

Nonlinear Adaptive Control
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Week 7
Lecture No: 37
Backstepping in Adaptive Control: Introduction (Part-1)

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Hello, everyone. Welcome to yet another session of our NPTEL on Nonlinear and Adaptive Control. I am Srikant Sukumar from Systems and Control, IIT Bombay. So welcome to week 7 of this course on Nonlinear Adaptive Control.

And by week 6, we have already started to learn about designing algorithms that can potentially drive systems such as what we see in our background which is essentially a SpaceX satellite orbiting the Earth.

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Instructor: Prof. Sukumar Srihant 28th September, 2020

Outline Introduction to Adaptive Control

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1 Introduction

Adaptive Control involves designing a feedback control for a system with some parameters that are unknown in order to achieve a particular tracking objective.

2 First order scalar system

Consider the first order system -

$$\dot{x}(t) = \theta f(x, t) + u(t); \quad x(t_0) = x_0 \quad (2.1)$$

where,

$$x(t) \in \mathbb{R}, \quad (2.2)$$
$$f: \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}, \quad (2.3)$$
$$u(t) \in \mathbb{R} \quad (2.4)$$

$\theta \in \mathbb{R}$ is some unknown constant parameter.

The control objective is to ensure that $x(t)$ tracks a smooth bounded trajectory, $r(t)$.

2.1 Assumptions

1. The model is linear parametrical, which implies that the unknown parameters app



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$$u(t) \in \mathbb{R} \quad (2.4)$$

$$\theta^* \in \mathbb{R} \text{ is some unknown constant parameter.} \quad (2.5)$$

The control objective is to ensure that $x(t)$ tracks a smooth bounded trajectory, $r(t)$.

2.1 Assumptions

1. The model is linearly parametrised, which implies that the unknown parameters appear linearly in the state space model.
2. The unknown parameters are constant.

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certainty Equivalence Principle - in order to design the controller in the unknown case, we retain the same controller structure as the known case, and replace the true values of the parameters by their estimate.

Note. The estimate $\hat{\theta}(t)$ will be prescribed later and evolves with time. We will come up with an update law for this.

Thus, the modified control law using the CE Principle is

$$u(t) = -kx(t) + \dot{r}(t) - \hat{\theta}(t)f(x, t) \quad (2.13)$$

Now, the error dynamics would be -

$$\dot{e}(t) = -kx(t) + \underbrace{(\theta^* - \hat{\theta}(t))}_{\text{Parameter Error}} f(x, t) \quad (2.14)$$

where,

$$\hat{\theta}(t) = \theta^* - \theta(t) \quad (2.15)$$

is the Parameter Error.

idea: use Lyapunov Candidate to derive $\dot{\theta}$ update law

Now, in order to analyse this system, and in order to prescribe $\hat{\theta}(t)$, we start with the stability analysis. We choose the quadratic Lyapunov Function -




where, γ is the 'Adaptation Gain'. It allows us to choose how fast the adaptation happens.

Note that V is radially unbounded. Now,

$$\dot{V}(t) = e(t) \dot{\theta}(t) \quad (2.17)$$

Now, substituting value of $\dot{e}(t)$ from (2.14), we have -

$$\dot{V} = -kx^2 + \hat{\theta}e f(x, t) - \gamma \hat{\theta} \dot{\theta} \quad (2.18)$$

$$= -kx^2 + \hat{\theta}(e f(x, t) - \gamma \dot{\theta}) \quad (2.19)$$

$\hat{\theta}$ is unknown θ cannot appear in the control or update law!

Now, we cancel out the 'mixed sign' terms using the adaptation law below,

$$\dot{\theta} = \frac{1}{\gamma} e f(x, t) \quad (2.20)$$

so that the entire term vanishes. This is how we get the update law. Thus, we get -

$$\dot{V} = -kx^2 \leq 0 \quad (2.21)$$

(eθ) is major (0,0) es

Note. We want to cancel terms that cannot be made negative definite.

In both the known and the unknown case, we get $\dot{V} = -kx^2$. However, here, \dot{V} is only semi-definite as we added another state $\hat{\theta}$ to the system. Thus, we can only claim **uniform**




So to summarize a little bit of what we did in week 6 was that we started with a first-order scalar system. So a very, very simple sort of system so we started with the first-order scalar system and we designed an adaptive controller for the system.

So the way we worked through it is that we started by designing a controller for the known case and then we use the certainty equivalence principle in order to design the unknown case adaptive controller.

So the adaptive controller essentially consists of a parameter estimator which feeds into the normal control signal. So this is what we did for the first order case. So we had this kind of controller and then we of course had a parameter estimator.

