

Lecture 2

Uncertainty Modeling and Robustness Analysis

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In the last lecture, we have introduced the feedback interconnection depicted in Figure 2.1 and briefly talked about its modeling power. Specifically, we talked about the case where G is LTI with $D = 0$ and Δ is a static nonlinearity. In today's lecture, we will further discuss the modeling power of such feedback interconnections. This type of feedback interconnections becomes a key object for robust control study due to the fact that it can model various "perturbed" versions of linear systems. The perturbation can be model uncertainty, delays, or nonlinearity. We will explain this in today's lecture and then talk about a general robustness analysis tool called dissipation inequality. In today's lecture, we will use ξ_k to denote the state of G since x_k will be used to denote the iteration of optimization methods.

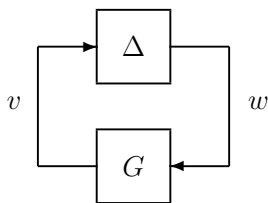


Figure 2.1. The Block-Diagram Representation for Feedback Interconnection $F_u(G, \Delta)$

2.1 Uncertainty Modeling in Control

In the controls field, the feedback interconnection $F_u(G, \Delta)$ is widely used to model uncertain or nonlinear systems. The idea is to separate a dynamical system into two pieces: a "nominal" part G and a perturbation Δ . The nominal part G is typically linear and easy to analyze. The perturbation Δ can be the uncertainty in the system dynamics or some troublesome element causing difficulty in the analysis. The feedback interconnection $F_u(G, \Delta)$ can be viewed as a "perturbed" version of the nominal system G . The study for such perturbed systems forms the foundation of robust control. Now let's look at a few examples of Δ .

- Parametric uncertainty: Consider a linear system $\xi_{k+1} = A\xi_k$. We want to know whether this system is stable or not. In practice, we will not know A exactly. Typically we have $A = \bar{A} + A_\delta$ where \bar{A} is some measured version of A and A_δ captures the uncertainty in the system dynamics. We do not know what A_δ is exactly equal to, but we do know that A_δ is a constant matrix whose input-output gain is bounded above by some small number. Therefore, the system dynamics becomes $\xi_{k+1} = (\bar{A} + A_\delta)\xi_k$, and

can be rewritten as a special case of $F_u(G, \Delta)$ where Δ maps v to w as $w_k = (A_\delta)v_k$, and G is defined as

$$\begin{aligned}\xi_{k+1} &= \bar{A}\xi_k + w_k \\ v_k &= \xi_k\end{aligned}$$

Although we do not know what A_δ is equal to, it is still possible that we can use the bound on A_δ to establish the stability of such a feedback interconnection.

- Time-varying parameters: In the above example, we can further allow A_δ to change over time, i.e. $w_k = (A_\delta^{(k)})v_k$. We can absorb the time-varying element into Δ and treat it as a perturbation.
- Time delay: Consider a control system $\xi_{k+1} = A\xi_k + Bu_k$ where the state feedback controller is affected by a delay, i.e. $u_k = K\xi_{k-\tau_k}$. Ideally, the control input should be determined based on the current state information. However, there may be a time delay in the system and eventually u_k is calculated based on a past state measurement $x_{k-\tau_k}$. Here τ_k is the delay at step k . We can choose G as an LTI system governed by $\xi_{k+1} = A\xi_k + BKw_k$ and $v_k = \xi_k$. Then the control system can be modeled as $F_u(G, \Delta)$ where Δ is a delay operator mapping v to w as $w_k = v_{k-\tau_k}$. Notice G and Δ should be thought as operators that map real sequences to real sequences.
- Dynamical uncertainty: Sometimes even the order of the model may not be correct. For example, one may use a rigid body model for control purposes when there are flexible modes in the true dynamics. In this case, Δ is a frequency domain uncertainty satisfying some norm bound. In this course, we focus less on dynamical uncertainty but it is worth mentioning that dynamical uncertainty plays a critical role for robust control of physical systems.
- Actuator saturation and other nonlinearity: Sometimes a few parts of a control system can not be modeled by linear approximations and the nonlinearity has to be taken into accounts for the stability analysis. It is possible to separate the nonlinearity from the linear dynamics and absorb it into Δ . One such example is the actuator saturation. Other examples include periodically changing nonlinear functions such as \cos and \sin .

To summarize, the perturbation Δ can model uncertain dynamics, time delay, and nonlinearity in the control system. All these perturbation operators have been extensively studied in the controls literature. Many LMIs have been formulated to test the stability of feedback systems involving such perturbations.

