium plays very important role in practice, because the stability region is the allowed working area of an engineering system. Particularly, consider a power system, there are many working points (stable equilibriums), and investigating their stability region is fundamental for the safety of the system.

### 19.1 Stability Region

Consider the following nonlinear dynamic system,

$$\dot{x} = f(x), \quad x \in \mathbb{R}^n, \quad (19.1)$$

where  $f(x)$  is an analytic field.

**Definition 19.1.** Let  $x_e$  be an equilibrium of (19.1).

1. The stable and unstable sub-manifold of  $x_e$ , denoted by  $W^s(x_e)$ , is defined as

$$W^s(x_e) = \left\{ p \in \mathbb{R}^n \mid \lim_{t \rightarrow \infty} x(t, p) \rightarrow x_e \right\}. \quad (19.2)$$

2. The unstable sub-manifold of  $x_e$ , denoted by  $W^u(x_e)$ , is defined as

$$W^u(x_e) = \left\{ p \in \mathbb{R}^n \mid \lim_{t \rightarrow -\infty} x(t, p) \rightarrow x_e \right\}. \quad (19.3)$$

**Definition 19.2.** 1. Let  $x_s$  be a stable equilibrium of (19.1). The region of attraction of  $x_s$  is defined as

$$A(x_s) = \left\{ p \in \mathbb{R}^n \mid \lim_{t \rightarrow \infty} x(t, p) \rightarrow x_s \right\}. \quad (19.4)$$

The boundary of  $A(x_s)$  is denoted by  $\partial A(x_s)$ .

2. An equilibrium  $x_e$  is said to be hyperbolic, if the Jacobi matrix of  $f$  at  $x_e$ ,  $J_f(x_e)$  has no zero real part eigenvalues.
3. A hyperbolic equilibrium is said to be of type- $k$ , if  $J_f(x_e)$  has  $k$  positive real part eigenvalues.

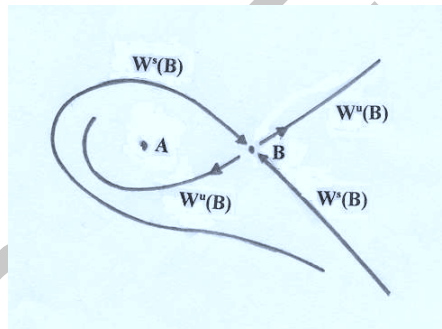
The following result is fundamental for our approach.

**Theorem 19.1 ([6, 3]).** Consider system (19.1). Assume  $x_s$  is a stable equilibrium, satisfying the following three assumptions

- (i) the equilibria on  $\partial A(x_s)$  are all hyperbolic;
- (ii) the stable and unstable sub-manifolds of the equilibria on  $\partial A(x_s)$  are transversal;
1. (iii) each trajectory on  $\partial A(x_s)$  converges to an equilibrium as  $t \rightarrow \infty$ .

Then the boundary of the stability region consists of the unstable sub-manifolds of the equilibria on the boundary.

Fig. 19.1 illustrates this.



**Fig. 19.1** Boundary of Stability Region

Note that two sub-manifolds  $N$  and  $S$  of a manifold  $M$  is said to be transversal, if for any  $x \in N \cap S$ , the union of their tangent spaces is the tangent space of  $M$ . Precisely,

$$T_x(N) \cup T_x(S) = T_x(M).$$

It is well known that [3] if the state manifold is of dimension  $n$ , then the boundary of the stability region is of dimension  $n - 1$ . Hence, the boundary is basically generated by the stable sub-manifolds of type-1 equilibria. Based on this consideration, the stable sub-manifolds of type-1 equilibria are particularly important. There are many algorithms to calculate approximations of the stable sub-manifolds of type-1 equilibria.

The purpose of this chapter is to explore the Taylor expansion of the equation of the sub-manifolds. Particularly, it can be used to obtain a best quadratic approximation, comparing previously existing results.

## 19.2 Stable Sub-Manifold

In this section we search a function to describe the stable sub-manifolds of type-1 equilibrium.

Without loss of generality, we assume  $x_u = 0$  is a type-1 equilibrium. Write down the Taylor series expansion of the  $f(x)$  in (19.1) as

$$f(x) = \sum_{i=1}^{\infty} F_i x^i = Jx + F_2 x^2 + \dots, \quad (19.5)$$

where  $F_1 = J = J_f(0)$ , and  $F_i = \frac{1}{i!} D^i f(0)$  are known  $n \times n^i$  matrices.

We use  $A^{-T}$  for the inverse of  $A^T$ . Matrix  $A$  is said to be hyperbolic if it has no zero real part eigenvalue.

**Lemma 19.1.** *Let  $A$  be a hyperbolic matrix. Denote by  $V_s$  and  $V_u$  the stable and unstable sub-manifolds of  $A$  respectively, and by  $U_s$  and  $U_u$  the stable and unstable sub-manifolds of  $A^{-T}$ . Then*

$$V_s^\perp = U_u, \quad V_u^\perp = U_s. \quad (19.6)$$

*Proof.* Assume  $A$  is of the type- $k$ , then we can convert  $A$  into a Jordan canonical form as

$$Q^{-1}AQ = \begin{bmatrix} J_s & 0 \\ 0 & J_u \end{bmatrix},$$

where  $J_s$  and  $J_u$  are stable and unstable blocks respectively. Splitting  $Q = [Q_1 \ Q_2]$ , where  $Q_1$  and  $Q_2$  are consisted by the first  $n-k$  and the last  $k$  columns of  $Q$ . Then

$$V_s = \text{Span col}\{Q_1\}, \quad V_u = \text{Span col}\{Q_2\}.$$

It is easy to see that

$$Q^T A^{-T} Q^{-T} = \begin{bmatrix} J_s^{-T} & 0 \\ 0 & J_u^{-T} \end{bmatrix}.$$

Similarly, splitting  $Q^{-T} = [\tilde{Q}_1 \ \tilde{Q}_2]$ , where  $\tilde{Q}_1$  and  $\tilde{Q}_2$  consist of the first  $n-k$  and last  $k$  columns of  $Q^{-T}$  respectively, we have

$$U_s = \text{Span col}\{\tilde{Q}_1\}, \quad U_u = \text{Span col}\{\tilde{Q}_2\}.$$

The conclusion follows from  $Q^{-1}Q = I$ . □

The following corollary is an immediate consequence of the above lemma.