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$V(e, \hat{\theta}) = \frac{1}{2}e^2 + \frac{1}{2}\Gamma\hat{\theta}^2 > 0 \quad \forall e, \hat{\theta}$
 $\dot{V} = -ke^2 \leq 0$
 $V(t)$ finite

2.5 Signal Chasing Analysis
 1. $V_\infty := \lim_{t \rightarrow \infty} V(t)$ exists and is finite since V is lower bounded and non-increasing.
 2. Since V is finite by $V \leq 0, e$ & $\hat{\theta} \in \mathcal{L}_\infty$ $V(t) \in \mathcal{L}_\infty$ $y(t) := V(e(t), \hat{\theta}(t))$
 3. So, $e \in \mathcal{L}_2$ from (2.21) (Integrating both sides) $\int_0^t e^2 dt \leq V(0) - V(t) \leq V(0) - V_\infty$
 4. From the Corollary of Barbalat's Lemma, $e \rightarrow 0$ as $t \rightarrow \infty$.
 Note: Hence, the tracking error goes to zero. Now, we want to know if the parameters converge to the true value or not.
 5. $\hat{\theta}$ is integrable since $e \rightarrow 0$ as $t \rightarrow \infty$. $\int_0^t \hat{\theta} dt = \int_0^t -\frac{1}{k} \dot{e} dt = -\frac{1}{k}(e(t) - e(0))$
 6. Compute $\hat{\theta}$ and verify that $\hat{\theta} \in \mathcal{L}_\infty$. Therefore, $\hat{\theta}$ is uniformly continuous. So, Barbalat's Lemma, $\hat{\theta} \rightarrow 0$ as $t \rightarrow \infty$.
 7. Thus, $\hat{\theta}(t) \rightarrow 0$ as $t \rightarrow \infty$.

3 Second Order Scalar System
 The second order system we are going to study is

$$\dot{x}_1 = x_2 \tag{3.1}$$

$$\dot{x}_2 = \theta^* f(x, t) + u(t) \tag{3.2}$$

where,

$$x_1(t), x_2(t) \in \mathbb{R}, \tag{3.3}$$

$$f: \mathbb{R} \times \mathbb{R}^+ \rightarrow \mathbb{R}, \tag{3.4}$$

$$u(t) \in \mathbb{R} \tag{3.5}$$

$$\theta^* \in \mathbb{R} \text{ is some unknown constant parameter.} \tag{3.6}$$

One problem here is that \dot{V} is only negative semi-definite. We can hence, claim, almost uniform stability. We can however, use Signal Chasing or La Salle's invariance to show that errors e_1 & e_2 both converge to 0.

These kind of Lyapunov Functions, where, the system is asymptotically stable, but the Lyapunov function chosen only yields negative semi-definite \dot{V} 's, are called Non-strict Lyapunov Functions. Such functions necessitate the use of either Signal Chasing or La Salle's Invariance to conclude asymptotic stability.

3.3 Unknown Parameter Controller Design

Using CE,

$$u(t) = -k_2 e_2 - k_1 e_1 + \dot{r}(t) - \hat{\theta} f(x, t) \quad (3)$$

Now,

$$\dot{e}_1 = e_2 \quad (3)$$

$$\dot{e}_2 = -k_2 e_2 - k_1 e_1 + \hat{\theta} f(x, t) \quad (3)$$

This, we augment the Lyapunov function...

Now, further that of course we use signal chasing and so on to prove that everything works out fine. Further that we started to look at the second order system, and of course, when we used like, like a very, very standard or basic choice of Lyapunov candidate function as you would, we realize that we end up with a detectability obstacle. So this is because of the fact that we chose a non-strict Lyapunov function.

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definitely not guarantee that parameters converge to the true values.

4 Overcoming the Detectability Obstacle

How to avoid this? Come up with strict Lyapunov construction OR *Ortega Construction*, proposed by Romeo Ortega in 1990's.

We consider the spring mass damper system -

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= -k_1 x_1(t) - k_2 x_2(t) \end{aligned} \quad (4.1)$$

We choose V -

$$V = \frac{1}{2} (x_2 + \alpha x_1)^2 \geq 0 \quad (4.2)$$

Handwritten notes: $V(x_1, x_2) = 0 \iff x_1 = -\alpha x_2$

Handwritten note: $\dot{V} < 0$ slow as $t \rightarrow \infty$

Note. V is not even a Lyapunov function. Functions like these are called Lyapunov-functions

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$$\alpha = \frac{k_1}{k_2 - \alpha} \Rightarrow \alpha = \frac{k_2 \pm \sqrt{k_2^2 - 4k_1}}{2} \quad (4.3)$$

