

Lecture 07: Stochastic Control Systems and Stochastic Control Problems

Stochastic Control Systems

Definition (Stochastic Control System). *Formally, we define a stochastic control system as a collection satisfying the relation*

$$\begin{aligned} & \text{cpm}((x(t+1), y(t)) \mid F_t^{x-} \vee F_{t-1}^{y-} \vee F_t^{u-}) \\ &= \text{cpm}((x(t+1), y(t)) \mid F^{x(t)} \vee F^{u(t)}) \quad \forall t \in T \end{aligned}$$

which implies that we have that the next state and current measurement and the previous measurements, states and control inputs are conditionally independent given the current state and input:

$$(F^{x(t+1)} \vee F^{y(t)}, F_t^{x-} \vee F_{t-1}^{y-} \vee F_t^{u-} \mid F^{x(t), u(t)}) \in CI \quad \forall t \in T$$

Where $u : \Omega \times T \rightarrow U$ is the input process, $c : \Omega \times T \rightarrow X$ the state process and $y : \Omega \times T \rightarrow Y$ the output process. If the above does not explicitly depend on time it is time-invariant and if $x_0 \in G$ and cpm^1 is conditionally Gaussian, the system is Gaussian. We denote

$$\{\Omega, F, P, T, Y, B_Y, X, B_X, U, B_U, y, x, u\} \in \text{StocCS}$$

Less formally, we can represent the systems defined above in terms of a recursive system:

$$x(t+1) = f(t, x(t), u(t), v(t)), \quad x(0) = x_0$$

where F^{x_0}, F_{∞}^v are independent for all $t \in T$. We also have that $F_{t-1}^{v(t)}, F_t^u$ also independent. This system is time invariant if f is not explicitly dependent on time. In the Gaussian (linear) case we can write this recursion as

$$\begin{aligned} x(t+1) &= A(t)x(t) + B(t)u(t) + M(t)v(t), \quad x(t_0) = x_0, \\ y(t) &= C(t)x(t) + D(t)u(t) + N(t)v(t), \end{aligned}$$

Where (A, M) is a supportable pair and (A, B) a controllable pair. Additionally, we often have $n_y \leq n_v$ and $\text{Rank}(N) = n_y$, $\text{Rank}([M^T, N^T]) = n_v$.

One can use the characteristic equation to prove that this Gaussian representation conforms to the abstract definition above.

Definition (Controlled Output). *Define the controlled output on a finite horizon of a Gaussian control system representation*

$$\begin{aligned} x(t) &= C_z(t)x(t) + D_z(t)u(t), \quad \forall t \in T \setminus \{t_1\} \\ z(t_1) &= C_z(t_1)x(t_1) \end{aligned}$$

Stochastic Controllability

Informally, this concept is needed to define the set of a reachable states in finite time t_1 . The idea is to go from input process on an interval and initial conditions to a conditional measure on the state at time t_1 . See slide 21/62 of lecture 07 for more details on notation. Intuitively we know that the set of probability measures is generally strictly smaller than the set of all probability measures on the set X . We consider the set P_{co} of control-objective probability measures, where

$$P_{co}(X, B(X)) \subseteq P_c(t_1, X, B(X))$$

Where P_c is the set of reachable measures and P_{co} the set of measures that our control objective states we *want* to reach.

We consider a system $\Sigma \in \text{StocCS}$. This is considered stochastically controllable in the control interval T_c with respect to the control objective probability measure P_{co} if

$$P_{co}(X, B(X)) \subseteq P_c(t_1, X, B(x)), \quad T_c = \{t_0 : t_1\} \subseteq T$$

We also define stochastic co-controllability via a similar argument but this is practically not been applied in literature so far.

It can be shown that the set of reachable measures depends on $F^{x(t_0)}, F_{t_1-1}^u$ and the conditional covariance of x given the mentioned σ -algebras. We can control the mean, *but not the variance, as the variance does not depend on $u(t)$.*

Practically speaking, we can check whether the pair (A, B) is controllable using

$$\text{Rank}(\mathcal{C}(A, B)) = \text{Rank} \begin{bmatrix} B & AB & \dots & A^{n_x-1}B \end{bmatrix} = n_x$$

Note that we need the property that (A, M) is a supportable pair. If this is not the case, then part of the stochastic system is deterministic and we need to check other properties. As before, if the system is *not* stochastically controllable, we can do a Kalman decomposition

$$\begin{aligned} x(t+1) &= \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} x(t) + \begin{bmatrix} B_1 \\ 0 \end{bmatrix} u(t) + \begin{bmatrix} M_1 \\ M_2 \end{bmatrix} v(t) \\ &\text{s.t. } (A_{11}, B_1) \text{ a controllable pair} \end{aligned}$$

Control Laws

For control we distinguish:

- Input process $y : \Omega \times T \rightarrow U$
- Control law $g : X \times T \rightarrow U$

In general

$$u(t) = g(t, x(t))$$

In general a control law is more useful than an input trajectory. A control law is a mapping which specifies the control input for each state.

