

01_Modeling and Analysis of NCS

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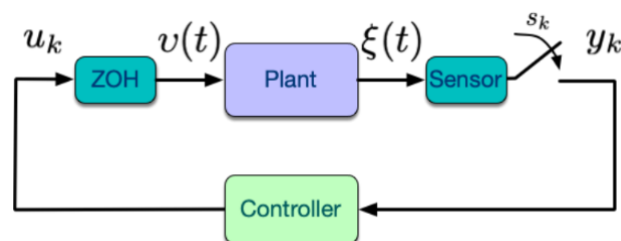
Summary

For a constant sample interval sampled-data control system, we can obtain its model:

$$\begin{aligned}x_{k+1} &= e^{Ah}x_k + \int_0^h e^{As}Bdsu_k \\ &=: F(h)x_k + G(h)u_k\end{aligned}$$

Because of the property that **the inter-sample gain is bounded** we can use the GES theorem of discrete-time model: **A discrete-time system is stable iff $\rho(\bar{A}) < 1$** . The stability of a sampled-data system depend on the sample interval.

1. Sampled-data Control Systems



1.1. Assumption

- constant sampling interval h
- full state measurement: $y(k) = x(k) := \epsilon(kh)$
- ZOH mechanism

1.2. Model

$$\begin{aligned}\dot{\xi}(t) &= A\xi(t) + Bv(t) & \forall t \in \mathbb{R}^+ \\ v(t) &= u_k & \text{for } t \in [s_k, s_{k+1})\end{aligned}$$

where ϵ is trajectory, x_k is points

so we have:

$$\xi(t) = e^{A(t-t_0)}\xi(t_0) + \int_{t_0}^t e^{A(t-s)}Bv(s)ds$$

and

$$x_{k+1} := \xi(s_{k+1}) = e^{Ah}\xi(s_k) + \int_{s_k}^{s_{k+1}} e^{A(s_{k+1}-s)}Bu_k ds$$

It can be denoted as:

$$\begin{aligned}x_{k+1} &= e^{Ah}x_k + \int_0^h e^{As}Bds u_k \\ &=: F(h)x_k + G(h)u_k\end{aligned}$$

If A is invertible

$$\int_0^h e^{As}ds = (e^{Ah} - 1)A^{-1}$$

If A is not invertible, we can use Jordan's Decomposition

1.3. Globally Exponentially Stable (GES) of Discrete Linear Systems

1.3.1 Definition

The **origin** of the linear discrete-time system

$$x_{k+1} = \bar{A}x_k$$

is said to be a **globally exponentially stable (GES)** fixed point if there exist $c > 0$ and $\rho \in (0, 1)$ such that

$$\|x_k\| \leq c\rho^{k-k_0} \|x_0\|$$

That means:

■ *For each start point, this system will get close to the origin with exponentially speed*

1.3.2. Theorem

The origin of the discrete-time system $x_{k+1} = \bar{A}x_k$ is **GES if and only if**

$$\rho(\bar{A}) = \max \left\{ |\lambda_1(\bar{A})|, |\lambda_2(\bar{A})|, \dots, |\lambda_n(\bar{A})| \right\} < 1$$

that is: **the spectral radius of \bar{A} is smaller than one**

1.4. Sampled Data System's Stability

For system

$$x_{k+1} = F(h)x_k + G(h)u_k$$

we consider a static state-feedback control law $u_k = -\bar{K}x_k$, then we will have

$$\begin{aligned} x_{k+1} &= (F(h) - G(h)\bar{K})x_k \\ \text{with } (F(h) - G(h)\bar{K}) &= e^{Ah} - \int_0^h e^{As} B\bar{K}ds \end{aligned}$$

The origin is GES iff:

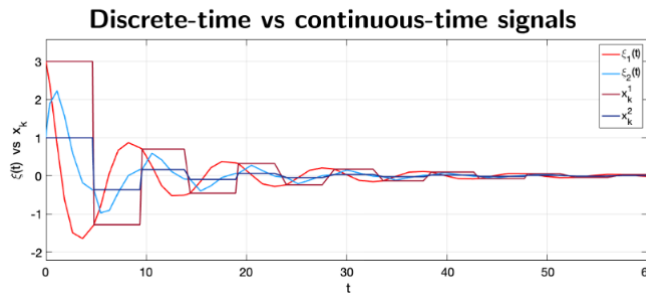
$$\rho(F(h) - G(h)\bar{K}) < 1$$

That means

For a sampled-data system, its stability depend on the sample period h

1.5. Sampled Data Behavior

Up to now, we ignore the inter-sample behavior. However, these behaviors is important



During each interval $t \in [s_k, s_{k+1})$

$$\xi(t) = \xi(s_k + \Delta t) = \left(e^{A\Delta t} - \int_0^{\Delta t} e^{As} B ds \bar{K} \right) x_k =: \tilde{F}_{cl}(\Delta t) x_k,$$

$$\tilde{F}_{cl}(\Delta t) := \left(e^{A\Delta t} - \int_0^{\Delta t} e^{As} B ds \bar{K} \right)$$

where $\Delta t \in [0, h)$

Relation between discrete-time model stable and sampled-data system stable

stability of exact discrete-time model \Rightarrow stability of the sampled-data system

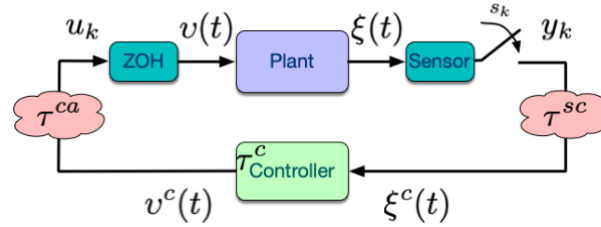
Proof

Because $e^{A\Delta t}$, $e^{As}B$ is bounded, so we have

$$\Delta t < \infty \Rightarrow \left\| \tilde{F}_{cl}(\Delta t) \right\| \leq M < \infty$$

That is

2. Networked Control Systems with Delays



2.1. Assumptions

- Sensor-to-controller delay τ^{sc}

$$\xi^c(t) = \xi(s_k), \text{ for } t \in [s_k + \tau^{sc}, s_{k+1} + \tau^{sc})$$

- Computational Delay τ^c

$$v^c(t) = \kappa(\xi^c(t - \tau^c))$$

- Controller-to-actuator delay τ^{ac}

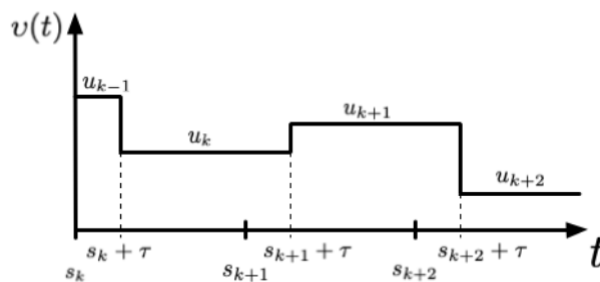
$$v(t) = v^c(t - \tau^{ac})$$

- **Constant and Small total delay:**

$$\tau = \tau^{SC} + \tau^C + \tau^{Ca}$$

$$0 \leq \tau \leq h$$

2.2. Modelling



For time interval $t \in [s_k, s_{k+1})$

$$\begin{aligned}\xi(s_{k+1}) &= e^{A(h)}\xi(s_k) + \int_{s_k}^{s_{k+1}} e^{A(t-s)} Bv(s)ds \\ v(t) &= u_{k-1} \quad \text{for } t \in [s_k, s_k + \tau) \\ v(t) &= u_k \quad \text{for } t \in [s_k + \tau, s_{k+1})\end{aligned}$$

