

Lecture notes: Linear control theory and state space design

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This lecture note is based on

- Chapter 6 of John Lygeros and Federico A. Ramponi, (2015). Lecture Notes on Linear System Theory.
- Karl Johan Aström Richard M. Murray, *Feedback Systems, An introduction to Scientists and Engineers*. Chapter 3. Cruise control example, Chap5, The Matrix Exponential.

State space form

State: A **minimum** set of variables, known as state variables, that fully describe the system and its response to **any given set of inputs**.

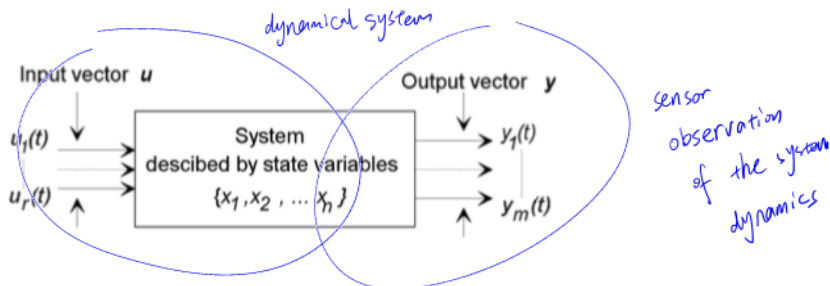


Figure 1: System inputs and outputs.

State space form

consider a general nonlinear, system:

$$\dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u}, t)$$

for time t and state vector \mathbf{x} and input vector \mathbf{u} .

$$\dot{x}_1 = f_1(\mathbf{x}, \mathbf{u}, t)$$

$$\dot{x}_2 = f_2(\mathbf{x}, \mathbf{u}, t)$$

$$\vdots = \vdots$$

$$\dot{x}_n = f_n(\mathbf{x}, \mathbf{u}, t)$$

A system is **time invariant** if $f(\mathbf{x}, \mathbf{u}, t) = f(\mathbf{x}, \mathbf{u})$.

A system is **autonomous** if $f(\mathbf{x}, \mathbf{u}, t) = f(\mathbf{x}, t)$.

unforced

Linear time invariant (LTI) system

The function $f_i(\mathbf{x}, \mathbf{u})$ is **linear** in the state \mathbf{x} and \mathbf{u} , and the parameter does not change with time.

$$\begin{aligned}\dot{x}_1 &= a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n + b_{11}u_1 + \dots + b_{1r}u_r \\ \dot{x}_2 &= a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n + b_{21}u_1 + \dots + b_{2r}u_r \\ &\vdots \\ \dot{x}_n &= a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n + b_{n1}u_1 + \dots + b_{nr}u_r\end{aligned}$$

Linear time invariant (LTI) system

The function $f_i(\mathbf{x}, \mathbf{u})$ is **linear** in the state \mathbf{x} and \mathbf{u} , and the parameter does not change with time.

which can be compactly represented as:

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & & & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} b_{11} & \dots & b_{1r} \\ b_{21} & & b_{2r} \\ \vdots & & \vdots \\ b_{n1} & \dots & b_{nr} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_r \end{bmatrix}$$

and $\dot{\mathbf{x}} = \mathbf{Ax} + \mathbf{Bu}$.

Stability: Basic definitions

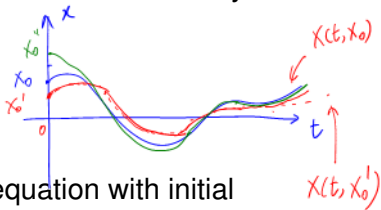
consider a general nonlinear, time varying and autonomous system:

$$\dot{x} = f(x, t)$$

for time t and state vector x .

Stability:

Let $x(t, x_0)$ be a solution to the differential equation with initial condition $x(0) = x_0$.



A solution is **stable** if **other solutions** starting near $x(t, x_0)$, stay close to $x(t, x_0)$.

Asymptotically stable: Stable and $\lim_{t \rightarrow \infty} (x(t, b) - x(t, a)) = 0$ for b is sufficiently close to a .

Stability

Let x_0 be the initial state and $x(t, x_0)$ be the solution of the ODE.