We specify the information structure as a σ -algebra family $\{G_t, t \in T\}$ such that for all $t \in T$. G_t specifies all the information available for the input $u(t)$. These are very useful for decentralized/distributed control.

Definition (Special Information structures). *Past-state information structure*

$$\{F_t^{x-}, \forall t \in T\}, F_t^{x-} = \sigma(\{x(s), t_0 \leq s \leq t\})$$

Markov information structure

$$\{F^{x(t)}, \forall t \in T\}, F^{x(t)} = \sigma(\{x(t)\})$$

Past-state information structure

$$\{F_{t-1}^{y-}, \forall t \in T\}, F_{t-1}^{y-} = \sigma(\{y(s), t_0 \leq s \leq t-1\})$$

Classical information structure

$$\{H_t, \forall t \in T\}$$

if there is only one controller with one information structure and 2 satisfies perfect recall:

$$\forall t \in T, H_t \subseteq H_{t+1}$$

We will generally work with past-state control laws (depend on past states) and Markov control laws (depend on current state).

Closed-Loop systems

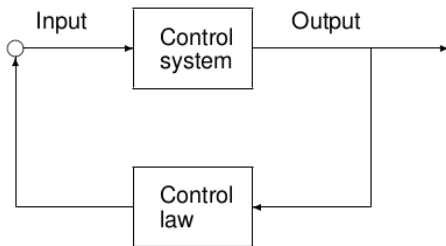


Figure 1: Classical Closed-loop system

Given Gaussian stochastic control system

$$\begin{cases} x(t+1) = A(t)x(t) + B(t)u(t) + M(t)v(t) \\ z(t) = C_z x(t) + D_z(t)u(t) \end{cases}$$

with control law $g_t : X^{t+1} \rightarrow U$, define recursively the closed-loop Gaussian stochastic system

$$\begin{cases} x^g(t+1) = A(t)x^g(t) + B(t)g_t(x^g(0:t)) + M(t)v(t) \\ z(t) = C_z x^g(t) + D_z(t)g_t(x^g(0:t)) \end{cases}$$

Note that the closed loop system x^g is a Markov process

under a Markov control law. Proof is on slide 49/62 lecture 7.

Control Objectives

A control objective is a property that a control system can have, and that an engineer strives to attain. Important ones are:

- **Stability**, finite and bounded variance asymptotically
- **Assignment of Dynamics**, pole placement
- **Optimal Control**, minimize the cost function over all control laws
- **Robustness under uncertainty**, satisfactory dynamics under different operating conditions, unmodelled dynamics and exogenous perturbations.
- **Adaption**, satisfactory performance under slow variations over time (e.g. power systems where load varies over 24h each day).

Note. The general stochastic control problem is then, given a stochastic control system, an information structure, a set of admissible control laws and a set of control objectives, synthesize a control law such that the closed-loop system satisfies the control objectives as well as possible.

More on optimal control later, but generally the goal is to minimize a cost function $J(g)$ over all control laws g such that the expected value of the (quadratic) cost function is minimized. More formally:

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) + Mv(t) \\ y(t) &= Cx(t) + Du(t) + Nv(t) \\ z(t) &= C_z x(t) + D_z u(t) + Nv(t) \\ z(t_1) &= C_z x(t_1); \\ J &: G \rightarrow \mathbb{R}_+, \\ J(g) &= \mathbb{E} \left[z(t_1)^T z(t_1) + \sum_{s=0}^{t_1-1} z(s)^T z(s) \right] \end{aligned}$$

Then we solve

$$J^* = \inf_{g \in G} J(g) = J(g^*)$$

Distinguish:

- **Control Synthesis:** Develop control theory and design procedures. Develop approaches and procedures for finding control laws
- **Control Design:** Develop and compute actual control laws. Domain dependent and use simulation and testing