

Nonlinear Adaptive Control
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Week 8
Lecture No: 48

Adaptive Integrator Backstepping Method: An Example (Part 1)

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, in this week number 8, we have been looking at Adaptive Integrated Backstepping in more details in the last few lectures.

And so, we essentially saw the unmatched design and how to generalize it to the vector case. And we also saw how to do an extended matching design which allows us to prevent, over parameterization. We are well into the design and development of algorithms that help drive systems such as the SpaceX satellites orbiting the Earth that we see in the background.

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The image shows a presentation slide with handwritten notes. The slide content includes a citation and a system model. The handwritten notes are as follows:

Lecture 8-6

Example:

Matched case

$$\begin{cases} \dot{x}_1 = p x_1 + x_2 \\ \dot{x}_2 = \theta x_2 + u \end{cases}$$

$u, x_1, x_2 \in \mathbb{R}^3, p \in \mathbb{R}^3, \theta \in \mathbb{R}^{3 \times 3}$

p known, θ unknown

The slide also features a citation: [1] M. Krstic, I. Kanelakopoulos, and P. V. Kokotovic, *Nonlinear and Adaptive Control Design*, 1st ed., ser. Adaptive and Learning Systems for Signal Processing, Communications and Control Series. Wiley-Interscience, 1995.

In the bottom right corner, there is a small video inset showing a man in a red shirt speaking.

3 Exercise

Consider an aerodynamic wing model given by,

$$\begin{aligned}\dot{\phi} &= p \\ \dot{p} &= \delta_A + \varphi(\phi, p)^\top \theta \\ \dot{\delta}_A &= u - \delta_A\end{aligned}$$

where δ_A is the aileron deflection angle, θ are unknown parameters, ϕ is the roll angle, p is the roll velocity.

Apply usual adaptive integrator backstepping (Week 7) and also use extended matching design $u, \hat{\theta}, \hat{\theta}$ to guarantee $\phi, p, \delta_A \rightarrow 0$ as $t \rightarrow \infty$ and all the states are bounded.

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Now, we have already looked at several methods now. And what I wanted to do was today in this session was to look at an example, that is a vector example for both the matched and the unmatched case. And look at both the conventional design and also the extended matching design. So, let us see how we can do this?

So, this is I mean, there was already an example that I asked all of you to a problem that I asked all of you to sort of try to solve, which is not a, which is also has vector parameters. So, of course, I wanted all of you to try this. But what I want to do is to look at a complete vector example with the states and control everything being vectors. So, and so that is what this is. So, this is sorry, just allow me a moment.

So, this is where we start. This is lecture 8.6. So, I think this was 8.5. So, we are at lecture 8.6. And this is the sort of system this is a concocted sort of system. So, I would not worry so much about what is the real relevance, but the aim here is to design a stabilizing adaptive controller with sort of parameters p and θ , we start with the matched case, where we assume that θ is the unknown, and θ in this case is a 3 by 3 vector x_1 and x_2 and the control are vectors in R^3 , p is also in R^3 . So therefore, you have a cross product here.

And θ is actually sorry, I apologize. θ is actually a 3 by 3 matrix. I am sorry, so θ is actually a 3 by 3 matrix. So, let me just give it a thought first, that if this is the example that I want to consider. Let us sort of look at this example. Let us sort of look at this example and see how things go. So, let me try to do the match case, in the matched case, p is assumed to be known, θ is assumed to be unknown. So, let us see how the design goes.

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Motivated case:

$$\begin{cases} \dot{x}_1 = p x_1 + x_2 \\ \dot{x}_2 = \theta x_2 + u \end{cases}$$

$u, x_1, x_2 \in \mathbb{R}^3, p \in \mathbb{R}^3, \theta \in \mathbb{R}^{3 \times 3}$

p known, θ unknown

$z_{2d} \rightarrow V_1 = \frac{1}{2} x_1^T x_1 = \frac{1}{2} \|x_1\|^2$

$$\dot{V}_1 = x_1^T (p x_1 + x_2) = x_1^T x_2 \quad (\text{note: } x_1^T (p x_1) = 0)$$




Adaptive_Control_Week9

$z_{2d} \rightarrow V_1 = \frac{1}{2} x_1^T x_1 = \frac{1}{2} \|x_1\|^2$

$$\dot{V}_1 = x_1^T (p x_1 + x_2) = x_1^T x_2 \quad (\text{note: } x_1^T (p x_1) = 0)$$

$x_{2d} = -k_1 x_1 \quad k_1 > 0$

$$z = (x_2 - z_{2d}) = (x_2 + k_1 x_1)$$

$$V = V_1(x_1) + \frac{1}{2} \|x_2 + k_1 x_1\|^2 + \frac{1}{2\gamma} \|\tilde{\theta}\|^2$$