Then,

$$\dot{V} = -(k_2 - \alpha) \cdot (x_2 + \alpha x_1)^2 \leq 0 \quad (4.4)$$

This gives us -

$$\dot{V} = -2(k_2 - \alpha)V \quad (4.5)$$

Integrating, V converges to 0 exponentially. So,

$$V(t) = V(0)e^{-2(k_2 - \alpha)t}$$

$$\lim_{t \rightarrow \infty} V(t, x) = 0 \Rightarrow \lim_{t \rightarrow \infty} (x_2 + \alpha x_1) = 0$$

Here we were able to claim that $\lim_{t \rightarrow \infty} (x_2 + \alpha x_1) = 0$. To show $x_1(t), x_2(t) \rightarrow 0$ as $t \rightarrow \infty$, we go along with the following analysis

1. V_∞ exists since $V \geq 0$ and $\dot{V} \leq 0$.
2. $x_2 + \alpha x_1 \in \mathcal{L}_\infty$, $x_2 + \alpha x_1 \in \mathcal{L}_2$ and $x_2 + \alpha x_1 \in \mathcal{L}_\infty$.

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Taking time derivative of the Lyapunov function

$$\dot{V} = (e_2 + \alpha e_1)(\dot{e}_2 + \alpha \dot{e}_1) - \frac{\dot{\theta}}{\sigma}$$

$$= (e_2 + \alpha e_1)[-k_1 e_1 - k_2 e_2 + \dot{\theta}(x, t) + \alpha e_2] - \frac{\dot{\theta}}{\sigma}$$

$$= -(k_2 - \alpha)(e_2 + \alpha e_1)^2 + \dot{\theta}(e_2 + \alpha e_1)f(x, t) - \frac{\dot{\theta}}{\sigma}$$

We arrive at the third equality by appropriately choosing $k_1, k_2, \alpha > 0, \alpha = \frac{k_1}{k_2 - \alpha}$. Choose $\dot{\theta} = \sigma(e_2 + \alpha e_1)f(x, t)$ to obtain

$$\dot{V} = -(k_2 - \alpha)(e_2 + \alpha e_1)^2 \leq 0, \quad \text{for } k_2 > \alpha.$$

Hence uniform stability is guaranteed by Lyapunov theorem. Here we won't be able to write $\dot{V} = -\gamma V$ as we can in known parameter case. So we use signal chasing arguments and Barbalat's Lemma to show

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And so, what we try to do after that is essentially use something like an Ortega construction in order to overcome this detectability obstacle for second-order scalar systems. And that is what we did in this section 4.

We first showed how to use this for the like, how this construction works for the general stability proof for a system like 4.1 which is like a spring mass damper system. And then we used it for adaptive control problem in this section and we showed that with this sort of construction which is not even a Lyapunov function, in fact, it is what we like to call a Lyapunov-like function, we could show that both the states that is the e_1 and e_2 converge to the origin as we desire.

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$$p(s) = \hat{e}_1(t) + Kq(t)$$

$$p(s) = sE_1(s) - e_1(t) + Kq(t)$$

$$\lim_{s \rightarrow 0} sE_1(s) = \frac{sE_1(s)}{s} \Big|_{s=0} = 0$$

2. $e_1, e_2 \rightarrow 0$ as $t \rightarrow \infty$.

$$\begin{matrix} e_1 \rightarrow 0 & \text{as } t \rightarrow \infty \\ e_2 \rightarrow 0 & \text{as } t \rightarrow \infty \end{matrix}$$

and we further know that $\hat{\theta} \in \mathcal{L}_\infty$.

So, so, this is where we stopped.

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Nonlinear Adaptive Control (NPTEL)
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Week 7 - Backstepping in Adaptive Control
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Outline *Backstepping Adaptive Control*

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Lecture 7.1

Now, what we, where we start off today is with the notion of backstepping in adaptive control. Now backstepping is a very very well-known and classical, by now classical method in nonlinear control. And in recent years it has also gained a lot of popularity in the adaptive control community also.

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1 Backstepping in Adaptive Control

- Detectability obstacle occurs in adaptive control when non-strict Lyapunov functions are considered.
- Backstepping method is used to generate strict Lyapunov functions (Crucial method for designing controllers in nonlinear system).

Consider a double integrator system given by,

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = \theta^* f(x, t) + u$$

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Lecture 7.1

So backstepping is of course, a well-known to be a method to generate strict Lyapunov functions for nonlinear systems. Great. So let us go back to the table and look at our usual double integrated dynamical system which is I mean, we are calling it a double integral but it is a nonlinear double integrator because of this.

And as always, we have an unknown θ^* and some function f of x, t where x is of course composed of both x_1 and x_2 . x consists of both x_1 and x_2 states. And we as always, our typical objective is that our states, our x_1 states track some trajectory, r and \dot{x}_1 accordingly tracks some trajectory \dot{r} .

This is obviously because of the matching condition, because our dynamics dictate that \dot{x}_1 is x_2 . Therefore, the trajectories also have to be identically designed. So we cannot have any arbitrary trajectory for x_1 and x_2 but they have to be related by the derivative. And this is essentially the matching condition that we have already spoken about in detail in the previous week. Great.