We can rewrite it as:

$$x_{k+1} = e^{A(h)}x_k + \int_{h-\tau}^h e^{As} Bds u_{k-1} + \int_0^{h-\tau} e^{As} Bds u_k$$

then rewrite as:

$$x_{k+1} = F_x(h)x_k + F_u(h, \tau)u_{k-1} + G_1(h, \tau)u_k$$

where

$$F_x(h) := e^{A(h)}, F_u(h, \tau) := \int_{h-\tau}^h e^{As} Bds, \text{ and } G_1(h, \tau) := \int_0^{h-\tau} e^{As} Bds$$

2.3. State Augmentation Modelling

with **extended state vector** $x_k^e = \begin{bmatrix} x_k^T & u_{k-1}^T \end{bmatrix}$

$$x_{k+1}^e = F(h, \tau)x_k^e + G(h, \tau)u_k$$

where

$$F(h, \tau) := \begin{bmatrix} F_x(h) & F_u(h, \tau) \\ 0 & 0 \end{bmatrix}, G(h, \tau) := \begin{bmatrix} G_1(h, \tau) \\ I \end{bmatrix}$$

2.4. Stability Analysis

For a given system we have fixed h and τ , so the rule for [Discrete-Time Stability](#) is still available.

We consider a **static state-feedback control law**

$$u_k = -Kx_k^e = -\bar{K}x_k - K_u u_{k-1}.$$

Then we have

$$x_{k+1}^e = (F(h, \tau) - G(h, \tau)K)x_k^e$$

The **origin** of the discrete-time closed-loop is a **GES** fixed point **iff**

$$\rho(F(h, \tau) - G(h, \tau)K) < 1$$

Stability depends on h and τ

The controller $K = [\bar{K} \quad K_u]$ is truly “static” iff $K_u = 0$.

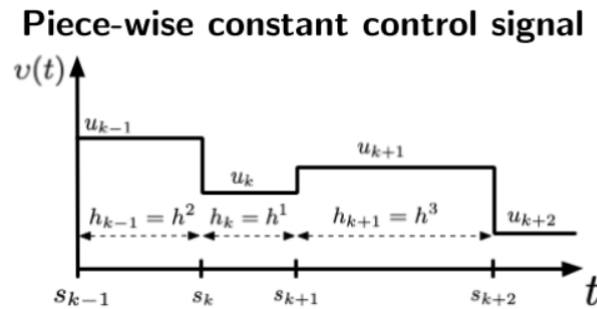
3. NCS with varying sampling intervals

3.1. Assumptions

- Time varying sampling intervals: $s_{k+1} = \sum_{i=0}^k h_i$
- Non-constant sampling interval: $h_k = s_{k+1} - s_k$
- $h_k \in \{h^1, \dots, h'\}, \forall k$
- ZOH

Piece-wise constant control signal

3.2. Modelling



Different from previous models, now we have a **Linear Time-Varing Discrete Time Systems**

$$\begin{aligned} x_{k+1} &= e^{Ah_k} x_k + \int_0^{h_k} e^{As} B ds u_k \\ &=: F(h_k) x_k + G(h_k) u_k \end{aligned}$$

Exact discrete-time system matrices depend on varying sampling interval h_k

Time-varying vs Uncertain but constant

- **Time-varying:** intervals vary but belongs to a certain set
- **Uncertain but constant:** many choice of interval but we do not know, however, after start, each interval are constant

3.3. Stability Analysis

Uncertain but Constant Sampling Interval

$$\rho \left(F(h^i) - G(h^i)\bar{K} \right) < 1, \forall h^i \in \mathcal{H} \Rightarrow \text{origin GES.}$$