2.2 Optimization Methods as Feedback Systems

In recent years it has been recognized that many first-order optimization methods for large-scale problems are just special cases of feedback systems. In this section, we will look at a

few examples including the gradient descent method, the Heavy-ball method, and Nesterov's accelerated method.

We have already talked about the gradient method that iterates as $x_{k+1} = x_k - \alpha \nabla f(x_k)$. The Heavy-ball method iterates as

$$x_{k+1} = x_k - \alpha \nabla f(x_k) + \beta(x_k - x_{k-1}) \quad (2.1)$$

The extra term $\beta(x_k - x_{k-1})$ is the so-called “momentum term.” One needs to choose the stepsize α and the momentum β , and also initialize the method at x_0 and x_{-1} . Then based on this iteration, one can compute x_1, x_2, \dots

Nesterov's accelerated method has a similar iterative form:

$$\begin{aligned} y_k &= x_k + \beta(x_k - x_{k-1}) \\ x_{k+1} &= y_k - \alpha \nabla f(y_k) \end{aligned}$$

We can simply rewrite Nesterov's method as

$$x_{k+1} = x_k - \alpha \nabla f((1 + \beta)x_k - \beta x_{k-1}) + \beta(x_k - x_{k-1}) \quad (2.2)$$

This looks very similar to the Heavy-ball method. The difference is that Nesterov's accelerated method uses a gradient evaluated at $(1 + \beta)x_k - \beta x_{k-1}$ while the Heavy-ball method uses a gradient evaluated at x_k . The Heavy-ball method and Nesterov's method only use the first-order derivative (gradient) and do not require evaluating the second-order derivative (Hessian). Hence they belong to “first-order optimization methods.”

All the above methods can be modeled as feedback interconnection $F_u(G, \Delta)$ where G is an LTI system with $D = 0$ and Δ is just the gradient ∇f . In this case, $F_u(G, \Delta)$ becomes the following feedback model

$$\begin{aligned} \xi_{k+1} &= A\xi_k + Bw_k \\ v_k &= C\xi_k \\ w_k &= \nabla f(v_k) \end{aligned} \quad (2.3)$$

where A, B , and C are matrices with compatible dimensions. In this general model, we can choose (A, B, C) accordingly to recover various first-order methods.

1. For gradient method, we choose $A = I$, $B = -\alpha I$, $C = I$, and $\xi_k = x_k$. Then $v_k = C\xi_k = x_k$, and $w_k = \nabla f(v_k) = \nabla f(x_k)$. The iteration $\xi_{k+1} = A\xi_k + Bw_k$ just becomes $x_{k+1} = Ax_k + Bw_k = x_k - \alpha \nabla f(x_k)$, which is exactly the gradient method.
2. For the Heavy-ball method, we choose $A = \begin{bmatrix} (1 + \beta)I & -\beta I \\ I & 0 \end{bmatrix}$, $B = \begin{bmatrix} -\alpha I \\ 0 \end{bmatrix}$, $C = [I \ 0]$, and $\xi_k = \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix}$. Then $v_k = C\xi_k = [I \ 0] \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix} = x_k$, and $w_k = \nabla f(v_k) = \nabla f(x_k)$. The iteration $\xi_{k+1} = A\xi_k + Bw_k$ becomes

$$\begin{bmatrix} x_{k+1} \\ x_k \end{bmatrix} = \begin{bmatrix} (1 + \beta)I & -\beta I \\ I & 0 \end{bmatrix} \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix} + \begin{bmatrix} -\alpha I \\ 0 \end{bmatrix} \nabla f(x_k) = \begin{bmatrix} (1 + \beta)x_k - \beta x_{k-1} - \alpha \nabla f(x_k) \\ x_k \end{bmatrix}$$

which is exactly the iteration for the Heavy-ball method.