And so the steps are pretty standard. So as you go on, you will start getting used to, sort of doing these steps again and again. So what do we do next? We essentially derive the transformed dynamics that is now we have generated or created an error variable and our aim is to, as always drag these errors to zero, and so now, all these Lyapunov theory of considering the origin to be the equilibrium point, it all should start to make sense to all of you by now. Yeah?

So what is the error dynamics? \dot{e}_1 comes out to be e_2 and \dot{e}_2 is $\theta^* f$ plus u minus \ddot{r} . So I am not even going to try to explain how we got to 1.3 and 1.4 because we have already done this in the previous week. So if you are, you still have any confusion, please go back and refer to the notes from the previous week.

So great. So now we have this dynamics, potentially unknown quantity θ^* and we want to do the standard adaptive control design. Now we already know from last week that if we use some standard Lyapunov candidate like a V equals to x_1^2 plus x_2^2 by; sorry no x_1 and x_2 . But if I use something basic like e_1^2 plus e_2^2 , then I will end up in some trouble,

And this will lead to, leads to detectability obstacle, and this will lead to detectability obstacle. So we already know that. And what was the way around it? We use an Ortega construction. So now, we will try to do the same thing with backstepping.

So think of this as like a beginning step and it is a sort of apples-to-apples comparison between the two methods. Just look at it as that and nothing more for now. But of course, you will see because this backstepping-based adaptive control is something we will do for several sessions now.

So you will start to see that this has much further implications than the Ortega construction. It can be used in many many more contexts than you can use Ortega construction, All right, great. When and of course, you will also understand that the Ortega construction itself is sort of inspired by backstepping-based methods, Great.

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Step 1:

$$\dot{e}_1 = e_2 \quad e_1^o = -k_1 e_1 \quad ; \quad k_1 > 0$$

Assume e_2 is the control and choose, $e_2 = e_{2d} := -k_1 e_1$, $k_1 > 0$. Here e_{2d} is e_2 (desired) which is required to stabilise the system.

Corresponding Lyapunov candidate and it's time derivative:

$$V_1(e_1) := \frac{1}{2} e_1^2 \implies \dot{V}_1 = -k_1 e_1^2$$

only when $e_2 = e_{2d}$.

Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.

So what do we do in backstepping? In case, for those who do not know or those who do not have not done this kind of nonlinear control design course before this, we first look at the first piece of dynamics which is $\dot{e}_1 = e_2$. Forget about the second piece.

Just look at the first piece and we will assume that e_2 is the control. So this variable right here, that is the second state is assumed as the control for the first state.

Remember, this is merely an assumption, an idealization for the purpose of design. You cannot actually think e_2 as the control because it is in fact, a state of the system. So if I was thinking of a robot, e_1 would be the position error and e_2 would be the velocity error.

Again, think of an airplane e_1 would be the position error, e_2 would be the velocity error. It is not actually a control but the state of the system.

But we assume it for now, again, for the sake of the design. So what do we do? If you assume e_2 to be the control, we want to design a stabilizing control. As obvious. Whenever we designed a controller, we want it to be stabilizing.

And what do we, what would be the stabilizing control? Remember, we always try to choose a model and we always try to choose a model. So what is a good model in this case? We know that if I have any \dot{e}_1 is minus $k_1 e_1$ for any k_1 positive, then we know that is an exponentially decaying system.

So this is what we have been doing. We have been choosing a sort of ideal system to follow and this is ideal enough for us, So that is what we do. We choose e_2 and we call it e_{2d} , e_{2d} . Because again, we know that in reality, e_2 cannot be exactly this.

So we call it e_2 desired and we define it as exactly this quantity: minus $k_1 e_1$ with a positive scale, k . And we know that this is under ideal circumstances: if e_2 was exactly e_{2d} or e_{2d} , then it will exponentially stabilize the system. Great.

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$\dot{e}_1 = e_2$ $\dot{e}_1 = -k_1 e_1 ; k_1 > 0$

Assume e_2 is the control and choose, $e_2 = e_{2d} := -k_1 e_1$, $k_1 > 0$. Here e_{2d} is e_2 (desired) which is required to stabilise the system.

Corresponding Lyapunov candidate and it's time derivative:

$$V_1(e_1) := \frac{1}{2} e_1^2 \implies \dot{V}_1 = -k_1 e_1^2$$

only when $e_2 = e_{2d}$.

Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.

$$\xi_2 := e_2 - e_{2d} = e_2 + k_1 e_1$$

$$\implies \dot{\xi}_2 = \theta^* f(x, t) + u - \tilde{r} + k_1 e_2$$

which is required to stabilise the system.