**Corollary 19.1.** *Let  $A$  be a matrix of type-1 with its unique unstable eigenvalue  $\mu$ . Assume  $\eta$  is the eigenvector of  $A^T$  with respect to  $\mu$ , then  $\eta$  is perpendicular to the stable subspace of  $A$ .*

*Proof.* Since the only unstable eigenvalue of  $A^{-T}$  is  $\frac{1}{\mu}$ , denote by  $\eta$  the eigenvector of  $A^{-T}$  corresponding to this unstable eigenvalue. Then by Lemma 19.1  $\text{Span}\{\eta\} =$

$U_u = V_s^\perp$ . Hence we need only to prove that  $\eta$  is also the eigenvector of  $A^T$  with respect to  $\mu$ . Since

$$A^{-T}\eta = \frac{1}{\mu}\eta \Rightarrow A^T\eta = \mu\eta,$$

the claim follows.  $\square$

Without loss of generality, we assume the unstable equilibrium  $x_u = 0$  of the system (19.1), concerned in the sequel, is of type-1.

The following theorem provides a necessary and sufficient condition for the stable sub-manifold of a type-1 equilibrium.

**Theorem 19.2.** *Let  $x_u = 0$  be an equilibrium of type-1 of the system (19.1).*

$$W^s(e_u) = \{x \mid h(x) = 0\}. \quad (19.7)$$

Then  $h(x)$  is uniquely determined by the following equations (19.8)–(19.10).

$$h(0) = 0, \quad (19.8)$$

$$h(x) = \eta^T x + O(\|x\|^2), \quad (19.9)$$

$$L_f h(x) = \mu h(x), \quad (19.10)$$

where  $L_f h(x)$  is the Lie derivative of  $h(x)$  with respect to  $f$ ,  $\eta$  is the eigenvector of  $J_f^T(0)$  with respect to its unique positive eigenvalue  $\mu$ .

*Proof.* (Necessity) The necessity of (19.8) and (19.9) are obvious. We need only to prove the necessity of (19.10). First, note that

$$\frac{\partial h}{\partial x} = \eta^T + O(\|x\|). \quad (19.11)$$

Hence, there exists a neighborhood  $U$  of the origin, such that

$$\text{rank}(h(x)) = 1, \quad x \in U. \quad (19.12)$$

Since  $W^s(e_u)$  is  $f$  invariant, we have

$$\begin{cases} h(x) = 0, \\ L_f h(x) = 0, \end{cases} \quad x \in W^s(e_u). \quad (19.13)$$

Since  $\dim(W^s(e_u)) = n - 1$ , we have

$$\text{rank} \left( \begin{bmatrix} h(x) \\ L_f h(x) \end{bmatrix} \right) = 1,$$

this implies that  $h(x)$  and  $L_f h(x)$  are linearly dependent. A straightforward computation shows that

$$L_f h(x) = \eta^T J_f(0)x + O(\|x\|^2) = \mu \eta^T x + O(\|x\|^2).$$

Hence for  $x \in U$ , the linearly dependence of  $h(x)$  and  $L_f h(x)$  yields (19.10). Finally, because of the analyticity of the system, we conclude that (19.10) is globally correct.

(Sufficiency) First, we prove that if  $h(x)$  satisfies (19.8)–(19.10), then locally we have

$$\{x \in U \mid h(x) = 0\}$$

is the stable sub-manifold over  $U$ . According to the rank condition (19.12), we know that (refer to [1], Theorem 5.8)

$$V := \{x \in U \mid h(x) = 0\}$$

is an  $(n - 1)$ -dimensional sub-manifold.

Next, since  $L_f h(x) = 0$ ,  $V$  is locally  $f$  invariant. Finally, (19.9) shows that zero is locally the asymptotically stable equilibrium of  $f|_V$ , which is the restriction of  $f$  on  $V$ . Hence, locally  $V$  is the stable sub-manifold of (19.1). But the stable sub-manifold is unique [2], it follows that locally  $V = W^s(e_u)$ .

Since the system is analytic,  $\{x \mid h(x) = 0\}$  coincides globally with  $W^s(e_u)$ .  $\square$

### 19.3 Quadratic Approximation

In general, it is not easy to figure out the equation  $h(x)$  of the stable sub-manifold. The quadratic approximation of the boundary of the stability region has been investigated by several authors [5, 4]. This section provides a quadratic approximation of  $h(x)$ . The precise formula is provided, which is the unique approximation with error  $O(\|x\|^3)$ .

Denote the Taylor series expansion of  $h(x)$  as

$$h(x) = H_1 x + H_2 x^2 + H_3 x^3 + \dots = H_1 x + \frac{1}{2} x^T \Psi x + H_3 x^3 + \dots \quad (19.14)$$

In the above we use two forms to express the quadratic terms: semi-tensor product form  $H_2 x^2$  and standard quadratic form  $\frac{1}{2} x^T \Psi x$ , where  $\Psi = \text{Hess}(h(0))$  is the Hessian matrix of  $h(x)$  at  $x = 0$ , and  $H_2 = V_c^T(\frac{1}{2} \Psi)$  is the row stacking form of  $\frac{1}{2} \Psi$ .

Note that for a real function  $f(x, y) : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$  its Hessian matrix is

$$\text{Hess}(f) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1 \partial y_1} & \dots & \frac{\partial^2 f}{\partial x_1 \partial y_m} \\ \vdots & & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial y_1} & \dots & \frac{\partial^2 f}{\partial x_n \partial y_m} \end{bmatrix}.$$

**Lemma 19.2.** *Assume 0 is the type-1 equilibrium of (19.1). Then the quadratic terms of (19.14) satisfies*

$$\Psi \left( \frac{\mu}{2} I - J \right) + \left( \frac{\mu}{2} I - J^T \right) \Psi = \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)), \quad (19.15)$$

where  $\mu$  and  $\eta$  are as in Corollary 19.1,  $\text{Hess}(f_i)$  is the Hessian matrix of the  $i$ -th component of  $f$ .