3. For Nesterov's accelerated method, we choose $A = \begin{bmatrix} (1+\beta)I & -\beta I \\ I & 0 \end{bmatrix}$, $B = \begin{bmatrix} -\alpha I \\ 0 \end{bmatrix}$, $C = [(1+\beta)I \quad -\beta I]$, and $\xi_k = \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix}$. Then $v_k = C\xi_k = [(1+\beta)I \quad -\beta I] \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix} = (1+\beta)x_k - \beta x_{k-1}$, and $w_k = \nabla f(v_k) = \nabla f((1+\beta)x_k - \beta x_{k-1})$. The iteration $\xi_{k+1} = A\xi_k + Bw_k$ becomes

$$\begin{aligned} \begin{bmatrix} x_{k+1} \\ x_k \end{bmatrix} &= \begin{bmatrix} (1+\beta)I & -\beta I \\ I & 0 \end{bmatrix} \begin{bmatrix} x_k \\ x_{k-1} \end{bmatrix} + \begin{bmatrix} -\alpha I \\ 0 \end{bmatrix} \nabla f(v_k) \\ &= \begin{bmatrix} (1+\beta)x_k - \beta x_{k-1} - \alpha \nabla f((1+\beta)x_k - \beta x_{k-1}) \\ x_k \end{bmatrix} \end{aligned}$$

which is exactly the iteration (2.2) for Nesterov's accelerated method.

We can see that the only difference between Nesterov's accelerated method and the Heavy-ball method is the choice of C . The different choices of C lead to completely different performance guarantees for these two methods when applied to smooth strongly-convex objective functions.

2.3 Robustness Analysis via Dissipation Inequalities

The impacts of the perturbation Δ on the performance of the closed-loop system $F_u(G, \Delta)$ can be assessed by various robustness analysis tools in the controls literature. One such analysis routine is provided by the dissipation inequality approach.

Let us first look at $\xi_{k+1} = A\xi_k + Bw_k$. Dissipation inequality just describes how the input w_k changes the energy of the state ξ_k .

Definition 1. *The system $\xi_{k+1} = A\xi_k + Bw_k$ is dissipative with respect to the supply rate $S(\xi, w)$ if there exists $V : \mathbb{R}^{n_\xi} \mapsto \mathbb{R}^+$ such that*

$$V(\xi_{k+1}) - V(\xi_k) \leq S(\xi_k, w_k) \quad (2.4)$$

for all k . The function V is called a storage function, which quantifies the energy stored in the state ξ . The supply rate S is a function that quantifies the energy supplied to the state ξ_k by the input w_k . In addition, (2.4) is called the dissipation inequality.

The dissipation inequality (2.4) states that the internal energy increase is equal to the sum of the supplied energy and the energy dissipation. Since there will always be some energy dissipating from the system, hence the internal energy increase (which is exactly $V(\xi_{k+1}) - V(\xi_k)$) is always bounded above by the energy supplied to the system (which is exactly $S(\xi_k, w_k)$).

One important variant of the original dissipation inequality is the so-called exponential dissipation inequality:

$$V(\xi_{k+1}) - \rho^2 V(\xi_k) \leq S(\xi_k, w_k) \quad (2.5)$$

where $0 < \rho^2 < 1$. The dissipation inequality (2.5) just states that at least a $(1 - \rho^2)$ fraction of the internal energy will dissipate at every step, and hence the internal energy at step $k + 1$ is bounded above by the sum of the remaining energy $\rho^2 V(\xi_k)$ and the supply energy S .

2.3.1 How to use dissipation inequality?

Suppose we can construct the dissipation inequality (2.5). What are we going to do about it? The answer is that the dissipation inequality (2.5) can be used to prove stability or convergence rate bounds for $F_u(G, \Delta)$. To make things concrete, let's focus on (2.3) which is a general model for optimization methods.

Notice by definition $V_k \geq 0$ (the internal energy should be non-negative). Typically V is chosen to be a distance metric between ξ_k and the equilibrium point ξ^* . For example, for gradient method, V is chosen as $V = \|x - x^*\|^2$. When applied to analyze optimization methods, the dissipation inequality is typically used to prove two types of bounds.

1. If one already knows $S \leq 0$, then the dissipation inequality (2.5) states $V(\xi_{k+1}) - \rho^2 V(\xi_k) \leq S(\xi_k, w_k) \leq 0$. This gives a bound $V(\xi_{k+1}) \leq \rho^2 V(\xi_k)$. This proves a linear convergence rate ρ when V is used as a distance metric. We will present such an example by analyzing the gradient method.
2. If one already knows $S \leq \rho^2(f(x_k) - f(x^*)) - (f(x_{k+1}) - f(x^*))$, then the dissipation inequality (2.5) states $V(\xi_{k+1}) - \rho^2 V(\xi_k) \leq S(\xi_k, w_k) \leq \rho^2(f(x_k) - f(x^*)) - (f(x_{k+1}) - f(x^*))$. This gives a bound $V(\xi_{k+1}) + f(x_{k+1}) - f(x^*) \leq \rho^2 (V(\xi_k) + f(x_k) - f(x^*))$. This proves a linear convergence rate ρ when $V(\xi_k) + f(x_k) - f(x^*)$ is used as a distance metric. There is going to be one lecture devoting to cover such an argument for the convergence rate analysis of Nesterov's accelerated method.