Corresponding Lyapunov candidate and its time derivative:

$$V_1(e_1) := \frac{1}{2} e_1^2 \Rightarrow \dot{V}_1 = -k_1 e_1^2$$

only when $e_2 = e_{2d}$.

Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.

$$\xi_2 := e_2 - e_{2d} = e_2 + k_1 e_1$$

$$\Rightarrow \dot{\xi}_2 = \theta^T f(x, t) + u - \dot{r} + k_1 e_2$$

$$V_2(\xi_2) = \frac{1}{2} \xi_2^2$$

$$\dot{V}_2 = \xi_2 (\theta^T f(x, t) + u - \dot{r} + k_1 e_2)$$

Now, we of course, also introduce a corresponding Lyapunov candidate function because honestly speaking, backstepping is a method of generating Lyapunov candidates by augmenting one piece to another piece. It is actually not a method of control design but a method of generating candidate Lyapunov functions.

And you as you might have already seen, we are by now used to design parameter update laws and control using; well, I mean, not the control yet but the parameter update laws are being designed using a Lyapunov candidate.

We take a derivative and we choose a parameter update law so that we ensure that \dot{V} is negative semi-definite. So this is called Lyapunov redesign and that is what we are used to do.

So it is like we are not doing all that in this course, the notions of control Lyapunov function but essentially what we are doing is choosing a control Lyapunov function and getting a corresponding feedback, u or in this case, $\hat{\theta}$ which is making \dot{V} negative semi-definite, at least.

So you of course, choose a correspondingly Lyapunov function for this ideal system. Not the \dot{e}_1 equal to e_2 but the ideal system which is this system. And what is the good Lyapunov candidate? It is very straightforward. Just take the first obvious quadratic that you can think of. And we have been doing this for a while now.

Of course, if this was something more complicated, you will not be able to choose a quadratic. But in this case, because it isn't, I get to choose a quadratic. And again, in the ideal case, \dot{V}_1 is minus $k_1 e_1$ squared. In fact, I can even, it might even not be completely

wrong to say this is V_1d because it is like V_1 desired. And then this, we say clearly when e_2 is exactly equal to e_{2d} .

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only when $e_2 = e_{2d}$.

Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.

→ dec. this mess with the original control objective??

$$\xi_2 := e_2 - e_{2d} = e_2 + k_1 e_1$$

$$\dot{\xi}_2 = \theta^* f(x, t) + u - \ddot{r} + k_1 e_2$$

$$V_2(\xi_2) = \frac{1}{2} \xi_2^2$$

$$\dot{V}_2 = \xi_2 (\theta^* f(x, t) + u - \ddot{r} + k_1 e_2) \quad (1.5)$$

Let $u = -\hat{\theta} f(x, t) + \ddot{r} - k_1 e_2 - k_2 \xi_2$, where $\hat{\theta}$ is an estimate of θ^* and substituting $\hat{\theta} = \theta^*$, then $\dot{V}_2 = -k_2 \xi_2^2$ and $V = V_1 + V_2$ serves as a strict Lyapunov function.

for the known case $\hat{\theta} = \theta^$*

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Now we go to the second step where we really understand that e_2 is not really the control. So what is the next best thing we can do? So I am actually trying to help you understand also what is backstepping?

So what is the next best thing I can do? I know that e_2 is not identically equal to e_{2d} . But what I can do, maybe, hopefully, is that I can drive e_2 to e_{2d} . I will make e_2 desired as the signal that e_2 has to track.

Remember, my earlier objective was for e_1 and e_2 to go to 0. But now I am sort of shifting the goalposts. It looks like. So what I am going to say is that now I do not want e_2 to go to 0 as t goes to infinity but I actually want e_2 to track e_{2d} .

Now one might ask, “Does this mess with the original control objective?” because we are of course, trying to, go to 0 and now we are trying to go to e_{2d} . So one might ask, “Am I actually messing with the original control objective?” You will answer this. Suspense. Soon.

So what we do is we define this because we want to drive e_2 to e_{2d} , you will design we will, of course, define a new variable ψ_2 , and this ψ_2 is defined as the error between e_2 and e_{2d} .

So this is what we have been always doing whatever we want to drive to 0, we define a new variable. So if we want e_2 to go to e_2 desired, we define a variable as the error between the 2, e_2 minus e_2 desired and that is ψ_2 in this case.

And so, if I plug in for e_2 desired because it was $\minus k_1 e_1$, I simply get ψ_2 is e_2 plus $k_1 e_1$ or I guess I get ψ_2 is e_2 plus $k_1 e_1$. And now, what do I do? Construct the dynamics for this error. Same steps. The steps are similar.

Find, compute an error that you want to drive to 0. Compute the dynamics of the error and then start doing Lyapunov analysis on that. So the steps are standard. So there should be no confusion as to what direction you need to do when you start with a problem.

