# Tentative schedule

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Recap of the previous lecture

- LTI system:

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t), \\
y(t) &= Cx(t) + Du(t).
\end{align*}
\]

- Time response:

\[
\begin{align*}
x(t) &= e^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau) \, d\tau, \\
y(t) &= Ce^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau) \, d\tau + Du(t).
\end{align*}
\]

- Easy to compute if the matrix \( A \) is diagonal, in which case:

\[
\begin{align*}
x_i(t) &= e^{\lambda_i t}x_{0,i} + \int_0^t e^{\lambda_i(t-\tau)}b_iu(\tau) \, d\tau, \\
y(t) &= \sum_{i=1}^n c_i x_i(t) + Du(t).
\end{align*}
\]
Qualitative behavior of a LTI system

- **Lyapunov stability**: A system is called **Lyapunov stable** if, for any bounded initial condition, and zero input, the state remains bounded, i.e.,
  \[
  \forall \|x_0\| < \epsilon, \text{ and } u = 0 \Rightarrow \|x(t)\| < \delta, \text{ for all } t \geq 0.
  \]

- A system is called **asymptotically stable** if, for any bounded initial condition, and zero input, the state converges to zero, i.e.,
  \[
  \forall \|x_0\| < \epsilon, \text{ and } u = 0 \Rightarrow \lim_{t \to +\infty} \|x(t)\| = 0.
  \]

- **Bounded-Input, Bounded Output stability**: A system is called **BIBO-stable** if, for any bounded input, the output remains bounded, i.e.,
  \[
  \forall \|u(t)\| < \epsilon \quad \forall t \geq 0, \text{ and } x_0 = 0 \Rightarrow \|y(t)\| < \delta \quad \forall t \geq 0.
  \]

- **For linear systems asymptotic stability** \(\Rightarrow\) **BIBO stability**.

- A system is called **unstable** if not stable.
Stability conditions

- We have learned that depending on the eigenvalues of $A$, the state/output response will be given by some linear combination of terms of the form:

  - $\lambda_i$ real and distinct: $\exp(\lambda_i t)$
  
  - $\lambda_i$ complex conjugate: $\exp(\sigma t) \sin(\omega t + \phi)$, where $\sigma_i = \text{Re}(\lambda_i), \omega_i = \text{Im}(\lambda_i)$
  
  - repeated $\lambda_i$: $t^m \exp(\lambda_i t), t^m \exp(\sigma t) \sin(\omega t + \phi)$

- Lyapunov stable if $\text{Re}(\lambda_i) \leq 0$ for all $i$, and there are no repeated eigenvalues with 0 real part; asymptotically stable if $\text{Re}(\lambda_i) < 0$ for all $i$. 

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Recall from Lecture 1

- **Signals** are maps from a set $\mathbb{T}$ to a set $\mathbb{W}$. They receive a number as input and produce a number as output.
  - Think of $\mathbb{T}$ as the time axis. It will be the real line, i.e., $\mathbb{T} = \mathbb{R}$, when talking about **continuous-time** systems. This is how “things work in nature”.
  - Or it could be the set of natural numbers: $\mathbb{T} = \mathbb{N}$, when talking about **discrete-time** systems. This is how things work on a computer.

Continuous-time signals $\Rightarrow$ Signals that are defined at every point in time.

Discrete-time signals $\Rightarrow$ Signals are defined only at the sampling instants $kT_s$, where $T_s$ is the sampling period and $k \in \mathbb{N}$
Questions of the day

Today, we will first ask ourselves:

- How does a discrete-time LTI system look like?
- How does what we know about time response and stability apply to discrete-time LTI system?

Then:

- How do we express LTI systems in diagonal form?
- What insight on the system behaviour do we gain by diagonalizing it?
Today’s learning objectives

After today's lecture, you should be able to:

- Understand the concept of discrete time systems and their applicability
- Discretize a continuous time LTI system and check its stability
- Diagonalize a matrix using similarity transformations.
- Understand concepts like controllability and observability.
- Understand how feedback control can affect the closed-loop dynamics.
Discrete time systems

- Why discrete time systems?
  - Algorithms (e.g., controller) often implemented on computers.
  - Computers do not have a concept of continuity.
  - All signals are evaluated (sampled) at specific time instants, multiples of a “sampling time” ($T_s$).
  - Signals are discretized in time (ADC), processed digitally, and then made continuous again (DAC).

![Diagram of discrete time system]
How obtain discrete-time version of LTI system state-space representation?