*Proof.* First, the linear approximation of  $h(x) = 0$  is

$$H_1 x = 0,$$

which is the tangent space of the stable sub-manifold  $W^s(x_u)$ . Since  $\eta$  is perpendicular to  $W^s(x_u)$  at  $x_u$ , we have  $H_1 = \eta$ .

According to Theorem 19.2, the Lie derivative satisfying

$$L_f h(x) = 0.$$

Using (15.74), we have

$$Dh(x) = H_1 + H_2 \Phi_1 x + H_3 \Phi_2 x^2 + \dots = H_1 + x^T \Psi + H_3 \Phi_2 x^2 + \dots.$$

Note that the vector field  $f$  can be expressed as

$$f(x) = Jx + \frac{1}{2} \begin{bmatrix} x^T \text{Hess}(f_1(0))x \\ \vdots \\ x^T \text{Hess}(f_n(0))x \end{bmatrix} + O(\|x\|^3).$$

Calculating  $L_f h$  out yields

$$\begin{aligned} L_f h &= \eta^T Jx + x^T \left( \frac{1}{2} \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) + \Psi J \right) x + O(\|x\|^3) \\ &= \mu \eta^T x + x^T \left( \frac{1}{2} \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) + \Psi J \right) x + O(\|x\|^3). \end{aligned} \quad (19.16)$$

Observing that as the invariant sub-manifold of  $f$ , we have

$$W^s(e_u) = \{x \mid h(x) = 0, L_f h(x) = 0\}. \quad (19.17)$$

Applying (19.14) and (19.17) to  $W^s(e_u)$  yields

$$x^T \left( \frac{1}{2} \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) + \Psi \left( J - \frac{\mu}{2} I \right) \right) x + O(\|x\|^3) = 0. \quad (19.18)$$

Expressing the quadratic form into the symmetric form, we then have (19.15).  $\square$

**Lemma 19.3.** Equation (19.15) has unique symmetric solution.

*Proof.* Express (19.15) into a linear system as

$$(A \otimes I_n + I_n \otimes A)V_c(\Psi) = V_c \left( \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \right), \quad (19.19)$$

where

$$A = \frac{\mu}{2}I - J^T.$$

(19.19) is the linear form of Lyapunov mapping. Hence, let  $\lambda_i \in \sigma(A)$ ,  $i = 1, \dots, n$  be the eigenvalues of  $A$ . Then the eigenvalues of  $A \otimes I_n + I_n \otimes A$  are

$$\{\lambda_i + \lambda_j \mid 1 \leq i, j \leq n, \lambda_i \in \sigma(A)\}.$$

(We refer to Chapter 3 for Lyapunov mapping and its properties.)

To show  $A \otimes I_n + I_n \otimes A^T$  is nonsingular, it suffices to show that all  $\lambda_i + \lambda_j \neq 0$ . Let  $\xi_i \in \sigma(J)$ ,  $i = 1, \dots, n$  be the eigenvalues of  $J$ . Then

$$\lambda_i = \frac{\mu}{2} - \xi_i, \quad i = 1, \dots, n.$$

Observing the eigenvalues of  $J$ , it is easy to see that the only negative eigenvalue of  $A$  is  $-\frac{\mu}{2}$ , and all other eigenvalues of  $A$  have positive real parts, which are greater than  $\frac{\mu}{2}$ . It follows that

$$\lambda_i + \lambda_j \neq 0, \quad 1 \leq i, j \leq n.$$

Hence (19.15) has unique solution. Finally, we prove the solution is symmetric. It is ready to verify that

$$(A \otimes I_n + I_n \otimes A)W_{[n]} = W_{[n]}(A \otimes I_n + I_n \otimes A). \quad (19.20)$$

Using (19.20), we have

$$\begin{aligned} (A \otimes I_n + I_n \otimes A)V_r(\Psi) &= (A \otimes I_n + I_n \otimes A)W_{[n]}V_c(\Psi) \\ &= W_{[n]}(A \otimes I_n + I_n \otimes A)V_c(\Psi) = W_{[n]}V_c \left( \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \right) \\ &= V_r \left( \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \right) = V_c \left( \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \right). \end{aligned} \quad (19.21)$$

The last equality comes from the fact that  $\sum_{i=1}^n \xi_i \text{Hess}(f_i(0))$  is a symmetric matrix, hence its row and column stacking forms are the same. (19.21) shows that  $V_r(\Psi)$  is the other solution of (19.19). But the solution of (19.19) is unique, which leads to

$$V_r(\Psi) = V_c(\Psi).$$

That is,  $\Psi$  is symmetric.  $\square$

Denote by  $V_c^{-1}$  the inverse mapping of  $V_c$ , which retrieves  $A$  from its column stacking form  $V_c(A)$ .

Summarizing the Lemmas 19.1, 19.2, 19.3, we have the following result about the quadratic approximation of the stable sub-manifold.

**Theorem 19.3.** *Assume  $x_u = 0$  is the type-1 equilibrium of the system (19.1), and its stable sub-manifold is determined by  $h(x) = 0$ . Then*

$$h(x) = H_1 x + \frac{1}{2} x^T \Psi x + O(\|x\|^3), \quad (19.22)$$

where

$$\begin{cases} H_1 = \eta^T \\ \Psi = V_c^{-1} \left\{ \left[ \left( \frac{\mu}{2} I_n - J^T \right) \otimes I_n + I_n \otimes \left( \frac{\mu}{2} I_n - J^T \right) \right]^{-1} V_c \left( \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \right) \right\}, \end{cases}$$

$\mu$  and  $\eta$  are defined as in Corollary 19.1 with respect to  $J = F_1$ ,  $\text{Hess}(f_i)$  is the Hessian matrix of the  $i$ -th component,  $f_i$ , of  $f$ .

