Model Order Reduction (MOR)

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1 MOR techniques for Linear Systems

1.1 Linear state-space Representation

$$\frac{d}{dt}\mathbf{x}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \tag{1-1a}$$

$$y(t) = \mathbf{C}^T \mathbf{x}(t) \tag{1-1b}$$

From the eq. (1-1a) in Laplace domain it is obtained,

$$s\mathbf{X}(s) - \mathbf{A}\mathbf{X}(s) = \mathbf{B}\mathbf{U}(s)$$

$$(s\mathbf{I} - \mathbf{A}) \mathbf{X}(s) = \mathbf{B}\mathbf{U}(s)$$

$$\mathbf{X}(s) = (s\mathbf{I} - \mathbf{A})^{-1}\mathbf{B}\mathbf{U}(s) \tag{1-2}$$

By substituting (1-2)in (1-1b) above one can get a direct relationship between inputs and outputs signals

$$Y(s) = \mathbf{C}^{T} (s\mathbf{I} - \mathbf{A})^{-1} \mathbf{B} \mathbf{U}(\mathbf{s}).$$
 (1-3)

In (1-3) the function relating inputs to outputs known as Transfer Function (TF) shown in below

$$H(s) = \mathbf{C}^{T} (s\mathbf{I} - \mathbf{A})^{-1} \mathbf{B}.$$
 (1-4)

1.2 Background on Arnoldi Method

Let transfer function H(s) in (1-4) be a smooth (continuously derivable, C^{∞}) matrix function. Hence, the Taylor expansion to approximate the function in proximity of s=0 is

$$H(s) = \sum_{i=0}^{\infty} \mathbf{M}_i s^i = \sum_{i=0}^{\infty} \frac{1}{i!} H^{(i)}(s)|_{s=0} s^i,$$
 (1-5)

where $\frac{1}{i!}H^{(i)}(s)|_{s=0} = -\mathbf{C}^T\mathbf{A}^{-\{i+1\}}\mathbf{B}$

Proof: For the sake of simplicity of calculation let obtain a slightly different form for transfer function by factoring out $-\mathbf{A}$ from (1-4) as

$$H(s) = -\mathbf{C}^T \mathbf{A}^{-1} \left(\mathbf{I} - s \mathbf{A}^{-1} \right)^{-1} \mathbf{B}. \tag{1-6}$$

Considering the Taylor expansion for $(\mathbf{I} - s\mathbf{A}^{-1})^{-1}$ in below

$$(\mathbf{I} - s\mathbf{A}^{-1})^{-1} \approx \mathbf{I} + \mathbf{A}^{-1}s + \mathbf{A}^{-2}s^2 + \mathbf{A}^{-3}s^3 + \dots,$$
 (1-7)

Lemma 1.1 The Taylor series approximating (1-6) will be

$$H(s) = -\mathbf{C}^{T} \mathbf{A}^{-1} \left(\mathbf{I} + \mathbf{A}^{-1} s + \mathbf{A}^{-2} s^{2} + \mathbf{A}^{-3} s^{3} + \dots \right) \mathbf{B}.$$
 (1-8)

For the proof of lemma (1.1), appendix A can be referred to. From (1-6) in lemma (1.1), we get

$$H(s) = \left(-\mathbf{C}^T \mathbf{A}^{-1} \mathbf{B}\right) + \left(-\mathbf{C}^T \mathbf{A}^{-2} \mathbf{B}\right) s + \left(-\mathbf{C}^T \mathbf{A}^{-3} \mathbf{B}\right) s^2 + \left(-\mathbf{C}^T \mathbf{A}^{-3} \mathbf{B}\right) s^3 + \dots$$
 (1-9)

2 MOR techniques for nonlinear Systems

3 Non-Linear state-space Representation

$$\begin{cases} \frac{d}{dt}\mathbf{G}\left(\mathbf{X}(t)\right) = \mathbf{F}\left(\mathbf{X}(t)\right) + \mathbf{B}\left(\mathbf{X}(t)\right)\mathbf{U}(t) \\ \mathbf{Y}(t) = \mathbf{C}^{T}\mathbf{X}(t). \end{cases}$$
(3-10)

The number of the inputs and outputs are m and n, respectively. The order of the original system is N and the order of reduced model is q. In 3-10 the vector of unknown states is

$$\mathbf{X}(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_N(t) \end{bmatrix}$$
 (3-11)

and $\mathbf{F}(\mathbf{X}(t))$ the nonlinear function of states in the most general form, is defined as

$$\begin{bmatrix} f_1(\mathbf{X}(t)) \\ f_2(\mathbf{X}(t)) \\ \vdots \\ f_N(\mathbf{X}(t)) \end{bmatrix} = \begin{bmatrix} f_1\left([x_1(t), x_2(t), \dots, x_N(t)]^T\right) \\ f_2\left([x_1(t), x_2(t), \dots, x_N(t)]^T\right) \\ \vdots \\ f_N\left([x_1(t), x_2(t), \dots, x_N(t)]^T\right) \end{bmatrix}.$$
(3-12)