### Differential eq.s

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t) \\
y(t) &= Cx(t) + Du(t)
\end{align*}
\]

### Finite differences eq.s

\[
\begin{align*}
x[k+1] &= A_dx[k] + B_du[k] \\
y[k] &= C_dx[k] + D_du[k]
\end{align*}
\]

- **Time response of Continuous system:**

\[
x(t) = e^{A(t-t_0)}x(t_0) + \int_{t_0}^{t} e^{A(t-\tau)}Bu(\tau) \, d\tau.
\]

- Let \( t_0 = kT_s \), and \( t = (k+1)T_s \)

\[
x((k+1)T_s) = e^{AT_s}x(kT_s) + \int_{kT_s}^{(k+1)T_s} e^{A((k+1)T_s-\tau)}Bu(\tau) \, d\tau.
\]
LTI discrete time system: implicit representation

Differential eq.s

\[ \dot{x}(t) = Ax(t) + Bu(t) \]
\[ y(t) = Cx(t) + Du(t) \]

Finite differences eq.s

\[ x[k + 1] = A_dx[k] + B_du[k] \]
\[ y[k] = C_dx[k] + D_du[k] \]

- Piecewise constant inputs over a sampling period (first order sample and hold):
  \[ u(t) = u(kT_s), \quad kT_s \leq t < (k + 1)T_s \]
  \[ x((k + 1)T_s) = e^{AT_s}x(kT_s) + \left( \int_{kT_s}^{(k+1)T_s} e^{A((k+1)T_s - \tau)} B \, d \tau \right)u(kT_s). \]

- Change of variable of integration: \( \lambda = (k + 1)T_s - \tau \).
  \[ x[k + 1] = e^{AT_s}x[k] + \left( \int_{0}^{T_s} e^{A\lambda} \, d\lambda B \right)u[k]. \]

- Where: \( x((k + 1)T_s) = x[k + 1] = x_{k+1} \), \( u(kT_s) = u[k] = u_k \),
  \( y(kT_s) = y[k] = y_k \).
LTI discrete time system: implicit representation

Differential eq.s
\[\dot{x}(t) = Ax(t) + Bu(t)\]
\[y(t) = Cx(t) + Du(t)\]

Finite differences eq.s
\[x[k + 1] = A_d x[k] + B_d u[k]\]
\[y[k] = C_d x[k] + D_d u[k]\]

\[x[k + 1] = e^{AT_s} x[k] + \left( \int_0^{T_s} e^{A\lambda} d\lambda B \right) u[k],\]
\[y[k] = C x[k] + D u[k]\]

- If \(A\) is invertible: \(\int e^{At} \, dt = A^{-1} e^{At} = e^{At} A^{-1}\)

\[A_d = e^{AT_s}\]
\[B_d = \int_0^{T_s} e^{A\lambda} d\lambda B = A^{-1} (e^{AT_s} - I) B\]
\[C_d = C\]
\[D_d = D\]
LTI discrete time system: explicit representation

- **Continuous time:**

  \[
  x(t) = e^{A(t)}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)\,d\tau,
  \]

  \[
  y(t) = Ce^{A(t)}x(0) + C \int_0^t e^{A(t-\tau)}Bu(\tau)\,d\tau + Du(t).
  \]

- **Discrete time:**

  \[
  x[1] = A_d x[0] + B_d u[0]
  \]

  \[
  \]

  \[
  \vdots
  \]

  \[
  x[k] = \Phi[k] + \sum_{i=0}^{k-1} H[k - i]u[i]
  \]
LTI discrete time system: explicit representation

- **Continuous time** \((t_0 = 0)\):

  \[
  x(t) = e^{At}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)\,d\tau,
  \]

  \[
  y(t) = Ce^{At}x(0) + C\int_0^t e^{A(t-\tau)}Bu(\tau)\,d\tau + Du(t).
  \]

- **Discrete time**:

  \[
  x[k] = A_d^k x[0] + \sum_{i=0}^{k-1} A_d^{k-1-i} B_d u[i]
  \]

  \[
  y[k] = CA_d^k x[0] + C\sum_{i=0}^{k-1} A_d^{k-1-i} B_d u[i] + Du[k]
  \]
We have derived the discrete-time LTI implicit:

- implicit representation: \((A, B, C, D) \rightarrow (A_d, B_d, C_d, D_d)\)

- explicit representation:
  
  - initial conditions (free) response: \(\Phi(t) = e^{At} \rightarrow \Phi[k] = A_d^k\)
  
  - forced response: \(\int_0^t \cdots \rightarrow \sum_{i=0}^{k-1} \ldots\)

Sampling time \(T_s\) plays an important role in the discretization process. The smaller \(T_s\) is, the smaller the approximation.