*Remark 19.1.* If  $e_u$  is an equilibrium of type- $n-1$ ,  $\mu$  is the unique negative eigenvalue, and its corresponding eigenvector is  $\eta$ , then all the above arguments remain available for describing the unstable sub-manifold. Particularly, (19.22) is the quadratic approximation of the function for unstable sub-manifold.

Observing (19.18), the following corollary is an immediate consequence, which is sometimes useful for simplifying computations.

**Corollary 19.2.** *Assume*

$$\sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \left( \frac{\mu}{2} I_n - J \right)^{-1}$$

*is symmetric, then the quadratic approximation of the equation of stable sub-manifold is*

$$h(x) = \eta^T x + \frac{1}{4} x^T \sum_{i=1}^n \eta_i \text{Hess}(f_i(0)) \left( \frac{\mu}{2} I_n - J \right)^{-1} x = 0. \quad (19.23)$$

*Example 19.1.* Consider the system

$$\begin{cases} \dot{x}_1 = x_1, \\ \dot{x}_2 = -x_2 + x_1^2, \quad x \in \mathbb{R}^2. \end{cases} \quad (19.24)$$

Its stable and unstable sub-manifolds are respectively (reported in [4])

$$\begin{aligned} W^s(0) &= \{x \in \mathbb{R}^2 \mid x_1 = 0\}, \\ W^u(0) &= \{x \in \mathbb{R}^2 \mid x_2 = \frac{1}{3} x_1^2\}. \end{aligned}$$

We use them to verify formula (19.23). For (19.24), we have



$$J = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}.$$

For stable sub-manifold  $W^s(0)$ , it is easy to verify that its stable eigenvalue is  $\mu = 1$ , its corresponding eigenvector is  $\eta = (1 \ 0)^T$ . Moreover,

$$\text{Hess}(f_1(0)) = 0, \quad \text{Hess}(f_2(0)) = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}.$$

Hence

$$\frac{1}{4} \sum_{i=1}^2 \eta_i \text{Hess}(f_i(0)) \left( \frac{1}{2} I - J \right)^{-1} = 0,$$

that is,

$$h_s(x) = (1 \ 0)x + 0 + O(\|x\|^3) = x_1 + O(\|x\|^3).$$

For unstable sub-manifold  $W^u(0)$ , it is easy to check that its unstable eigenvalue is  $\mu = -1$ , its corresponding eigenvector is  $\eta = (0 \ 1)^T$ . Hence

$$\frac{1}{4} \sum_{i=1}^2 \eta_i \text{Hess}(f_i(0)) \left( \frac{-1}{2} I - J \right)^{-1} = \begin{bmatrix} -\frac{1}{3} & 0 \\ 0 & 0 \end{bmatrix}.$$

That is,

$$h_u(x) = (0 \ 1)x + x^T \begin{bmatrix} -\frac{1}{3} & 0 \\ 0 & 0 \end{bmatrix} x + O(\|x\|^3) = x_2 - \frac{1}{3}x_1^2 + O(\|x\|^3).$$

In fact, if we use the conclusion in the next section, we can prove that the errors for the approximations  $h_s(x)$  and  $h_u(x)$  are both 0. Alternatively, we can also use Theorem 19.2 to verify this directly. For instance, we verify  $h_u(x)$ : Assume  $h_u(x) = x_2 - \frac{1}{3}x_1^2$ , then  $W^u(e_u) = \{x \mid h_u(x) = 0\}$ , if and only if  $h_u(x) = 0$  implies  $L_f h_u(x) = 0$ . This is true, because

$$L_f(h_u(x)) = \begin{bmatrix} -\frac{2}{3}x_1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ -x_2 + x_1^2 \end{bmatrix} = -x_2 + \frac{1}{3}x_1^2 = -h_u(x).$$

## 19.4 Higher Order Approximation

This section considers the Taylor series expansion of the equation of stability sub-manifold. In the following calculation we need  $\Phi_k$ . To calculate it, the following proposition is necessary.

**Proposition 19.1.**

$$W_{[n^s, n]} = \prod_{i=0}^{s-1} (I_{n^i} \otimes W_{[n, n]} \otimes I_{n^{s-i-1}}). \quad (19.25)$$

*Proof.* Using Proposition 2.12, we have

$$W_{[n^s, n]} = \left( W_{[n^{s-1}, n]} \otimes I_n \right) \left( I_{n^{s-1}} \otimes W_{[n, n]} \right).$$

Using the first decomposition of Proposition 2.12 again, and again, we finally obtain (19.25). Note that as a convention we have  $I_{n^0} = 1$ ,  $\Phi_0 = I_n$ .  $\square$

Using (19.25), it is easy to calculate  $\Phi_k$ . We use an example to depict it.

*Example 19.2.* Assume  $n = 2$ , then

$$\Phi_0 = I_n,$$

$$\Phi_1 = W_{[n, n]} + I \otimes W_{[1, n]} = W_{[n]} + I_{n^2} = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix},$$

$$\begin{aligned} \Phi_2 &= W_{[n^2, n]} + I_n \otimes W_{[n, n]} + I_{n^2} \otimes W_{[1, n]} \\ &= (W_{[n]} \otimes I_n) (I_n \otimes W_{[n]}) + I_n \otimes W_{[n]} + I_{n^3} \\ &= \begin{bmatrix} 3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 2 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 3 \end{bmatrix}, \dots \end{aligned}$$

Next, we proceed to solve  $H_k$  from equations (19.8) - (19.10). First problem is: since  $x^k$  is a redundant generator of  $k$ , we are not able to get unique solution from (19.8)–(19.10). To overcome this difficulty we have to convert the equations to natural basis. Recall Chapter 15, let  $S \in \mathbb{Z}_+^n$ . The natural basis is defined as

$$N_n^k = \{x^S \mid S \in \mathbb{Z}_+^n, |S| = k\}.$$

We arrange the elements in  $N_n^k$  in the alphabetic order. That is, for  $S^1 = (s_1^1, \dots, s_n^1)$  and  $S^2 = (s_1^2, \dots, s_n^2)$  we use order  $x^{S^1} \prec x^{S^2}$ , if there exists a  $t$ ,  $1 \leq t \leq n-1$ , such that

$$s_1^1 = s_1^2, \dots, s_t^1 = s_t^2, s_{t+1}^1 > s_{t+2}^2.$$

In this way we arrange the elements of  $N_n^k$  as a column and denote it as  $x_{(k)}$ .