The Jacobian matrix (first order derivative) of the nonlinear function F with respect to X is

$$\mathbf{J}(\mathbf{X}) = \frac{d}{d\mathbf{X}}\mathbf{F}(\mathbf{X}(t)) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}, & \frac{\partial f_1}{\partial x_2}, & \dots, & \frac{\partial f_1}{\partial x_N} \\ \frac{\partial f_2}{\partial x_1}, & \frac{\partial f_2}{\partial x_2}, & \dots, & \frac{\partial f_2}{\partial x_N} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial f_N}{\partial x_1}, & \frac{\partial f_N}{\partial x_2}, & \dots, & \frac{\partial f_N}{\partial x_N} \end{bmatrix}.$$
 (3-13)

Let an arbitrarily selected initial (equilibrium) state vector be

$$\mathbf{X}_{i} = \begin{bmatrix} x_{1}(t_{i}) \\ x_{2}(t_{i}) \\ \vdots \\ x_{N}(t_{i}) \end{bmatrix} = \begin{bmatrix} x_{1_{i}} \\ x_{2_{i}} \\ \vdots \\ x_{N_{i}} \end{bmatrix}, \qquad (3-14)$$

The Jacobian matrix of the nonlinear function in (3-13) evaluated at the initial states \mathbf{X}_i is represented as follows

$$\mathbf{J}(\mathbf{X}_{i}) = \frac{d}{d\mathbf{X}}\mathbf{F}(\mathbf{X}(t))\Big|_{\mathbf{X}_{i}} = \begin{bmatrix} \frac{\partial f_{1}}{\partial x_{1}}\Big|_{\mathbf{X}_{i}}, & \frac{\partial f_{1}}{\partial x_{2}}\Big|_{\mathbf{X}_{i}}, & \dots, & \frac{\partial f_{1}}{\partial x_{N}}\Big|_{\mathbf{X}_{i}} \\ \frac{\partial f_{2}}{\partial x_{1}}\Big|_{\mathbf{X}_{i}}, & \frac{\partial f_{2}}{\partial x_{2}}\Big|_{\mathbf{X}_{i}}, & \dots, & \frac{\partial f_{2}}{\partial x_{N}}\Big|_{\mathbf{X}_{i}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial f_{N}}{\partial x_{1}}\Big|_{\mathbf{X}_{i}}, & \frac{\partial f_{N}}{\partial x_{2}}\Big|_{\mathbf{X}_{i}}, & \dots, & \frac{\partial f_{N}}{\partial x_{N}}\Big|_{\mathbf{X}_{i}} \end{bmatrix}.$$
(3-15)

The Hessian matrix (second divertive) of the above nonlinear function also is defined as

$$\mathbf{W}(\mathbf{X}) = \frac{d^2}{d\mathbf{X}^2} \mathbf{F} \left(\mathbf{X}(t) \right) = \begin{bmatrix} \frac{\partial^2 f_1}{\partial x_1^2}, & \frac{\partial^2 f_1}{\partial x_2 \partial x_1}, & \dots, & \frac{\partial^2 f_1}{\partial x_N \partial x_1} \\ \frac{\partial^2 f_2}{\partial x_1 \partial x_2}, & \frac{\partial^2 f_2}{\partial x_2^2}, & \dots, & \frac{\partial^2 f_2}{\partial x_N \partial x_2} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial^2 f_N}{\partial x_1 \partial x_N}, & \frac{\partial^2 f_N}{\partial x_2 \partial x_N}, & \dots, & \frac{\partial^2 f_N}{\partial x_N^2} \end{bmatrix} . \tag{3-16}$$

The Hessian matrix also, can be evaluated at X_i . On the same line the Jacobian and Hessian matrices for G(X) the other nonlinear function in the left hand side of (3-10) are formed.

3.1 Linearized Approximation

Using the Jacobian matrix of G(X) and F(X) these nonlinear functions can be linearized in the neighborhood of X_i , where $X = X_i + \Delta X$, as follows

$$\mathbf{G}(\mathbf{X}) \approx \widehat{\mathbf{G}(\mathbf{X})} = \mathbf{G}(\mathbf{X}_i) + \mathbf{J}_{\mathbf{G}}(\mathbf{X}_i) \times (\mathbf{X} - \mathbf{X}_i)$$
 (3-17)

and

$$\mathbf{F}(\mathbf{X}) \approx \mathbf{F}(\mathbf{X}) = \mathbf{F}(\mathbf{X}_i) + \mathbf{J}_{\mathbf{F}}(\mathbf{X}_i) \times (\mathbf{X} - \mathbf{X}_i)$$
 (3-18)

Eq.s (3-17) and (3-18) are adequately accurate approximants for the corresponding original nonlinear functions when $\|\Delta \mathbf{X}\|$ is sufficiently small.