2.3.2 How to choose supply rate?

The supply rate S typically takes a form of a quadratic function:

$$S(\xi, w) = \begin{bmatrix} \xi - \xi^* \\ w \end{bmatrix}^T X \begin{bmatrix} \xi - \xi^* \\ w \end{bmatrix} \quad (2.6)$$

where X is some given matrix. The key issue is how to choose X .

Recall that the feedback dynamics $F_u(G, \Delta)$ consists of two parts: $v = G(w)$ and $w = \Delta(v)$. If we want to choose X to guarantee the supply rate S satisfying some inequality, e.g. $S \leq 0$, we need to use the property of Δ .

For example, consider the gradient method. Here Δ is just ∇f . If f is L -smooth and m -strongly convex, we know the following inequality holds for any $w_k = \nabla f(C\xi_k)$

$$\begin{bmatrix} C\xi_k - C\xi^* \\ w_k \end{bmatrix} \begin{bmatrix} -2mLI & (m+L)I \\ (m+L)I & -2I \end{bmatrix} \begin{bmatrix} C\xi_k - C\xi^* \\ w_k \end{bmatrix} \geq 0. \quad (2.7)$$

We can simply choose $X = \begin{bmatrix} C^\top & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} 2mLI & -(m+L)I \\ -(m+L)I & 2I \end{bmatrix} \begin{bmatrix} C & 0 \\ 0 & I \end{bmatrix}$ and then the supply rate (2.6) satisfies $S \leq 0$ due to the fact $w_k = \nabla f(C\xi_k)$.

Many control papers focus on developing X for various types of Δ . We will see more supply rate conditions in the rest of this course.

2.3.3 How to construct the dissipation inequality?

Now suppose we have already constructed the supply rate (2.6) with desired properties. How can we construct the dissipation inequality (2.5) for such a supply rate? We can use the following approach.

Theorem 2. Suppose $\xi_{k+1} = A\xi_k + Bw_k$ and $\xi^* = A\xi^*$. Consider a quadratic supply rate (2.6). If there exists a positive semidefinite matrix $P \in \mathbb{R}^{n_\xi \times n_\xi}$ s.t.

$$\begin{bmatrix} A^\top PA - \rho^2 P & A^\top PB \\ B^\top PA & B^\top PB \end{bmatrix} - X \leq 0 \quad (2.8)$$

then we have $V(\xi_{k+1}) - \rho^2 V(\xi_k) \leq S(\xi_k, w_k)$ with $V(\xi) = (\xi - \xi^*)^\top P(\xi - \xi^*)$.

Proof: Based on (2.8), we directly have

$$\begin{bmatrix} \xi_k - \xi^* \\ w_k \end{bmatrix}^\top \left(\begin{bmatrix} A^\top PA - \rho^2 P & A^\top PB \\ B^\top PA & B^\top PB \end{bmatrix} - X \right) \begin{bmatrix} \xi_k - \xi^* \\ w_k \end{bmatrix} \leq 0$$

Notice we have $V(\xi_{k+1}) = \begin{bmatrix} \xi_k - \xi^* \\ w_k \end{bmatrix}^\top \begin{bmatrix} A^\top PA & A^\top PB \\ B^\top PA & B^\top PB \end{bmatrix} \begin{bmatrix} \xi_k - \xi^* \\ w_k \end{bmatrix}$. This immediately leads to the desired conclusion. ■

Example: Analysis of the gradient method. Now we apply the above theorem to analyze the gradient method. For the gradient method, we have $A = I$, $B = -\alpha I$, and $C = I$. As discussed in the last section, we can choose the following X to guarantee $S \leq 0$:

$$X = \begin{bmatrix} C^\top & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} 2mLI & -(m+L)I \\ -(m+L)I & 2I \end{bmatrix} \begin{bmatrix} C & 0 \\ 0 & I \end{bmatrix} = \begin{bmatrix} 2mLI & -(m+L)I \\ -(m+L)I & 2I \end{bmatrix}$$

Now it is straightforward to verify that the condition (2.8) leads to the following condition

$$\begin{bmatrix} 1 - \rho^2 & -\alpha \\ -\alpha & \alpha^2 \end{bmatrix} + \lambda \begin{bmatrix} -2mL & m+L \\ m+L & -2 \end{bmatrix} \leq 0 \quad (2.9)$$

if we choose $P = \frac{1}{\lambda}I$. Now we can apply this condition to obtain the convergence rate ρ for the gradient method with various stepsize choices.