$x'_0 \neq x_0$ and $x(t, x'_0)$ be the solution of the ODE with x'_0 as the initial state.

Question: Which formula is stability condition, and which is asymptotically stable?



Stable

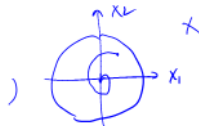
$$\forall \epsilon > 0, \exists \delta_\epsilon > 0, \|x'_0 - x_0\| \leq \delta_\epsilon, \implies \|x(t, x'_0) - x(t, x_0)\| \leq \epsilon, \forall t \geq t_0.$$

Local

AS: $\exists \delta > 0, \|x'_0 - x_0\| \leq \delta, \implies \|x(t, x'_0) - x(t, x_0)\| \rightarrow 0 \text{ as } t \rightarrow \infty$

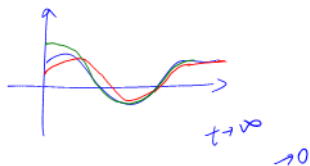
Global asymptotical stability:

$\forall \delta > 0, ($



Stability

exponential stability of $x = x_0$: $x(t, x_0)$



$$\exists \delta, c, \lambda > 0 : \quad \|x'_0 - x_0\| < \delta \rightarrow \|x(t, x'_0) - x(t, x_0)\| \leq \underbrace{c \exp^{-\lambda t}}_{\substack{e^{-\lambda t} \rightarrow e^{-t} \\ \text{const.} < \delta}} \|x'_0 - x_0\|.$$

Equilibrium: A special case of solution $f(x_e, t) = 0$ for all $t \geq 0$.

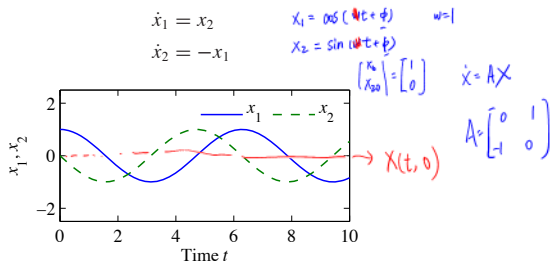
- An equilibrium is **stable** if the solution starting from the equilibrium is **stable**.
- An equilibrium is **Asymptotically stable** if the solution starting from the equilibrium is **Asymptotically stable**.

Example

Q: Can you find a solution for the system with initial state (1, 0)?

Q: What is the equilibrium? $AX_e = 0$; $x_e = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

Q: Is the equilibrium stable? Is the equilibrium asymptotically stable?

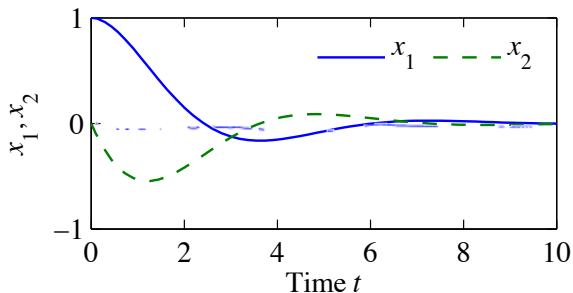


Example

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = -x_1 - x_2$$

$$x_e = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$



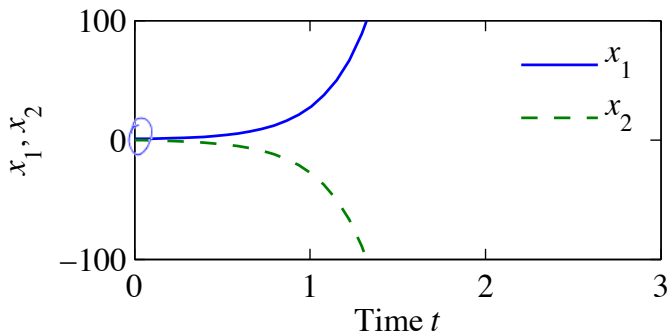
Example

$$\begin{aligned}\dot{x}_1 &= 2x_1 - x_2 \\ \dot{x}_2 &= -x_1 + 2x_2\end{aligned}$$

unstable.