For the purpose of simplicity, in the rest of this context, a short-hand form for (3-17) and (3-18) are considered as follows, respectively

$$\mathbf{G}(\mathbf{X}) = \mathbf{G}_i + \mathbf{J}_{\mathbf{G}_i} (\mathbf{X} - \mathbf{X}_i)$$
 (3-19)

and

$$\mathbf{F}(\mathbf{X}) = \mathbf{F}_i + \mathbf{J}_{\mathbf{F}_i} (\mathbf{X} - \mathbf{X}_i) . \tag{3-20}$$

3.2 Quadratic Form Approximation

Using the Jacobian and Hessian matrices defined above and considering $\Delta \mathbf{X}_i = (\mathbf{X} - \mathbf{X}_i)$, the nonlinear functions in (3-10) can be approximated in the quadratic form within the neighborhood of \mathbf{X}_i , as follows

$$G(\mathbf{X}) = \mathbf{G}_i + \mathbf{J}_{\mathbf{G}_i} \Delta \mathbf{X}_i + \Delta \mathbf{X}_i^T \mathbf{W}_{\mathbf{G}_i} \Delta \mathbf{X}_i$$
 (3-21)

and

$$\mathbf{F}(\mathbf{X}) = \mathbf{F}_i + \mathbf{J}_{\mathbf{F}_i} \Delta \mathbf{X}_i + \Delta \mathbf{X}_i^T \mathbf{W}_{\mathbf{F}_i} \Delta \mathbf{X}_i.$$
 (3-22)

The latter eq. (e.g.) can be rewritten using kronecker multiplication as

$$\mathbf{F}(\mathbf{X}) = \mathbf{F}_i + \mathbf{J}_{\mathbf{F}_i} \Delta \mathbf{X}_i + \mathbf{W}_{\mathbf{F}_i} \Delta \mathbf{X}_i^T \otimes \Delta \mathbf{X}_i.$$
 (3-23)

A Appendix: proof for lemma 1.1

To make notation simpler let the core part of (1-6) be denoted as

$$F(s) = (\mathbf{I} - s\mathbf{A}^{(} - 1))^{-1}. \tag{1-24}$$

Proof: To obtain Taylor expansion of F(s) the subsequent derivatives can be worked out as

i.
$$F(s) = (\mathbf{I} - s\mathbf{A}^{-1})^{-1} \longrightarrow F(0) = F(s)|_{s=0} = \mathbf{I},$$

ii .
$$F^{(1)}(s) = -F(s) \frac{d}{ds} (\mathbf{I} - s\mathbf{A}^{-1}) F(s) = F(s) \mathbf{A}^{-1} F(s) \longrightarrow F^{(1)}(s)|_{s=0} = F(0) \mathbf{A}^{-1} F(0) = \mathbf{A}^{-1}$$

iii .
$$F^{(2)}(s) = F^{(1)}(s)\mathbf{A}^{-1}F(s) + F(s)\mathbf{A}^{-1}F^{(1)}(s) \longrightarrow F^{(2)}(s)|_{s=0} = F^{(1)}(0)\mathbf{A}^{-1}F(0) + F(0)\mathbf{A}^{-1}F^{(1)}(0) = 2\mathbf{A}^{-2}$$

iv.
$$F^{(3)}(s) = F^{(2)}(s)\mathbf{A}^{-1}F(s) + F^{(1)}(s)\mathbf{A}^{-1}F^{(1)}(s) + F^{(1)}(s)\mathbf{A}^{-1}F^{(1)}(s) + F(s)\mathbf{A}^{-1}F^{(2)}(s) \longrightarrow F^{(3)}(s)|_{s=0} = 2\mathbf{A}^{-3} + \mathbf{A}^{-3} + \mathbf{A}^{-3} + 2\mathbf{A}^{-3} = 6\mathbf{A}^{-3}$$

 \mathbf{v} . and so on so force!

Plunging all above evaluated derivatives in the general form of the Taylor expansion for (1-24) results in (1-25) below.

$$F(s) = (\mathbf{I} - s\mathbf{A}^{-1})^{-1} \approx \mathbf{I} + \mathbf{A}^{-1}s + \mathbf{A}^{-2}s^{2} + \mathbf{A}^{-3}s^{3} + \dots$$
 (1-25)