

Lecture 7: Review Session #7

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Disclaimer: Zhikun is fully responsible for the errors and typos appeared in the notes.

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7.1 Systems of Linear ODE with Constant coefficients

Theorem 7.1

$$\begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u(t) & [C] \\ \dot{x}(t) = A(t)x(t) & [H] \end{cases} \quad (7.1)$$

Then e^{At} is a fundamental matrix of $[H]$. $e^{A(t-t_0)}$ is a state transition matrix.

Proof: e^{At} is invertible, $(e^{At})^{-1} = e^{-At}$. And $\frac{d}{dt}(e^{At}) = Ae^{At}$. By Theorem 6.9, we know $e^{A(t-t_0)} = e^{At}(e^{At_0})^{-1}$ is a state transition matrix. ■

Theorem 7.2 General solution to $[H]$ is $x(t) = e^{A(t-t_0)}x(t_0)$.

General solution to $[C]$ is $x(t) = e^{A(t-t_0)}x(t_0) + \int_{t_0}^t e^{A(t-s)}B(s)u(s)ds$.

Exercise: Find the general solution of

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_1(t) \\ u_2(t) \end{bmatrix}$$

7.2 Stability of Systems of ODE

Theorem 7.3 Consider a linear system $\dot{x}(t) = Ax(t)$

(a) 0 is a unique equilibrium point $\iff \det A \neq 0$

(b) 0 is a stable equilibrium point \iff all eigenvalues of A have negative real parts.

Proof: (a) Suppose $Ax = 0$

“ \implies ” part: $Ax \neq 0$ for any $x \neq 0 \implies \det(A) \neq 0$. Contradiction!

“ \impliedby ” part: $Ax = 0 \implies x = 0$ is the unique equilibrium point.

(b) Suppose A is diagonalizable [if not, a similar argument can be developed using Jordan decomposition].

So $A = PDP^{-1} \implies \dot{x} = PDP^{-1}x \implies \underbrace{P^{-1}\dot{x}}_y = D \underbrace{P^{-1}x}_y \iff \dot{y} = Dy$.

¹Visit <http://www.luzk.net/misc> for updates.

Note that $\lim_{t \rightarrow \infty} x(t) = 0 \iff \lim_{t \rightarrow \infty} y(t) = 0$.

Now look at $\dot{y} = Dy$:

$$\dot{y} = \begin{bmatrix} \dot{y}_1 \\ \vdots \\ \dot{y}_n \end{bmatrix} = \begin{bmatrix} d_1 & & 0 \\ & \ddots & \\ 0 & & d_n \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \iff \dot{y}_j = d_j y_j, \quad j = 1, \dots, n.$$

$y_j(t) = c_j e^{\alpha_j t} = c_j e^{(a_j + ib_j)t}$. Then $\lim_{t \rightarrow \infty} y_j(t) = 0 \iff a_j < 0$. Hence the conclusion follows. ■

Theorem 7.4 Consider a non-linear system $\dot{x} = f(x)$, $f : \mathbb{Q}^n \rightarrow \mathbb{R}^n$. Suppose f is C^1 and \tilde{x} is an equilibrium point. Then

(a) all eigenvalues of $Df(\tilde{x})$ have negative real parts $\implies \tilde{x}$ is locally asymptotically stable.

(b) at least one eigenvalue of $Df(\tilde{x})$ has positive real part $\implies \tilde{x}$ is unstable.

Proof: (For a rigorous argument, see Hartman-Grobman theorem.)

By Taylor theorem,

$$\underbrace{f(x)}_{\tilde{x}} = \underbrace{f(\tilde{x})}_{=0} + Df(\tilde{x})(x - \tilde{x}) + \Gamma(x - \tilde{x})$$

and $\lim_{x \rightarrow \tilde{x}} \frac{\Gamma(x - \tilde{x})}{\|x - \tilde{x}\|} = 0$.

$$\begin{aligned} \implies \dot{x} &= Df(\tilde{x})(x - \tilde{x}) + \Gamma(x - \tilde{x}) \\ \iff \frac{d}{dt}(x - \tilde{x}) &= Df(\tilde{x}) \underbrace{(x - \tilde{x})}_y + \Gamma(x - \tilde{x}) \\ \implies \dot{y} &= Df(\tilde{x})y + \Gamma(y) \end{aligned}$$

Then when x is close to \tilde{x} , or y is close to 0, the stability of the original system is determined by the stability of its linearized version: $\dot{y} = Df(\tilde{x})y$. The conclusion follows from Theorem 7.3. ■

Phase Diagrams

$$\begin{cases} \dot{x}_1 = f_1(x_1, x_2) \\ \dot{x}_2 = f_2(x_1, x_2) \end{cases} \quad (7.2)$$

Example:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_1 \end{cases} \iff \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad (7.3)$$

[Insert a phase diagram here]

■ **Remark:** Saddle path correspondences to an eigenvector with eigenvalue that has negative real part. ■

[The rest part is missing]