*Example 19.3.* Let  $n = 3$  and  $k = 2$ . Then

$$x^2 = (x_1^2, x_1x_2, x_1x_3, x_2x_1, x_2^2, x_2x_3, x_3x_1, x_3x_2, x_3^2)^T,$$

and

$$x_{(2)} = (x_1^2, x_1x_2, x_1x_3, x_2^2, x_2x_3, x_3^2)^T.$$

In Chapter 15 it has been proved that the size of  $B_n^k$  is

$$|B_n^k| := d = \frac{(n+k-1)!}{k!(n-1)!}, \quad k \geq 0, \quad n \geq 1. \quad (19.26)$$

Recall that in Chapter 15 we have defined two matrices:  $T_N(n, k) \in M_{n^k \times d}$  and  $T_B(n, k) \in M_{d \times n^k}$ , which can convert two generators  $x^k$  and  $x_{(k)}$  back and forth. Precisely,

$$x^k = T_N(n, k)x_{(k)}, \quad x_{(k)} = T_B(n, k)x^k.$$

Moreover,

$$T_B(n, k)T_N(n, k) = I_d.$$

We write a special pair as follows:

*Example 19.4.* Let  $n = 2, k = 3$ . Then the  $T_B(n, k)$  is

$$T_B(2, 3) = \begin{array}{cccccccc} (111) & (112) & (121) & (122) & (211) & (212) & (221) & (222) \\ \left[ \begin{array}{cccccccc} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/3 & 1/3 & 0 & 1/3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/3 & 0 & 1/3 & 1/3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array} \right] & \begin{array}{l} (111) \\ (112) \\ (122) \\ (222) \end{array} \end{array}. \quad (19.27)$$

Meanwhile,  $T_N(2, 3)$  is

$$T_N(2, 3) = \begin{array}{cccc} (111) & (112) & (122) & (222) \\ \left[ \begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right] & \begin{array}{l} (111) \\ (112) \\ (121) \\ (122) \\ (211) \\ (212) \\ (221) \\ (222) \end{array} \end{array}. \quad (19.28)$$

Recall (19.14), instead of solving  $H_k$ , we will try to solve  $G_k$ , which satisfies

$$H_k x^k = G_k x_{(k)}.$$

Recall that  $H_k$  is a symmetric coefficient matrix, if any two equal elements in  $x^k$  have the equal coefficients in  $H_k x^k$ . We use the following example to explain it.

*Example 19.5.* Let  $n = 3$  and  $k = 2$ . Then  $x^2$  is as in Example 19.3. For a given second order homogeneous polynomial  $p(x) = x_1^2 + 2x_1x_2 - 3x_1x_3 + x_2^2 - x_3^2$ , we can express it as

$$p(x) = H_1 x^2 = (1, 2, -3, 0, 1, 0, 0, 0, -1)x^2.$$

Alternatively, we can also express it as

$$p(x) = H_2 x^2 = \left(1, 1, -\frac{3}{2}, 1, 1, 0, -\frac{3}{2}, 0, -1\right) x^2.$$

It is easy to see that  $H_1$  is not symmetric, while  $H_2$  is.

We also know the following.

**Proposition 19.2.** 1. The symmetric coefficient matrix  $H_k$  is unique.  
2.

$$H_k = G_k T_B(n, k), \quad G_k = H_k T_N(n, k). \quad (19.29)$$

Now we are ready to construct the higher terms of the  $h(x)$  in the equation of stable sub-manifold. Denote by

$$f(x) = F_1 x + F_2 x^2 + \dots;$$

and

$$h(x) = H_1 x + H_2 x^2 + \dots.$$

Note that we already known that  $F_1 = J_f(0) = J$ ,  $H_1 = \eta^T$ , and  $H_2$  can be uniquely determined by (19.17).

**Proposition 19.3.** The coefficients  $H_k$ ,  $k \geq 2$ , of  $h(x)$  satisfy the following equations

$$\left[ \sum_{i=1}^k H_i \Phi_{i-1} (I_{n^{i-1}} \otimes F_{k-i+1}) - \mu H_k \right] x^k = 0, \quad k \geq 2. \quad (19.30)$$

*Proof.* Note that  $h(x) = 0$  is invariant with respect to vector field  $f(x)$ , that is the Lie derivative

$$L_f h(x) = 0. \quad (19.31)$$

Using Proposition 15.4, we have

$$Dh(x) = H_1 + H_2 \Phi_1 x + H_3 \Phi_2 x^2 + \dots = H_1 + 2x^T \Psi + H_3 \Phi_2 x^2 + \dots.$$

A straightforward computation shows

$$\begin{aligned} L_f h(x) &= \mu \eta^T x + [H_2 \Phi_1 (I_n \otimes F_1) + H_1 F_2] x^2 + \dots \\ &\quad + \left[ \sum_{i=1}^k H_i \Phi_{i-1} (I_{n^{i-1}} \otimes F_{k+1-i}) \right] x^k + \dots. \end{aligned}$$

Note that  $h(x)$  satisfies

$$\begin{cases} h(x) = 0, \\ L_f h(x) = 0. \end{cases} \quad (19.32)$$

Subtracting  $\mu$  from the second equation of (19.32), and then multiply it with the first equation of (19.32), we can prove, inductively on  $k$ , that

$$\left[ \sum_{i=1}^k H_i \Phi_{i-1}(I_{n^{i-1}} \otimes F_{k-i+1}) - \mu H_k \right] x^k + O(\|x\|^{k+1}) = 0, \quad k \geq 2,$$

The conclusion follows.  $\square$

Observing (19.30), according to Proposition 19.2, it can be expressed as

$$\begin{aligned} & G_k [\mu I_d - T_B(n, k) \Phi_{k-1}(I_{n^{k-1}} \otimes F_1) T_N(n, k)] x_{(k)} \\ & \equiv \left[ \sum_{i=1}^{k-1} G_i T_B(n, i) \Phi_{i-1}(I_{n^{i-1}} \otimes F_{k-i+1}) \right] T_N(n, k) x_{(k)}, \quad k \geq 3. \end{aligned} \quad (19.33)$$

The following theorem is a summarization of the above arguments, which can be used for general case.