What about stability, can we still infer it from the eigenvalues of \(A_d\), like for the continuous time case?
(Lyapunov) Stability: real and distinct eigenvalues of $A_d$

- The initial condition response of an $n$-th order discrete time LTI system:

  \[ x_{k+1} = A_d x_k, \ x[0] = x_0, \]

  is:

  \[ x_k = A_d^k x_0 = \sum_{i=1}^{n} \lambda_i^k c_i u_i, \]

  where: \((A_d - \lambda_i I)u_i = 0\), and \(c_i = v_i x_0\).

**Stability conditions**

- \(|\lambda_i| < 1, \ \forall i \Rightarrow \text{Asymptotic stable}\)
- \(|\lambda_i| > 1, \ \text{for some } i \Rightarrow \text{Unstable}\)
- \(|\lambda_i| \leq 1, \ \forall i, \text{ and } \lambda_i = 1 \text{ for some } i \Rightarrow \text{Lyapunov stable}\)
Stability: complex conjugate eigenvalues of $A_d$

- Given $x_{k+1} = A_d x_k$, $x[0] = x_0$, with $A_d$ having complex conjugate eigenvalues $\lambda_i = \sigma_i \pm j\omega_i$, $i = 1, \ldots, n/2$.
- Let $\rho_i = \sqrt{\sigma^2 + \omega^2}$, $\theta_i = \angle \lambda_i$.
- Then, $\lambda_i = \rho_i e^{j\theta_i}$. Accordingly, we have:

$$x[k] = \sum_{i=1}^{n} \rho_i^k e^{jk\theta_i} c_i u_i.$$ 

Stability conditions

- $\rho_i < 1$, $\forall i \Rightarrow$ Asymptotic stable
- $\rho_i > 1$, for some $i \Rightarrow$ Unstable
- $\rho_i \leq 1$, $\forall i$, and $\rho_i = 1$ for some $i \Rightarrow$ Lyapunov stable

For discrete time systems stability depends on the magnitude of the eigenvalues of $A_d$, not the sign of the real part. Eigenvalues inside the unit circle $= \text{stability}$. 
Similarity Transformations

- The choice of a state-space model for a given system is not unique.
- For example, let $T$ be an invertible matrix, and consider a coordinate transformation $x = T\tilde{x}$, i.e., $\tilde{x} = T^{-1}x$. This is called a similarity transformation.
- The standard state-space model can be written as

\[
\begin{align*}
\dot{x} &= Ax + Bu, \\
y &= Cx + Du.
\end{align*}
\]

\[
\Rightarrow \begin{align*}
T\dot{\tilde{x}} &= AT\tilde{x} + Bu, \\
y &= CT\tilde{x} + Du.
\end{align*}
\]

i.e.,

\[
\begin{align*}
\dot{\tilde{x}} &= (T^{-1}AT)\tilde{x} + (T^{-1}B)u = \tilde{A}\tilde{x} + \tilde{B}u \\
y &= (CT)\tilde{x} + Du = \tilde{C}\tilde{x} + \tilde{D}u.
\end{align*}
\]

- You can check that the time response is exactly the same for the two models $(A, B, C, D)$ and $(\tilde{A}, \tilde{B}, \tilde{C}, \tilde{D})$!
Diagonalization

- Let $\lambda_i, v_i$ be respectively an eigenvalue and an eigenvector of $A$, i.e.,

$$Av_i = \lambda_i v_i.$$ 

- Now assume we have $n$ (=dim. of $x$ and $A$) independent eigenvectors; then we can assemble the eigenvectors into an invertible matrix $V$ whose columns are the eigenvectors $v_i$. Then

$$AV = A \begin{bmatrix} v_1 & v_2 & \ldots & v_n \end{bmatrix} = \begin{bmatrix} \lambda_1 v_1 & \lambda_2 v_2 & \ldots & \lambda_n v_n \end{bmatrix} = V \Lambda.$$ 

- In other words, if a square matrix $A$ has a full set of independent eigenvectors, then it is diagonalizable (and vice-versa), with the similarity transformation given by a matrix whose columns are the eigenvectors.
Modal decomposition

- The entries in the diagonal matrix $\tilde{A} = \Lambda$ are the **eigenvalues** $\lambda_1, \ldots, \lambda_n$ of the matrix $A$.