$$x_e = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$x_0 = \begin{bmatrix} 0.001 \\ 0.002 \end{bmatrix}$$



Stability of a linear system

A linear system has the form

$$\dot{x} = Ax, \quad x(0) = x_0$$

Equilibrium: $x_e = 0$

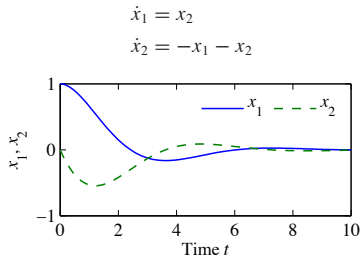
Question: Given a linear system, how to know if the system is stable or not?

Direct method: Solve the ODE.

- consider the simple scalar system $\dot{x} = ax$, $x(0) = x_0$. The solution is $x(t) = e^{at}x_0$.
- For a linear system $\dot{x} = Ax$ for A is a matrix, x is a vector. The solution is $x(t) = e^{At}x_0$.

Example

Consider the example: Given the initial state $(1, 0)$, what is the solution $x(t)$?



$$A = \begin{bmatrix} 0 & 1 \\ -1 & -1 \end{bmatrix}$$
$$x(t) = e^{At} x_0$$

Arrows indicate A is the matrix, t is the time variable, x_0 is the initial state, and $x_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$.

The matrix exponential

matrix exponential

$$e^{At} = I + At + \frac{1}{2}A^2t^2 + \frac{1}{3!}A^3t^3 + \cdots = \sum_{k=0}^{\infty} \frac{1}{k!}A^k t^k,$$

and differentiate w.r.t t

Question: How to determine the stability **without** solving the ODE?

Relating e^{At} with the eigenvalue of A

Given a matrix A , v is an **eigenvector** of A , and λ is the corresponding **eigenvalue**.

$$Av = \lambda v$$

- v is in the nullspace of $A - \lambda I$. *← identity.*
- For $v \neq 0$ to exist, $A - \lambda I$ must not be full rank
 - $A - \lambda I$ not invertible.
 - and $\det(A - \lambda I) = 0$.

$$(A - \lambda I)v = 0$$

Relating e^{At} with the eigenvalue of A

Given a matrix A , v is an **eigenvector** of A , and λ is the corresponding **eigenvalue**.

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— which means λ is are the roots of the **characteristic polynomial** $\det(sI - A)$.

$$\lambda(A) = \{s : \det(sI - A) = 0\}.$$

Example

let $A = \begin{bmatrix} 0 & 1 \\ -1 & -1 \end{bmatrix}$. Exercise: What are the eigenvalues and eigenvectors of A .

$$|A - \lambda I| = \begin{vmatrix} -\lambda & 1 \\ -1 & -1-\lambda \end{vmatrix} = 0$$

$$\Rightarrow -\lambda(-1-\lambda) + 1 = 0$$

$$\Rightarrow \lambda^2 + \lambda + 1 = 0$$

$$\lambda = \frac{-1 \pm \sqrt{3}i}{2}$$

Eigen decomposition

$$(A - \lambda I)v = 0.$$

$$A \in \mathbb{R}^{n \times n}$$
$$\lambda_1 \dots \lambda_n$$

Let $\lambda_1, \dots, \lambda_k$ be k different eigenvalues and v_1, \dots, v_k be their corresponding eigenvector.

$$A \begin{bmatrix} v_1 & v_2 & \dots & v_k \end{bmatrix} = \begin{bmatrix} v_1 & \dots & v_k \end{bmatrix} \Lambda$$
$$\begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \ddots \\ & & & \lambda_n \end{bmatrix}$$

Eigen decomposition

$$(A - \lambda I)v = 0.$$

Let $\lambda_1, \dots, \lambda_k$ be k different eigenvalues and v_1, \dots, v_k be their corresponding eigenvector.

$$A \begin{bmatrix} v_1 & v_2 & \dots & v_k \end{bmatrix} =$$

Thus, let $T = \begin{bmatrix} v_1 & v_2 & \dots & v_k \end{bmatrix}$, we have

$$AT = T\Lambda$$

with $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_k)$. So that $A = \underbrace{T} \underbrace{\Lambda} \underbrace{T^{-1}}$.

