## 1.5 Discrete-time state-space systems

A discrete-time system represents the evolution of a system at discrete instants of time, taken at time points  $kT_s$  with  $k \in \mathbb{Z}$  and  $T_s$  a short amount of time, called *sampling time*.

Discrete-time systems can be expressed as difference equations:

$$\mathbf{x}[k+1] = \mathbf{f}(\mathbf{x}[k], \mathbf{u}[k])$$
$$\mathbf{y}[k] = \mathbf{g}(\mathbf{x}[k], \mathbf{u}[k])$$

**Transformation between continuous-time System and discrete-time system** Consider linear continuous-time dynamics:

$$\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B\mathbf{u}(t) \tag{1.24}$$

We can express the relation of  $\mathbf{x}[k+1] \triangleq \mathbf{x}((k+1)T_s)$  and  $\mathbf{x}[k] \triangleq \mathbf{x}(kT_s)$ , using the solution (1.15) for continuous-time ODE:

$$\mathbf{x}((k+1)T_s) = e^{\mathbf{A}T_s}\mathbf{x}(kT_s) + \int_{0}^{T_s} e^{\mathbf{A}(T_s-\tau)}\mathbf{B}\mathbf{u}(\tau)\mathrm{d}\tau$$
(1.25)

Assume that the control signal is constant over each sampling interval, i.e. for an interval from  $k^{\text{th}}$  to  $(k+1)^{\text{th}}$  samples:  $\mathbf{u}(t) = \mathbf{u}[k], t \in [kT_s, (k+1)T_s)$  (this is called *zero order hold* sampling).

By defining:

$$\mathbf{\Phi} = e^{\mathbf{A}T_s}, \quad \Gamma = \left(\int_{0}^{T_s} e^{\mathbf{A}s} \mathrm{d}s\right) \mathbf{B}$$
(1.26)

we have the discrete-time system that is sampled from (1.24):

$$\mathbf{x}[k+1] = \mathbf{\Phi}\mathbf{x}[k] + \Gamma \mathbf{u}[k] \tag{1.27}$$

Reversely, with given matrices for the discrete-time system, we can also find the matrices of the continuous-time system using relations:

$$\mathbf{A} = \frac{1}{T_s} \log \mathbf{\Phi}, \quad \mathbf{B} = \left( \int_0^{T_s} e^{\mathbf{A}s} \mathrm{d}s \right)^{-1} \Gamma$$
(1.28)

If **A** is invertible, we have the relation:

$$\Gamma = \mathbf{A}^{-1} \left( e^{\mathbf{A}T_s} - I \right) \mathbf{B} \tag{1.29}$$

MATLAB command for converting continuous-time and discrete-time linear systems: sysd = c2d(sysc, Ts); sysc = d2c(sysd).

**Discrete-time System as an Approximation of continuous-time system** For nonlinear continuous-time systems, we don't have analytic solution of the nonlinear ODE, hence it is difficult to find the exact transformation from continuous-time to discrete-time like in the linear case. Instead, we use numerical approximation to compute the discretized values.

Consider Taylor expansion series of function  $\mathbf{x}(t)$  around the point  $t_0 = kT_s$ :

$$\mathbf{x}(t) = \mathbf{x}(t_0) + \nabla \mathbf{x}(t_0)\Delta_t + \mathcal{O}(\Delta_t^2)$$
(1.30)

with  $\Delta_t = \mathbf{x}(t) - \mathbf{x}(t_0)$ . The notation  $\nabla \mathbf{x}(t_0)$  is the derivative of the multi-dimensional function  $\mathbf{x}$  with respect to time t.

We omit the last term which stands for the contribution of high order derivatives, and get linear approximation for  $t = (k + 1)T_s$ :

$$\mathbf{x}[k+1] \approx \mathbf{x}[k] + \nabla \mathbf{x}(t_0) \tag{1.31}$$

In order to implement the computation following (1.31), at each sampling time  $kT_s$ , we first compute the derivative of  $\mathbf{x}$  at that time (we may substitute  $\mathbf{x}[k], \mathbf{u}[k]$  into the nonlinear ODE to get that derivative).

The formula (1.31) is called *Forward Euler* approximation. There are other ways that are widely used: *Backward Euler*, *Runge Kutta* methods.

## **1.6** Linearization of nonlinear systems

Given a nonlinear dynamical system, we may want to examine the behavior of the system around a reference or steady-state point by linearization of the ODE. The following procedure is applied:

- 1. Find equilibrium points.
- 2. Linearize system around the equilibrium point that we are interested.

Equilibrium of a dynamical system Recall the ODE describing a system:

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

Equilibrium points are the points  $(\mathbf{x}_e, \mathbf{u}_e)$  so that  $\mathbf{f}(\mathbf{x}_e, \mathbf{u}_e) = 0$ , hence  $\dot{\mathbf{x}}|_{(\mathbf{x}_e, \mathbf{u}_e)} = 0$ , the state does not change and remains at  $\mathbf{x}_e$ .

Then, we define a new set of variables:  $\mathbf{z}, \mathbf{v}, \mathbf{w}$  are new state, input, and output variables, respectively:

$$\mathbf{z} = \mathbf{x} - \mathbf{x}_e, \quad \mathbf{v} = \mathbf{u} - \mathbf{u}_e, \quad \mathbf{w} = \mathbf{y} - \mathbf{g}(\mathbf{x}_e, \mathbf{u}_e)$$
 (1.32)

Linearization around an equilibrium point The linearized system has the form:

$$\dot{\mathbf{z}}(t) = \mathbf{A}\mathbf{z} + \mathbf{B}\mathbf{v} \tag{1.33}$$

$$\mathbf{w} = \mathbf{C}\mathbf{z} + \mathbf{D}\mathbf{v} \tag{1.34}$$

where:

$$\mathbf{A} = \frac{\mathrm{D}\mathbf{f}}{\mathrm{D}\mathbf{x}}\Big|_{(\mathbf{x}_e, \mathbf{u}_e)}, \quad \mathbf{B} = \frac{\mathrm{D}\mathbf{f}}{\mathrm{D}\mathbf{u}}\Big|_{(\mathbf{x}_e, \mathbf{u}_e)}, \quad \mathbf{C} = \frac{\mathrm{D}\mathbf{g}}{\mathrm{D}\mathbf{x}}\Big|_{(\mathbf{x}_e, \mathbf{u}_e)}, \quad \mathbf{D} = \frac{\mathrm{D}\mathbf{g}}{\mathrm{D}\mathbf{u}}\Big|_{(\mathbf{x}_e, \mathbf{u}_e)}$$
(1.35)

The notation  $\frac{\mathrm{D}\mathbf{f}}{\mathrm{D}\mathbf{x}}$  means the partial Jacobian matrix of the multi-dimensional function  $\mathbf{f} \in \mathbb{R}^m$  with respect to variables  $\mathbf{x} \in \mathbb{R}^n$ , with formula:

$$\frac{\mathbf{D}\mathbf{f}}{\mathbf{D}\mathbf{x}} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$
(1.36)