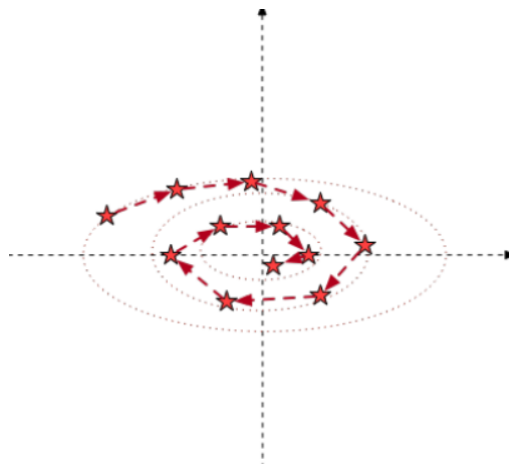
Time Varying interval

$$\rho \left(F(h_k) - G(h_k)\bar{K} \right) < 1, \forall k$$

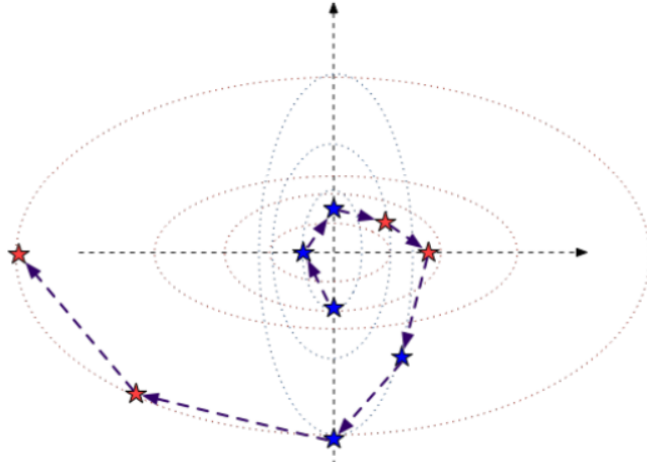
is **Neither Sufficient Nor Necessary**

Example

For a system, if with uncertain but constant sampling interval, it can be:



However, after change it to a Switching System



4. Stability Analysis for non-linear discrete time systems

4.1. Framework

a Discrete-time non-linear time-varying system:

$$x(k+1) = f(x(k), k), \forall k$$

with $x_k \in \mathbb{R}^n$ and the origin is a fixed point, i.e.

$$0 = f(0, k), \quad \forall k$$

4.2. Stability Definitions

Stability

The origin of system is said to be **stable** if for every $\epsilon > 0$ and $k_0 \geq 0$ there exists a function δ of ϵ and k_0 , i.e. $\delta = \bar{\delta}(\epsilon, k_0)$, such that:

$$\|x_{k_0}\| < \bar{\delta}(\epsilon, k_0) \Rightarrow \|x_k\| < \epsilon \quad \forall k \geq k_0$$

For a given standard (ϵ) and a given state, we can always find a value $\bar{\delta}(\epsilon, k_0)$ that if the given state is bounded by the value, the following trajectory is bounded by the standard

a system pass some δ – ball around the equilibrium at time step k_0 will not leave a ϵ – ball around the equilibrium

Uniform Stability

The origin of system is said to be **uniformly stable** if for every $\epsilon > 0$ and $k_0 \geq 0$ there exists a $\delta = \bar{\delta}(\epsilon)$ such that:

$$\|x_{k_0}\| < \bar{\delta}(\epsilon) \Rightarrow \|x_k\| < \epsilon \quad \forall k \geq k_0$$

Uniformity $\Rightarrow \delta$ is independent of the initial time k_0

For a given standard (ϵ), we can always find a value $\bar{\delta}(\epsilon)$ that **no matter from which point, as long as this point is bounded by the value**, the following trajectory is bounded by the standard

a system starting in some δ – ball around the equilibrium will not leave a ϵ – ball around the equilibrium

Global Exponential Stability

The origin of system (1) is said to be said **globally uniformly asymptotically** stable if there exists an exponential function $\beta \in \mathcal{KL}$, i.e. $\beta(\|x\|, k) = c\rho^k\|x\|$ with $c > 0, \rho \in (0, 1)$, such that:

$$\|x_k\| \leq \beta(\|x_{k_0}\|, k), \forall k \geq k_0$$

4.3. Attractivity Definitions

Attractivity

The origin of system is said to be **attractive** if for every $k_0 \geq 0$ there exists a scalar η function of k_0 , i.e. $\eta = \bar{\eta}(k_0) > 0$, such that

$$\|x_{k_0}\| < \bar{\eta}(k_0) \Rightarrow \|x_k\| \rightarrow 0; \text{ as } k \rightarrow \infty$$