- Case 1: If we choose $\alpha = \frac{1}{L}$, $\rho = 1 - \frac{m}{L}$, and $\lambda = \frac{1}{L^2}$, we have

$$\begin{bmatrix} 1 - \rho^2 & -\alpha \\ -\alpha & \alpha^2 \end{bmatrix} + \lambda \begin{bmatrix} -2mL & m + L \\ m + L & -2 \end{bmatrix} = \begin{bmatrix} -\frac{m^2}{L^2} & \frac{m}{L^2} \\ \frac{m}{L^2} & -\frac{1}{L^2} \end{bmatrix} = \frac{1}{L^2} \begin{bmatrix} -m^2 & m \\ m & -1 \end{bmatrix} \quad (2.10)$$

The right side is clearly negative semidefinite due to the fact that $\begin{bmatrix} a \\ b \end{bmatrix}^\top \begin{bmatrix} -m^2 & m \\ m & -1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = -(ma - b)^2 \leq 0$. Therefore, the gradient method with $\alpha = \frac{1}{L}$ converges as

$$\|x_k - x^*\| \leq \left(1 - \frac{m}{L}\right)^k \|x_0 - x^*\| \quad (2.11)$$

- Case 2: If we choose $\alpha = \frac{2}{m+L}$, $\rho = \frac{L-m}{L+m}$, and $\lambda = \frac{2}{(m+L)^2}$, we have

$$\begin{bmatrix} 1 - \rho^2 & -\alpha \\ -\alpha & \alpha^2 \end{bmatrix} + \lambda \begin{bmatrix} -2mL & m + L \\ m + L & -2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (2.12)$$

The zero matrix is clearly negative semidefinite. Therefore, the gradient method with $\alpha = \frac{2}{m+L}$ converges as

$$\|x_k - x^*\| \leq \left(\frac{L-m}{L+m}\right)^k \|x_0 - x^*\| \quad (2.13)$$

Notice $L \geq m > 0$ and hence $1 - \frac{m}{L} \geq \frac{L-m}{L+m}$. This means the gradient method with $\alpha = \frac{2}{m+L}$ converges slightly faster than the case with $\alpha = \frac{1}{L}$. However, m is typically unknown in practice. The step choice of $\alpha = \frac{1}{L}$ is also more robust (we will discuss this in later sections). The most popular choice for α is still $\frac{1}{L}$.

The key message in the above example is that to apply the dissipation inequality for linear convergence rate analysis, one typically follows two steps:

1. Choose a proper quadratic supply rate function S satisfying certain desired properties, e.q. $S(\xi_k, w_k) \leq 0$.
2. Find a positive semidefinite matrix P satisfying (2.8) and obtain a quadratic storage function V which is then used to construct the dissipation inequality.

2.3.4 Graphical Interpretation

When analyzing $F_u(G, \Delta)$, we aim to draw conclusions on the pair (v, w) in the set $\{(v, w) : v = G(w), w = \Delta(v)\}$. If for any $w = \Delta(v)$, we have $S \leq 0$, then we have

$$\{(v, w) : v = G(w), w = \Delta(v)\} \subset \{(v, w) : v = G(w), S \leq 0\} \quad (2.14)$$

If we can prove ξ_k converges at a certain linear rate for any pair (v, w) in the set $\{(v, w) : v = G(w), S \leq 0\}$, then we guarantee that ξ_k converges at the same linear rate for any pair

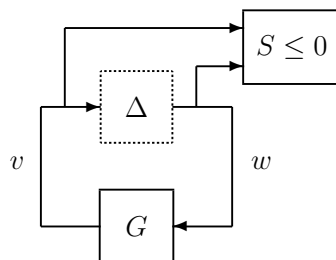


Figure 2.2. Removing Δ by Enforcing the Supply Rate Condition $S \leq 0$

(v, w) satisfying $v = G(w)$ and $w = \Delta(v)$ simultaneously. Hence we can completely remove the troublesome element Δ from our analysis by enforcing the condition $S \leq 0$. A graphical interpretation for this idea is shown in Figure 2.2. We still have $v = G(w)$. But we remove Δ by enforcing the inequality $S \leq 0$.