Eigen decomposition

$$(A - \lambda I)v = 0.$$

Let $\lambda_1, \dots, \lambda_k$ be k different eigenvalues and v_1, \dots, v_k be their corresponding eigenvector.

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$\text{diag}(\text{lambda}_1, \text{lambda}_2, \dots, \text{lambda}_k)$

Relating e^{At} with the eigenvalue of A

What is the relation between the eigenvalue of A and the solution of $\dot{x} = Ax$?

$x \neq 0$

$\dot{x} = Ax$ transforms to $\dot{z} = T\Lambda T^{-1}x$.

$z \rightarrow 0$
 $x = Tz \rightarrow 0$

Introducing the state-transformation $z = T^{-1}x$.

$$\dot{z} = \Lambda z.$$

$$\Lambda = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

Simple case: Λ is a diagonal matrix.

$$e^{\Lambda t} = \begin{bmatrix} e^{\lambda_1 t} & & 0 \\ & e^{\lambda_2 t} & \\ & & \ddots \\ & & & e^{\lambda_n t} \end{bmatrix}$$

$$z(t) = e^{\Lambda t} z_0$$

\uparrow
 $T^{-1}x_0$

$$e^{\lambda t} \begin{cases} \lambda > 0 & \nearrow \infty \\ \lambda = 0 & 1 \\ \lambda < 0 & \searrow 0 \end{cases}$$

Stable or Hurwitz matrix

- A square matrix of A is called stable if and only if every eigenvalue λ_i of A has strictly negative real part.
- $x(t) \rightarrow 0$ as $t \rightarrow \infty$.

Example

$$\dot{x}_1 = x_2, \quad \dot{x}_2 = -x_1 - x_2$$

- What is A matrix?
- What are the eigenvalues of A ? Is A stable.
- Find the state transformation $z = T^{-1}x$ such that $\dot{z} = \Lambda z$ for a diagonal matrix Λ .

Relating e^{At} with the eigenvalue of A

$A \in \mathbb{R}^{n \times n}$

If Λ is Jordan form J : Each eigenvalue corresponds to multiple eigenvector.

$$J = \begin{bmatrix} J_1 & 0 & \dots & 0 & 0 \\ 0 & J_2 & 0 & 0 & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & 0 & & J_{k-1} & 0 \\ 0 & 0 & \dots & 0 & J_k \end{bmatrix}, \text{ where } J_i = \begin{bmatrix} \lambda_i & 1 & 0 & \dots & 0 \\ 0 & \lambda_i & 1 & & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & 0 & & \lambda_i & 1 \\ 0 & 0 & \dots & 0 & \lambda_i \end{bmatrix}$$

Handwritten notes: $\lambda_1 \dots \lambda_n$, \downarrow , $v_1 \dots v_n$, $\lambda_i \neq \lambda_j$, $\exists i, j: \lambda_i = \lambda_j$

$$e^J = \begin{bmatrix} e^{J_1} & 0 & \dots & 0 \\ 0 & e^{J_2} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \dots & 0 & e^{J_k} \end{bmatrix}, \quad e^{J_i t} = \begin{bmatrix} 1 & t & \frac{t^2}{2!} & \dots & \frac{t^{n-1}}{(n-1)!} \\ 0 & 1 & t & \dots & \frac{t^{n-2}}{(n-2)!} \\ \vdots & & 1 & \ddots & \vdots \\ & & & \ddots & t \\ 0 & \dots & 0 & 1 \end{bmatrix} e^{\lambda_i t}$$

Stability of a linear time invariant (LTI) system

Given linear system

$$\dot{x} = Ax, \quad x(0) = x_0$$

The solution is $x_0 e^{At}$.

Theorem:

Local A.S. = global A.S. = Exp. stable

The linear system $\dot{x} = Ax$ is

- **asymptotically stable** at the equilibrium if and only if all eigenvalues of A have neg. real parts.
- **unstable** if and only if **any** eigenvalues of A has positive real parts.

Exercise: check the stability of previous examples.