For each start point, we can find a bound that is the point meet the bound, the trajectory will be attracted by the origin

Uniform Attractivity

The origin of system is said to be **uniformly attractive** if for every $k_0 \geq 0$ there exists a scalar $\eta > 0$, such that

$$\|x_{k_0}\| < \eta \Rightarrow \|x_k\| \rightarrow 0; \text{ as } k \rightarrow \infty, \text{ uniformly in } k_0$$

uniformity \Rightarrow independent with k_0

For all points, we can find a uniform bound that if the points meet this bound, the trajectory will be attracted by the origin

Attractive but not stable

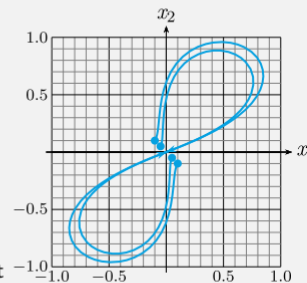
Does the convergence mean asymptotic stability?

Let's look at the following nonlinear system given in the book *Stability of Motion* by W. Hahn in 1967.

$$\dot{x}_1 = \frac{x_1^2(x_2 - x_1) + x_2^5}{(x_1^2 + x_2^2)(1 + (x_1^2 + x_2^2)^2)}$$

$$\dot{x}_2 = \frac{x_2^2(x_2 - 2x_1)}{(x_1^2 + x_2^2)(1 + (x_1^2 + x_2^2)^2)}$$

Note that, the origin is attractive but not asymptotically stable.



4.4. Asymptotic Stability

Local Asymptotic Stability

The origin of system is said to be said **locally asymptotically stable** if it is **both stable and attractive**

Local Uniform Asymptotic Stability

The origin of system is said to be said **locally asymptotically uniformly stable** if it is **both uniformly stable and uniformly attractive**.

Global Uniform Asymptotic Stability

The origin of system is said to be said **globally uniformly asymptotically stable** if there exists a function $\beta \in \mathcal{KL}$ such that:

$$\|x_k\| \leq \beta(\|x_{k_0}\|, k), \forall k \geq k_0$$

- The trajectory should always below a \mathcal{KL} function

4.5. Comparison Functions

\mathcal{K}

A function $\gamma : \mathbb{R}_0^+ \rightarrow \mathbb{R}_0^+$, is of class \mathcal{K} if

- it is continuous,
- strictly increasing
- $\gamma(0) = 0$.

\mathcal{K}_∞

A function $\gamma \in \mathcal{K}$ is of class \mathcal{K}_∞ if additionally it satisfies:

- $\gamma(s) \rightarrow \infty$ as $s \rightarrow \infty$

A continuous function $\beta : \mathbb{R}_0^+ \times \mathbb{R}_0^+ \rightarrow \mathbb{R}_0^+$ is of class \mathcal{KL} if

- $\beta(\cdot, \tau)$ is of class \mathcal{K} for each $\tau \geq 0$
- $\beta(s, \cdot)$ is monotonically decreasing to zero for each $s \geq 0 : \beta(s, \tau) \rightarrow 0$ as $\tau \rightarrow \infty$.

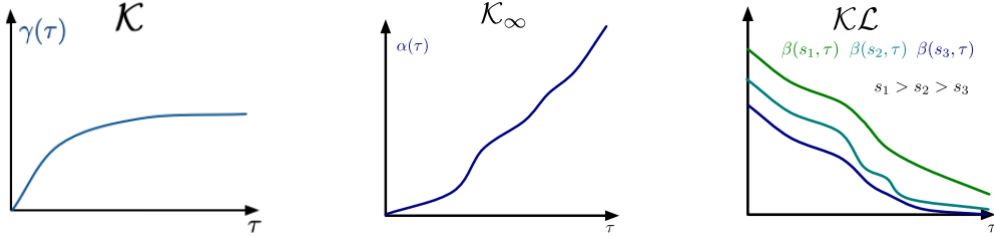
For fixed τ , when s increase, β increase