- Since $\tilde{x}(t) = e^{\tilde{A}t} \tilde{x}(0)$, we get that each component of the homogeneous solution is given by

  $$\tilde{x}_i(t) = e^{\lambda_i t} \tilde{x}_i(0).$$

- Furthermore, if $x(0) = v_i$ for some $i = 1, \ldots, n$, then by the definition of matrix exponential and eigenvalues/eigenvectors

  $$x(t) = e^{At} v_i = e^{\lambda_i t} v_i.$$

- If the eigenvectors $v_i, i = 1, \ldots, n$ form a basis, then we can always express any initial condition as a linear combination of eigenvectors, i.e., $x(0) = V\tilde{x}(0)$, with $\tilde{x}_0 = V^{-1}x_0$, and write

  $$x(t) = \sum_{i=1}^{n} e^{\lambda_i t} \tilde{x}_i(0) v_i.$$
Modal coordinates

- Eigenvalues and eigenvectors of $A$ define the **modes** of the system; the transformed coordinates $\tilde{x} = Vx$ are also called the modal coordinates.
  
  - The eigenvector $v_i$ defines the **shape** of the $i$-th mode;
  
  - The modal coordinate $\tilde{x}_i$ scales the mode (e.g., at the initial condition);
  
  - The eigenvalue $\lambda_i$ defines how the amplitude of the mode **evolves over time**.

  1. As an exponential $e^{\lambda_i t}x_0$ for real $\lambda_i$
  
  2. As a sinusoid with exponentially changing amplitude $e^{\sigma_i t} \sin(\omega_i t + \phi_0)x_0$ for complex-conjugate $\lambda_i = \sigma_i \pm j\omega_i$.
  
  3. As polynomially-scaled versions of the above $t^p e^{\lambda_i t}$ for repeated $\lambda_i$.

- The amplitude of the $i$ mode goes to zero as $t$ increases if and only if $\text{Re}(\lambda_i) < 0$. 

Complex numbers can be represented in basically two ways:

- Cartesian form: \( z = a + jb \)
- Polar form: \( z = |z|e^{j\angle z} \)

In the above formulas, \(|z| = \sqrt{a^2 + b^2}\), and \(\angle z = \arctan(b/a)\) (arctan understood as the four-quadrant version).

The Cartesian form makes addition easy:

\[
(a_1 + jb_1) + (a_2 + jb_2) = a_1 + a_2 + j(b_1 + b_2)
\]

The polar form makes multiplication easy:

\[
m_1e^{i\phi_1} \cdot m_2e^{i\phi_2} = (m_1 m_2)e^{i(\phi_1 + \phi_2)}
\]
Towards feedback control

So far we have looked at how a given system, represented as a state-space model or as a transfer function, behaves given a certain input (and/or initial condition).

Typically the system behavior may not be satisfactory (e.g., because it is unstable, or too slow, or too fast, or it oscillates too much, etc.), and one may want to change it. This can only be done by feedback control!

However, we need to understand to what extent we can change the system behavior. More precisely, for control design, one must also understand

- how the control **input** can affect the **state** of the system;
- how the **state** of the system affects the **output**.
An LTI system of the form \( \dot{x} = Ax + Bu \) is said to be **controllable** if for any given initial state \( x(0) = x_c \) there exists a control signal that takes the state to the origin \( x(t) = 0 \) for some finite time \( t \).

An LTI system of the form \( \dot{x} = Ax + Bu, \quad y = Cx + Du \) is said to be **observable** if any given initial condition \( x(0) = x_o \) can be reconstructed based on the knowledge of the input and output signal only, over a finite time interval \( [0, t] \).
Recall that if the matrix $A$ has a complete set of independent (right) eigenvectors $\{v_1, \ldots, v_n\}$, with eigenvalues $\{\lambda_1, \ldots, \lambda_n\}$ it can be diagonalized by the matrix $T = [v_1 \ v_2 \ \ldots \ v_n]$.

The transformed state in the diagonalized system is such that $x = T\tilde{x}$.

The transformed model is $(\tilde{A}, \tilde{B}, \tilde{C}, \tilde{D}) = (T^{-1}AT, T^{-1}B, CT, D)$.

Component-wise, the dynamics of each modal coordinate $\tilde{x}_i$ are given by

$$\frac{d}{dt}\tilde{x}_i(t) = \lambda_i\tilde{x}_i(t) + \tilde{b}_i u(t), \quad i = 1, \ldots, n.$$ 

The output is given by

$$y = \tilde{c}_1\tilde{x}_1(t) + \tilde{c}_2\tilde{x}_2(t) + \ldots + \tilde{c}_n\tilde{x}_n(t) + Du(t).$$
Controllability/observability for diagonal systems

From the previous slide, we can deduce

- The $i$-th coordinate can be controlled if and only if $\tilde{b}_i \neq 0$.
- The $i$-th coordinate appears in the output if and only if $\tilde{c}_i \neq 0$.