**Theorem 19.4.** Assume the matrix

$$C_k := \mu I_d - T_B(n, k) \Phi_{k-1}(I_{n^{k-1}} \otimes F_1) T_N(n, k), \quad k \geq 3 \quad (19.34)$$

is non-singular, then

$$G_k = \left[ \sum_{i=1}^{k-1} G_i T_B(n, i) \Phi_{i-1}(I_{n^{i-1}} \otimes F_{k-i+1}) \right] T_N(n, k) C_k^{-1}. \quad (19.35)$$

*Remark 19.2.* In fact,  $H_2$  can also be solved in this way. (19.15) and (19.35) can produce the same result. In fact, when  $H_2$  is solved from (19.15), since the symmetric quadratic equation is used, the symmetry of the coefficients has been automatically assured.

It is obvious that the efficiency of (19.35) depends on whether  $C_i$  is singular. Unfortunately, in quadratic case, we are not able to assure it in certain way. It is discussed in the following example.

*Example 19.6.* Consider the following system

$$\begin{cases} \dot{x}_1 = -cx_1, & c > 0, \\ \dot{x}_2 = x_2 - 2x_1^2 + x_1^3, \end{cases} \quad (19.36)$$

where  $c > 0$  is a parameter.

We calculate the equation of the stable sub-manifold. It is easy to calculate that  $\mu = 1$ ,  $\eta = (0 \ 1)^T$ ,

$$J = \begin{bmatrix} -c & 0 \\ 0 & 1 \end{bmatrix},$$

and

$$\text{Hess}(f_1(0)) = 0, \quad \text{Hess}(f_2(0)) = \begin{bmatrix} -4 & 0 \\ 0 & 0 \end{bmatrix}.$$

Hence we can use (19.23) to calculate that

$$h(x) = (0 \ 1)x + x^T \begin{bmatrix} -\frac{2}{2c+1} & 0 \\ 0 & 0 \end{bmatrix} x + O(\|x\|^3). \quad (19.37)$$

Using (19.26), (19.27), and the  $\Phi_2$  calculated in Example 19.2, we can calculate  $C_3$  as

$$C_3 = \begin{bmatrix} 3c+1 & 0 & 0 & 0 \\ 0 & 2c & 0 & 0 \\ 0 & 0 & c-1 & 0 \\ 0 & 0 & 0 & -2 \end{bmatrix}. \quad (19.38)$$

Assume  $c \neq 1$ , then  $C_3$  is invertible. Then we have

$$H_1 = (0, 1), \quad H_2 = \left( -\frac{2}{2c+1}, 0, 0, 0 \right),$$

$$F_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ -2 & 0 & 0 & 0 \end{bmatrix}, \quad F_3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

Plugging them into (19.34) yields

$$G_3 = \left( \frac{1}{3c+1}, 0, 0, 0 \right).$$

Hence we have

$$h(x) = x_2 - \frac{2}{2c+1}x_1^2 + \frac{1}{3c+1}x_1^3 + O(\|x\|^4).$$

In fact, it is easy to verify that

$$h(x) = x_2 - \frac{2}{2c+1}x_1^2 + \frac{1}{3c+1}x_1^3 = 0,$$

and

$$L_f h(x) = h(x) = 0.$$

We conclude that

$$W^s(0) = \left\{ x \in \mathbb{R}^2 \mid x_2 - \frac{2}{2c+1}x_1^2 + \frac{1}{3c+1}x_1^3 = 0 \right\}.$$

According to Theorem 19.4 and Example 19.6, we give the following algorithm:

**Algorithm 4.** Step 1. If  $C_3, \dots, C_{k-1}$  are nonsingular, we continue to search  $H_k$  to approximate  $h(x)$  till the accuracy is satisfied.  
Step 2. If  $C_k$  is singular, we search for the least square solution  $G_k$  via

$$\begin{aligned} & G_k [\mu I_d - T_B(n, k) \Phi_{k-1} (I_{n^{k-1}} \otimes F_1) T_N(n, k)] \\ &= \left[ \sum_{i=1}^{k-1} G_i T_B(n, i) \Phi_{i-1} (I_{n^{i-1}} \otimes F_{k-i+1}) \right] T_N(n, k) \end{aligned} \quad (19.39)$$

Then use  $G_3, \dots, G_k$  to construct a  $k$ -th order approximation of  $h(x)$ .

Step 3. (possible further improvement) If the least square solution is a real number solution for (19.39), solve the following system:

$$\begin{cases} G_k [\mu I_d - T_B(n, k) \Phi_{k-1} (I_{n^{k-1}} \otimes F_1) T_N(n, k)] \\ \quad = \left[ \sum_{i=1}^{k-1} G_i T_B(n, i) \Phi_{i-1} (I_{n^{i-1}} \otimes F_{k-i+1}) \right] T_N(n, k), \\ 0 = \left[ \sum_{i=1}^k G_i T_B(n, i) \Phi_{i-1} (I_{n^{i-1}} \otimes F_{k-i+1}) \right] T_N(n, k+1). \end{cases} \quad (19.40)$$

In fact, considering the  $k$ -th and  $k+1$ -th order terms leaders to (??).

Recall Example 19.6. When  $c = 1$ , the least square solution is

$$G_3 = \left( \frac{1}{3c+1}, 0, t, 0 \right),$$

where  $t$  is an arbitrary parameter. It is ready to verify that  $G_3$  is a real number solution of (19.39). Hence, we can try to solve (19.40). A careful calculation shows that (19.40) has a solution  $G_3 = \left( \frac{1}{3c+1}, 0, 0, 0 \right)$ . It is easy to check that this  $G_3$  is a real number solution.

In the following we consider another more general example.