Always try to construct an error. Then try to design a Lyapunov candidate. Then try to define a control. Then try to find update law. Same steps. Anyway, so as of now we are not even assuming. Until this point we are not assuming θ^* is unknown.

So we will find the dynamics of ψ_2 which is $\dot{\psi}_2$ which is \dot{e}_2 plus $k_1 \dot{e}_1$. So $k_1 \dot{e}_1$ is just $k_1 \dot{e}_2$ and \dot{e}_2 is just the dynamics plugged in from above. Great.

Now, what do we do? We add an additional, we add a new piece to the Lyapunov candidate. So which is again just a quadratic- half ψ_2 square because we want to drag ψ_2 to 0. So this is the obvious choice. And therefore, we get \dot{V}_2 as ψ_2 multiplied by $\dot{\psi}_2$ which is just this quantity.

Now, if I choose my control to be of this form. What is this form? This form is essentially trying to cancel everything. I introduce a good term. Because the other terms are not definite, so we do not know how they will behave. So what we do is we try to get rid of it and we introduce a good term.

Of course, we are calling this $\hat{\theta}$, which is an estimate of θ^* but I would say for the known case, for the known case we use $\hat{\theta}$ equal to θ^* . When we actually know the value of the parameter, $\hat{\theta}$ is just equal to θ^* .

And then what are we left with? \dot{V}_2 is $\minus k_2 \psi_2$ squared. \dot{V}_2 is $\minus k_2 \psi_2$ squared. And what happens? V equal to V_1 plus V_2 serves as a strict Lyapunov function.

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Let $u = -\hat{\theta}f(x, t) + \ddot{r} - k_1 e_2 - k_2 \xi_2$, where $\hat{\theta}$ is an estimate of θ^* .

If $\hat{\theta} = \theta^*$, then $\dot{V}_2 = -k_2 \xi_2^2$ and $V = V_1 + V_2$ serves as a Lyapunov function.

$$V = V_1 + V_2 = e_1^2 + \xi_2^2$$

$$= e_1^2 - k_2 \xi_2^2 = e_1^2 - k_2 \xi_2^2$$

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$$= -k_1 e_1^2 - k_2 \xi_2^2 + e_1^2$$

sum of squares!

$$2\|a\| \leq \|a\|^2 + \|b\|^2$$

$$\leq -k_1 e_1^2 - k_2 \xi_2^2 + \frac{1}{2} e_1^2 + \frac{1}{2} \xi_2^2 \Rightarrow V < 0$$

if $k_1 > \frac{1}{2}$
if $k_2 > \frac{1}{2}$
 $\Rightarrow V < 0$

$\dot{V}_2 = -k_2 \xi_2^2$ and $V = V_1 + V_2$ serves as a strict Lyapunov function.

$$= e_1^2 - k_2 \xi_2^2$$

sum of squares!

$$= -\begin{pmatrix} e_1 & \xi_2 \end{pmatrix} \begin{pmatrix} k_1 & 1/2 \\ 1/2 & k_2 \end{pmatrix} \begin{pmatrix} e_1 \\ \xi_2 \end{pmatrix}$$

if $k_1 > \frac{1}{2}$
if $k_2 > \frac{1}{2}$
 $\Rightarrow V < 0$

$k_1 > 0$
 $k_1 k_2 - 1/4 > 0$
 $3 > 0$

So this is not complete yet because remember what we computed here was \dot{V}_1 desired dot not actually \dot{V}_1 . So the analysis is a little bit remaining. So if I take and I will do that here now. I will complete that here.

If I do take V equal to V_1 plus V_2 and now I compute the actual derivative instead of the desired derivatives, \dot{V}_1 was if you notice half e_1 squared. So this is $e_1 \dot{e}_1$ and V_2 $\xi_2 \dot{\xi}_2$.

So this is $e_1 \dot{e}_1$ is e_2 and $\xi_2 \dot{\xi}_2$ is what? We just did this. $\xi_2 \dot{\xi}_2$ in fact $\xi_2 \dot{\xi}_2$ dot is just wait a sec, $\xi_2 \dot{\xi}_2$ is exactly this guy- minus $k_2 \xi_2^2$. As of now, there is no definiteness here; does not seem very evident.

However, notice that we have transformed e_2 to ψ_2 . So I have to write e_2 in terms of ψ_2 . So what is e_2 in terms of ψ_2 ? I can get that from here. So e_2 is simply ψ_2 minus $k_1 e_1$ and this is minus $k_2 \psi_2$ squared.

So now I start to see nice things. This is minus $k_1 e_1$ squared minus $k_2 \psi_2$ squared plus e_1 times ψ_2 . Now we use a very, very standard trick which says that absolute value of ab is less than equal to a squared plus b squared.