Hence:

- An LTI system in diagonal form is **controllable** if $\tilde{b}_i \neq 0$, $i = 1, \ldots, n$.
- An LTI system in diagonal form is **observable** if $\tilde{c}_i \neq 0$, $i = 1, \ldots, n$.

An LTI system is **stabilizable** if all unstable modes are controllable.

An LTI system is **detectable** if all unstable modes are observable.
An example

\[ \tilde{A} = \begin{bmatrix} 1.618j & -1.618j \\ 0.618j & -0.618j \end{bmatrix}, \quad \tilde{B} = \begin{bmatrix} 0.4472j \\ -0.4472j \\ 0.4472 \\ 0.4472 \end{bmatrix} \]

\[ \tilde{C} = [0.276j \ -0.276j \ 0.724 \ 0.724], \quad \tilde{D} = [0]. \]
An example

\[ A = \begin{bmatrix} j & -j \\ j & -j \end{bmatrix}, \quad B = \begin{bmatrix} 0.707j \\ -0.707j \\ 0 \\ 0 \end{bmatrix} \]

\[ C = \begin{bmatrix} 0 & 0 & 0.707 & 0.707 \end{bmatrix}, \quad D = [0]. \]
More general conditions

- Consider the derivatives of the output:
  
  \[ y(0) = Cx(0), \quad y'(0) = CAx(0), \quad y''(0) = CA^2x(0), \ldots \]

- One can reconstruct \( x(0) \), i.e., the system is **observable**, as long as the observability matrix

\[
\begin{bmatrix}
  C \\
  CA \\
  CA^2 \\
  \vdots \\
  CA^{n-1}
\end{bmatrix}
\]

has full rank.

- Note that it is sufficient to compute the observability matrix only up to the power \( n - 1 \) of \( A \) (Cayley-Hamilton theorem).

- A similar condition can be obtained for controllability, with a somewhat more complicated proof: a system is **controllable** if the controllability matrix

\[
\begin{bmatrix}
  B & AB & A^2B & \ldots & A^{n-1}B
\end{bmatrix}
\]

has full rank.
Consider a first-order control system with dynamics $\dot{x} = ax + bu$, and assume that we are not happy about its behavior (e.g., it is unstable since $a > 0$, or maybe stable but “slow” because $|a|$ is small).

Can we change the behavior by choosing $u$ in a clever way?

Feedback control: choose $u = -kx$; then the dynamics would become

$$\dot{x} = (a - bk)x$$

As long as $b \neq 0$ (i.e., if the system is controllable), by choosing $k = (a-a^*)/b$, we can place the “closed-loop” eigenvalue at a desired value $a^*$, or anywhere we want on the real axis!

This is the simplest example of a general technique called “pole placement”.
Example

- Assume $\dot{x} = 0.5x + u$, i.e., the system is unstable with time constant $2$.
- We would like the system to be stable, with time constant $1/2$.
- Choose $u = -(0.5 + 2)x = -2.5x$; the closed loop will be $\dot{x} = -2x$ as desired.
Effect on feedback for closed-loop dynamics

- If we have an open-loop LTI system
  \[
  \dot{x}(t) = Ax(t) + Bu(t), \\
y(t) = Cx(t),
  \]

by choosing a linear feedback \( u = -ky = -kCx \), we can transform it into another, closed-loop LTI system:

\[
\dot{x}(t) = (A - BkC)x(t), \\
y(t) = Cx(t),
\]

- In general “negative feedback” (i.e., \( u = -ky \)) has “stabilizing” effects, and the bigger \( k \), the faster the closed-loop system is, and the smaller the errors are.

- However this is not generally the case.

- In the rest of the course, we will look at ways to analyze the behavior of the closed-loop system, and choosing the feedback control law, without necessarily lots of computation — but rather using primarily “graphical” methods.
Examples

\[ \dot{x}(t) = 0.5x(t) + u(t), \]
\[ y(t) = x(t), \]
Examples

\[
\dot{x}(t) = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1.5 \end{bmatrix} u(t),
\]

\[
y(t) = \begin{bmatrix} 1.34 & 0.67 \end{bmatrix} x(t),
\]
Examples

\[
\dot{x}(t) = \begin{bmatrix} -1 & 1 & 0 \\ -1 & -1 & 1 \\ 0 & 0 & -2 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 5 \end{bmatrix} u(t),
\]

\[
y(t) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} x(t),
\]
Today’s learning objectives

After today's lecture, you should be able to:

- Understand the concept of discrete time systems and their applicability
- Discretize a continuous time LTI system and check its stability
- Diagonalize a matrix using similarity transformations.
- Understand concepts like controllability and observability.
- Understand how feedback control can affect the closed-loop dynamics.