*Example 19.7.* Consider the following system

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = -x_1 - 2x_2, \\ \dot{x}_3 = 2x_3 - x_2(e^{x_1} - 1). \end{cases} \quad (19.41)$$

It is easy to show that  $\mu = 2$ ,  $\eta = (0 \ 0 \ 1)^T$ ,

$$J = \begin{bmatrix} 0 & 1 & 0 \\ -1 & -2 & 0 \\ 0 & 0 & 2 \end{bmatrix},$$

$$A = \frac{\mu}{2}I_3 - J^T = \begin{bmatrix} 1 & 1 & 0 \\ -1 & 3 & 0 \\ 0 & 0 & -1 \end{bmatrix},$$

$$\text{Hess}(f_1(0)) = \text{Hess}(f_2(0)) = 0,$$

$$\text{Hess}(f_3(0)) = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

Using formula (19.22), we have

$$\begin{aligned} h(x) &\approx \eta^T x + x^T \left( \frac{1}{2} \Psi \right) x \\ &= (0 \ 0 \ 1)x + x^T \begin{bmatrix} 0.09375 & -0.09375 & 0 \\ -0.09375 & -0.03125 & 0 \\ 0 & 0 & 0 \end{bmatrix} x \\ &= x_3 + 0.09375x_1^2 - 0.1875x_1x_2 - 0.03125x_2^2. \end{aligned} \quad (19.42)$$

To calculate the third order terms, we verify  $C_3$ . Using (19.34), we have

$$C_3 = \begin{bmatrix} 2 & -3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 4 & 0 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 6 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 2 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -2 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 & 8 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -4 \end{bmatrix}.$$

It can be calculated and verified to be invertible via computer. From the quadratic part of  $h(x)$  we have

$$H_1 = \eta^T = (0, 0, 1),$$

$$H_2 = (0.09375, -0.09375, 0, -0.09375, -0.03125, 0, 0, 0, 0),$$

$F_2 \in M_{3 \times 9}$  has all zero components except  $F_2(3,2)$  and  $F_2(3,4)$  which are

$$F_2(3,2) = F_2(3,4) = -\frac{1}{2},$$

$F_3 \in M_{3 \times 29}$  has all zero components except 3 elements:  $F_3(3,2)$ ,  $F_3(3,4)$ ,  $F_3(3,10)$ , which are

$$F_3(3,2) = F_3(3,4) = F_3(3,10) = -\frac{1}{6}.$$

Plugging them into (19.35) yields

$$G_3 = (0.0408, -0.0816, 0, -0.0256, 0, 0, -0.0032, 0, 0, 0).$$



Hence the equation of the stable sub-manifold, approximated to third order terms, is

$$h(x) \approx x_3 + 0.09375x_1^2 - 0.1875x_1x_2 - 0.03125x_2^2 + 0.0408x_1^3 - 0.0816x_1^2x_2 - 0.0256x_1x_2^2 - 0.0032x_2^3. \quad (19.43)$$

Continuing this process, we can calculate the even higher order terms of  $h(x)$ .

In fact, for this special system the stable sub-manifold can be obtained by a suitable coordinate transformation. Hence the above result can be confirmed.

## 19.5 Differential-Algebraic System

This section considers the stability region of a differential-algebraic system. Such systems exist widely. For instance, the power network is of this type. Consider the following system

$$\begin{cases} \dot{x} = f(x, y), & x \in \mathbb{R}^n, y \in \mathbb{R}^m, \\ \Phi(x, y) = 0, & \Phi(x, y) \in \mathbb{R}^m, \end{cases} \quad (19.44)$$

where  $f(0, 0) = 0$ ,  $\Phi(0, 0) = 0$ . Moreover, the dynamics determined by this set of equations is unique, hence we require that

$$\text{rank} \left( \frac{\partial \Phi}{\partial y}(0, 0) \right) = m. \quad (19.45)$$

Based on the aforementioned reason, we assume  $(0, 0)$  is type-1 unstable equilibrium. We will use the result obtained in the previous sections to deduce the equation of the stable sub-manifold. For convenience, we consider only the quadratic approximation of the (19.44). Higher order terms can be calculated in a similar way.

According to the Implicit Function Theory, (19.45) implies that  $y$  can be solved from the second equation of (19.44) as  $y = y(x)$ . Substituting it into the first equation of (19.44) yields an equation of the form of (19.1) as

$$\dot{x} = f(x, y(x)). \quad (19.46)$$

Of course, equation (19.46) is locally true. But the Taylor series expansion requires only local information, hence local expression is enough. Now the only obstacle is solving  $y = y(x)$ , which is, in general, impossible. Recall (19.15), what do we need is only

$$\begin{aligned} J &:= \frac{\partial f(x, y(x))}{\partial x}, \\ H_i &:= \text{Hess}(f_i(0, 0)), \quad i = 1, \dots, n. \end{aligned} \quad (19.47)$$

Hence instead of solving  $y$ , we can calculate  $J$  and  $H_i$ , and then the formula (19.15) can be used to find the quadratic approximation.

Since

$$\frac{\partial \Phi}{\partial x} + \frac{\partial \Phi}{\partial y} \frac{\partial y}{\partial x} = 0,$$

then

$$\frac{\partial y}{\partial x} = - \left( \frac{\partial \Phi}{\partial y} \right)^{-1} \frac{\partial \Phi}{\partial x}. \quad (19.48)$$

Using Chain Rule, we have

$$J = \frac{\partial f}{\partial x}(0,0) - \frac{\partial f}{\partial y}(0,0) \left( \frac{\partial \Phi}{\partial y}(0,0) \right)^{-1} \frac{\partial \Phi}{\partial x}(0,0). \quad (19.49)$$

Recall Corollary 15.1, Let  $A(x)$  and  $B(x)$  be  $p \times q$  and  $q \times r$  functional matrices. Then

$$DA(x)B(x) = DA(x)B(x) + A(x)DB(x). \quad (19.50)$$

Moreover, according the Chain Rule, we have

$$DA(x, y(x)) = D_x A(x, y) + D_y A(x, y) \left( I_n \otimes \frac{\partial y}{\partial x} \right). \quad (19.51)$$

Here we use  $D_x$  to express the differential with respect to  $x$  only.