So we use that to write this quantity as less than equal to minus $k_1 e_1$ square minus $k_2 \psi_2$ square plus half e_1 squared plus half ψ_2 squared. And now this can get clubbed with this guy and this can be clubbed with this guy.

So if k_1 is larger than half and k_2 is larger than half, then this is negative definite implies \dot{V} is strictly negative definite. So I got a strict Lyapunov function. Notice. This was a strict Lyapunov function.

So if both k_1 and k_2 which are essentially gains of our choice. This is like a control gain that the designer can choose and as long as these k_1 and k_2 s are greater than half, then I am guaranteed to have \dot{V} to be negative definite.

So this method that you sort of go from here to here using this kind of an inequality is called the sum of squares method. This is called the sum of squares. And we will constantly refer to this terminology.

So whenever I say the sum of squares method, it means that I took the mixed term that look like $2ab$. So notice that these things, although I have written it in terms of absolute values, although I have written it in terms of absolute values, this can actually be written in terms of norms. This is like a norm inequality also. No problem.

This is essentially like, I mean, this is just a standard a squared plus b squared plus $2ab$ equal to $(a + b)^2$ type of inequality. This is just using the fact that $(a - b)^2$ is greater than equal to zero. So that is what this is using, So this is just using the $(a - b)^2$ is greater than or equal to zero or some such thing.

But you can, we use things like the Cauchy Schwarz inequality that we saw some time ago. Triangle inequality, Cauchy Schwarz inequality and things like that. So all these inequalities come into play when we are using the sum of squares method.

The idea behind the sum of squares method is to use any technique, any inequality, standard inequalities which will help you convert the mixed terms into squared terms which can then be combined, right, which can then be combined with this term, the other squared terms. Because that is what we did.

Because I have no idea of saying how big this is in comparison to these guys. So what I do is I write it as a sum of squares and then this can be combined now with this and this can be combined with this and so now I have a way of saying that if k_1 and k_2 are greater than half, then I am good to go.

Now remember that this is pretty conservative. This is fairly conservative. We can also do another thing. The only thing is it does not help us write it analytically very nicely but I can always write this whole thing as a quadratic form which is like this, which I e_1^2 and e_2^2 if I write it like that, then this is k_1, k_2 , half and half.

So what do you want? What you want in reality is that this matrix in between be positive definite. You have to choose the gains k_1 and k_2 such that this matrix is positive definite. And in fact, the conditions for that are pretty straightforward.

I hope all of you know this. This just requires that the principal minors are positive. So k_1 has to be positive and $k_1 k_2$ minus one-fourth has to be positive. So these are the realistic, more realistic and because the least conservative conditions. The only thing is, it just easier to write it out in this way and more tractable. That is it.

So anyway. So the steps are not over here. Once you compute V_2 dot, the point is, when you take V equal to V_1 plus V_2 and you compute V_1 dot. Earlier, we had actually computed only V_1 desired dot because we assumed V_2 is exactly equal to V_2 desired.

But if you do not, then you start to get an additional mixed term, $e_1 e_2$ and then you write this mixed term as in terms of ψ^2 . You get something like this. And then you get 2 nice negative definite terms and a mixed term which you use sum of squares to dominate. So this is really the idea behind backstepping. This is the backstepping method for the known case. It is the backstepping method for the known case.

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Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.

$$\xi_2 := e_2 - e_{2d} = e_2 + k_1 e_1$$

$$\Rightarrow \dot{\xi}_2 = \theta^* f(x, t) + u - \ddot{r} + k_1 \dot{e}_1$$

$$V_2(\xi_2) = \frac{1}{2} \xi_2^2$$

$$\dot{V}_2 = \xi_2 (\theta^* f(x, t) + u - \ddot{r} + k_1 \dot{e}_1)$$

Let $u = -\hat{\theta} f(x, t) + \ddot{r} - k_1 e_2 - k_2 \xi_2$, where $\hat{\theta}$

Handwritten notes: $e_1 \rightarrow 0$, $\xi_2 = e_2 + k_1 e_1 \rightarrow 0$, $e_2 \rightarrow 0$.

Now, so we are sort of, sort of done in this case. See. So what have we proved? We have essentially been able to prove that e_1 goes to 0 and ψ_2 which is equal to $e_2 + k_1 e_1$ goes to 0. So we have proved these 2, Because why?

Because we took V as e_1 squared plus ψ_2 squared by 2 and we prove that \dot{V} is negative semi-definite, So by standard Lyapunov theorems, both of them e_1 and ψ_2 have to go to 0 and of course, everything is asymptotically stable and all that nice jazz, excellent.

Now, we have had asked ourselves the question, “Does this mess with the original objective of driving the errors to 0?” The answer is no. Why? Because we just proved that e_1 goes to 0 and $e_2 + k_1 e_1$ goes to 0 but then because in this piece e_1 has already going to 0, what we have essentially proved is that e_2 also has to go to 0.