For fixed s , when τ increase, β decrease

Exponential

A class \mathcal{KL} function β is called **exponential** if

$$\beta(s, \tau) \leq \sigma s e^{-c\tau} \text{ where } \sigma > 0, c > 0$$



4.6. Stability Characterization (For discrete-time systems)

Theorem for Uniform Asymptotic Stability

The origin of system is **local uniformly asymptotically stable** if **there exists** a function $V : \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}_0^+$, a scalar $r > 0$, and \mathcal{K} functions α_1, α_2 , and α_3 such that:

$$\begin{aligned} \alpha_1(\|x\|) &\leq V(x, k) \leq \alpha_2(\|x\|), \forall k \geq k_0, \forall x \in B_r \\ V(x_{k+1}, k+1) - V(x_k, k) &\leq -\alpha_3(\|x_k\|), \forall k \geq k_0, \forall x \in B_r \\ \text{where } B_r &= \{x \in \mathbb{R}^n \mid \|x\| \leq r\} \end{aligned}$$

- Can be regarded as energy decrease
- bounded by two \mathcal{K} function
- decrease and decrease more and more rapidly

Theorem for Global Uniform Asymptotic Stability

The origin of system is globally uniformly asymptotically stable if there exists a function $V : \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}_0^+$, and \mathcal{K} functions α_1, α_2 , and α_3 such that:

$$\alpha_1(\|x\|) \leq V(x, k) \leq \alpha_2(\|x\|), \forall k \geq k_0, \forall x \in \mathbb{R}^n$$

$$V(x_{k+1}, k+1) - V(x_k, k) \leq -\alpha_3(\|x_k\|), \forall k \geq k_0, \forall x \in \mathbb{R}^n$$

$V(x, k)$ is radially unbounded, i.e. $V(x, k) \rightarrow \infty$ as $\|x\| \rightarrow \infty$ uniformly in k .

Theorem for Global Exponential Stability

The origin of system (1) is globally exponentially stable if there exists a function $V : \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}_0^+$, constants $\alpha_1, \alpha_2, \alpha_3 > 0$, and $p > 1$ such that:

$$\alpha_1\|x\|^p \leq V(x, k) \leq \alpha_2\|x\|^p, \forall k \geq k_0, \forall x \in \mathbb{R}^n$$

$$V(x_{k+1}, k+1) - V(x_k, k) \leq -\alpha_3\|x_k\|^p, \forall k \geq k_0, \forall x \in \mathbb{R}^n$$

4.7. LTI Systems Stability

Consider now a Linear Time-Invariant (LTI) system:

$$x_{k+1} = Ax_k$$

and $V(x) = x^T Px$, with $P = P^T > 0$ as a Lyapunov candidate function. Observe:

$$\lambda_{\min}(P)\|x\|^2 \leq V(x) \leq \lambda_{\max}(P)\|x\|^2$$

$$V(x_{k+1}) - V(x_k) = x_k^T (A^T P A - P) x_k$$

$$(A^T P A - P) \leq -Q, Q > 0 \Rightarrow V(x_{k+1}) - V(x_k) \leq -x_k^T Q x_k \leq -\lambda_{\min}(Q)\|x\|^2,$$

i.e. GES with $p = 2$.

Above first equation:

- we can always find a Unit Orthogonal Array to transform P to a diagonal format, and because orthogonal transformation does not change the norm of the vector, so it can be easily proved.

And we can prove that:

A Schur ¹ \Leftrightarrow for each $Q > 0 \exists! P > 0$ such that $A^T P A - P = -Q$

Spectral and Lyapunov stability tests equivalence for LTI systems

5. NCS with varying sampling intervals. LMIs for Stability

The origin of the system is **GES** if there **exist** a matrix $P = P^T > 0$ such that the following LMIs hold for all $h \in \mathcal{H}$:

$$(F(h) - G(h)\bar{K})^T P (F(h) - G(h)\bar{K}) - P \leq -Q$$

for some $Q = Q^T > 0$.

This result is based on finding a common Lyapunov function.