Now we calculate  $H_i$ . First, the gradient of  $f_i$  can be expressed as

$$\begin{aligned} \nabla f_i(x, y(x)) &= \nabla_x f_i(x, y) + \left( d_y f_i(x, y) \frac{\partial y}{\partial x} \right)^T \\ &= \nabla_x f_i(x, y) - \left( \frac{\partial \Phi}{\partial x} \right)^T \left( \frac{\partial \Phi}{\partial y} \right)^{-T} \nabla_y f_i(x, y). \end{aligned} \quad (19.52)$$

Since  $y = y(x)$  is a function of  $x$ , we use  $\nabla_x f_i(x, y)$  and  $\nabla_y f_i(x, y)$  for the gradients with respect to  $x$  and  $y$  respectively.

Then, by definition we have

$$H_i = D(\nabla f_i)|_{(0,0)}, \quad i = 1, \dots, n. \quad (19.53)$$

Applying (19.51) to the first term of (19.52), we have

$$D(\nabla_x f_i) = \frac{\partial^2 f_i}{\partial x \partial x} + \frac{\partial^2 f_i}{\partial x \partial y} \left( \frac{\partial y}{\partial x} \right). \quad (19.54)$$

Similarly, we have

$$D(\nabla_y f_i) = \frac{\partial^2 f_i}{\partial y \partial x} + \frac{\partial^2 f_i}{\partial y \partial y} \left( \frac{\partial y}{\partial x} \right). \quad (19.55)$$

Note that hereafter for any function  $\xi(x, y)$ , we use  $\frac{\partial^2 \xi(x, y)}{\partial x \partial y}$  to represent an  $n \times m$  matrix, which has its  $(i, j)$ -th element as  $\frac{\partial^2 \xi}{\partial x_i \partial y_j}$ . Hence in general,

$$\frac{\partial^2 \xi(x, y)}{\partial x \partial y} \neq \frac{\partial^2 \xi(x, y)}{\partial y \partial x}.$$

Applying (19.51) to the second term of (19.52), we have

$$\begin{aligned} D \left[ d_y f_i(x, y) \frac{\partial y}{\partial x} \right]^T &= D \left\{ \left( \frac{\partial y}{\partial x} \right)^T (\nabla_y f_i(x, y)) \right\} \\ &= D \left( \frac{\partial y}{\partial x} \right)^T (\nabla_y f_i(x, y) \otimes I_n) + \left( \frac{\partial y}{\partial x} \right)^T D (\nabla_y f_i(x, y)). \end{aligned} \quad (19.56)$$

Next, we calculate (19.56) term by term. Using (19.48), we have

$$\left( \frac{\partial y}{\partial x} \right)^T \left( \frac{\partial \Phi}{\partial y} \right)^T + \left( \frac{\partial \Phi}{\partial x} \right)^T = 0,$$

Differentiate both sides of the above equation and applying (19.50) yield

$$D \left( \frac{\partial y}{\partial x} \right)^T \left[ \left( \frac{\partial \Phi}{\partial y} \right)^T \otimes I_n \right] + \left( \frac{\partial y}{\partial x} \right)^T D \left( \frac{\partial \Phi}{\partial y} \right)^T + D \left( \frac{\partial \Phi}{\partial x} \right)^T = 0. \quad (19.57)$$

Each terms are calculated as follows:

$$\begin{aligned} X &:= D \left( \frac{\partial \Phi}{\partial x} \right)^T \Big|_{(0,0)} \\ &= \left[ \left( \frac{\partial^2 \Phi_1}{\partial x \partial x} + \frac{\partial^2 \Phi_1}{\partial x \partial y} \cdot \frac{\partial y}{\partial x} \right), \dots, \left( \frac{\partial^2 \Phi_m}{\partial x \partial x} + \frac{\partial^2 \Phi_m}{\partial x \partial y} \cdot \frac{\partial y}{\partial x} \right) \right] \Big|_{(0,0)}. \end{aligned} \quad (19.58)$$

$$\begin{aligned} Y &:= D \left( \frac{\partial \Phi}{\partial y} \right)^T \Big|_{(0,0)} \\ &= \left[ \left( \frac{\partial^2 \Phi_1}{\partial y \partial x} + \frac{\partial^2 \Phi_1}{\partial y \partial y} \cdot \frac{\partial y}{\partial x} \right), \dots, \left( \frac{\partial^2 \Phi_m}{\partial y \partial x} + \frac{\partial^2 \Phi_m}{\partial y \partial y} \cdot \frac{\partial y}{\partial x} \right) \right] \Big|_{(0,0)}. \end{aligned} \quad (19.59)$$

Substituting (19.58) and (19.59) into (19.57) yields

$$D \left( \frac{\partial y}{\partial x} \right)^T \Big|_{(0,0)} = - \left[ \left( \frac{\partial y}{\partial x}(0, 0) \right)^T Y + X \right] \left[ \left( \frac{\partial \Phi}{\partial y}(0, 0) \right)^{-T} \otimes I_n \right]. \quad (19.60)$$

Finally, substituting (19.54), (19.55), and (19.60) into (19.53), we can get the expression of  $H_i$  as follows:

$$\begin{aligned}
H_i = & \frac{\partial^2 f_i}{\partial x \partial x} + \frac{\partial^2 f_i}{\partial x \partial y} \left( \frac{\partial y}{\partial x} \right) - \left[ \left( \frac{\partial y}{\partial x} \right)^T Y + X \right] \left[ \left( \frac{\partial \Phi}{\partial y} \right)^{-T} \otimes I_n \right] (\nabla_y f_i \otimes I_n) \\
& + \left( \frac{\partial y}{\partial x} \right)^T \left[ \frac{\partial^2 f_i}{\partial y \partial x} + \frac{\partial^2 f_i}{\partial y \partial y} \left( \frac{\partial y}{\partial x} \right) \right], \quad (19.61)
\end{aligned}$$

where  $X$ ,  $Y$  and the detailed expression of  $\frac{\partial y}{\partial x}$  are (19.58), (19.59), and (19.48) respectively.

### Exercise 19

1. (to be completed).

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