In this, if this summation is going to 0 and this piece is already going to 0 from here, then the only way the summation can go to 0 is if this guy also goes to 0, If this guy was not going to 0, then e_2 would have been non-zero as t goes to infinity.

But that is not the case. e_1 is in fact already going to 0 as t goes to infinity and therefore the only way for the summation ψ_2 to go to 0 is if e_2 also goes to 0, So this is like an equivalent thing. So we have essentially been able to recover that e_1 and e_2 both go to 0 as we require. Excellent.

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Step 1:

$$\dot{e}_1 = e_2 \quad e_1^0 = -k_1 e_1 \quad ; \quad k_1 > 0$$

Assume e_2 is the control and choose, $e_2 = e_{2d} := -k_1 e_1$, $k_1 > 0$. Here e_{2d} is e_2 (desired) which is required to stabilise the system.

Corresponding Lyapunov candidate and its time derivative:

$$V_1(e_1) := \frac{1}{2} e_1^2 \Rightarrow \dot{V}_1 = -k_1 e_1^2$$

only when $e_2 = e_{2d}$.

Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.



Step 2: Since e_2 is not really the control we need: $e_2 - e_{2d} \rightarrow 0$.

the original objective !!

$$\xi_2 := e_2 - e_{2d} = e_2 + k_1 e_1$$

$$\Rightarrow \dot{\xi}_2 = \theta^* f(x, t) + u - \bar{r} + k_1 e_2$$

$$V_2(\xi_2) = \frac{1}{2} \xi_2^2$$

$$\dot{V}_2 = \xi_2(\theta^* f(x, t) + u - \bar{r} + k_1 e_2) \quad (1.5)$$

Let $u = -\hat{\theta} f(x, t) + \bar{r} - k_1 e_2 - k_2 \xi_2$, where $\hat{\theta}$ is an estimate of θ^* and substitute it in (1.5).

For the known case: $\hat{\theta} = \theta^*$, then $\dot{V}_2 = -k_2 \xi_2^2$ and $V = V_1 + V_2$ serves as a strict Lyapunov function ($\dot{V} < 0$).

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For the known case

$$V = V_1 + V_2 = \frac{1}{2} e_1^2 + \frac{1}{2} \xi_2^2 = \frac{1}{2} e_1^2 + \frac{1}{2} (e_2 + k_1 e_1)^2 = \frac{1}{2} e_1^2 + \frac{1}{2} (e_2^2 + 2k_1 e_1 e_2 + k_1^2 e_1^2) = \frac{1}{2} (1 + k_1^2) e_1^2 + \frac{1}{2} e_2^2 + k_1 e_1 e_2$$

if $k_1 > k_2$ then $V < 0$



4 Overcoming the Detectability Obstacle

How to avoid this? Come up with strict Lyapunov construction OR *Ortega Construction*, proposed by Romeo Ortega in 1990's.

We consider the spring mass damper system -

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= -k_1 x_1(t) - k_2 x_2(t) \end{aligned} \quad (4.1)$$

We choose V -

$$V = \frac{1}{2} (x_2 + \alpha x_1)^2 \quad (4.2)$$

Note. V is not even a Lyapunov function. Functions like these are called Lyapunov-like functions

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So this is sort of how we do backstepping for a general nonlinear system. Because I say that it is for a general nonlinear system because we did not consider any unknowns. We assume theta is known, theta star is known.

So, the next step would of course be to go for the unknown theta stuff. So now notice, already you should be able to see that the Lyapunov candidate was e_1 squared plus ψ_2 squared where ψ_2 is e_2 plus $k_1 e_1$.

Now, this term is sort of very similar to what you had in the Ortega construction. I mean, again, not the adaptive problem but the non-adaptive problem. It is like x_2 plus αx_1 . So e_2 and in this case, you have e_2 plus $k_1 e_1$ squared.

So this term essentially looks very much like the Ortega construction. But then in backstepping, there is also this additional term. So that it becomes a Lyapunov candidate and a Lyapunov function. So for this particular case, you see that the Ortega construction piece is part of the Lyapunov candidate function for the backstepping. Excellent.

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Okay, so what did we look at today? We sort of started looking at backstepping in adaptive control and we started with a non-adaptive problem. Until now we have done the non-adaptive problem and we have seen how backstepping control is actually design.

Essentially, backstepping is a way of constructing additional Lyapunov functions by augmenting Lyapunov functions corresponding to each state and that is what we did. Started with a e_1 state, created a Lyapunov candidate.

And then we started with the e_2 state. So that is the idea of basically constructing these Lyapunov functions. So we will see further the unknown case in the upcoming session and I hope to see you there. Thank you.