$\theta x_2 = W \mu \quad W = \begin{pmatrix} \theta_{11} \\ \theta_{12} \\ \theta_{13} \\ \theta_{21} \\ \theta_{22} \\ \theta_{23} \\ \theta_{31} \\ \theta_{32} \\ \theta_{33} \end{pmatrix}$

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$$V_1 = \frac{1}{2} x_1^T x_1$$

$$\dot{V}_1 = x_1^T (p x_1 + x_2)$$
 (note: $x_1^T (p x_1) = 0$)

$$= x_1^T x_2$$

$$x_{2d} = -k_1 x_1 \quad k_1 > 0$$

$$z = (x_2 - x_{2d}) = (x_2 + k_1 x_1)$$

$$V = V_1(x_1) + \frac{1}{2} \|(x_2 + k_1 x_1)\|^2 + \frac{1}{2\gamma} \|\tilde{\mu}\|^2$$

$$\theta_{x_2} = w(x_2) \tilde{\mu} \quad \mu = \begin{bmatrix} \theta_{11} \\ \theta_{12} \\ \theta_{13} \\ \theta_{21} \\ \theta_{22} \\ \theta_{23} \\ \theta_{31} \\ \theta_{32} \\ \theta_{33} \end{bmatrix}$$

$$\tilde{\mu} = \mu - \hat{\mu}$$

So, I will start with the first stage and I want to prescribe x_{2d} , but before I prescribe x_{2d} , I want to prescribe a V_1 as half x_1 transpose x_1 or the norm. This is the standard choice whenever vector states are involved. And we can also try a weighted version of this, but for us, this is okay. And I take V_1 dot and this I used to actually obtain my x_2 desired right because I assumed my x_2 to be the control.

So, V_1 dot comes out to be x_1 transpose x_1 dot, which is p cross x_1 plus x_2 . Now, the interesting thing is that, so I am going to say note, x_1 transpose p cross x_1 is actually 0. Why? Because p cross x_1 is orthogonal to x_1 and dot product of orthogonal quantities is 0. Or you can also think of this as a scalar triple product. So, this also can be thought of as a dot b cross c and I can rearrange it to obtain again x_1 cross x_1 , which will give me 0.

So, this quantity is 0, so this product does nothing. So, I am left with x_1 transpose x_2 . So, a good choice of x_2 desired still my usual nice choice, which is some minus $k_1 x_1$ where k_1 is some like for now, I just take it as a positive scalar. Just a scalar quantity. Great. Now, what do I do? I define my backstepping variable as z as being equal to what my backstepping error, because x_2 is my true state, and I wanted to follow x_2 desired.

So, this just becomes x_2 plus $k_1 x_1$. And now, what do I do? I define my V as V_1 , which is I am going to say this V_1 for now, $V_1 x_1$ plus half the norm of the backstepping error square x_2 plus $k_1 x_1$ norm square I apologies. And then of course, because it is the unknown parameter case, I will always deal with the unknown parameter.

So, I have to add some term corresponding to that. I am going to add some term corresponding to that, and I am going to call it if you may, I am going to call it as $\frac{1}{2} \gamma \mu^T \text{norm squared}$. And I will explain what is μ soon... Why do I need μ ? Let us look at this. So, here, the parameter is actually a matrix, and I do not we do not like to deal with matrix parameters.

So, what do we say? We say that $\theta^T x$ is equal to something like $a^T \mu$, you know that this left-hand side is linear in the elements of the matrices of the matrix θ . Therefore, I rearrange it. So, what is μ ? μ is actually equal to $\theta_{11}, \theta_{12}, \theta_{13}$. So, these are basically just the columns stacked. $\theta_{21}, \theta_{22}, \theta_{23}, \theta_{31}, \theta_{32}, \theta_{33}$. So, that is what is your μ .

So, this is very simple, I have just, in fact, I can be careful and say that this is actually just x^T times my new parameter μ , which is nothing but the θ s, which was a matrix stacked in vector, column wise, and then μ is just μ minus its estimated $\hat{\mu}$. So, this is just because I have a matrix parameters θ and I do not like to deal with matrix parameters.

Yes, I did it the, you know, model reference adaptive control case, but I do not want to do it. So, I am going to deal with the vector parameter μ . So, this is what is now my, you know, candidate Lyapunov function for the entire system. This is what is my candidate, Lyapunov function for the entire system. Great. So now, what do I do? I take derivatives and try to find the controller.

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$$V = V_1(x_1) + \frac{1}{2} \| (x_2 + k_1 x_1) \|^2 + \frac{1}{2\gamma} \|\hat{\mu}\|^2$$

$$\dot{V} = x_1^T (p x_1 + z_2) + z^T (W\mu + u + k_1 (p x_1 + z_2)) - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$= x_1^T (z - k_1 x_1) + z^T (\quad) - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$= -k_1 \|x_1\|^2 + z^T [x_1 + W\mu + u + k_1 (p x_1 + z_2)] - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$u = -x_1 - k_1 (p x_1 + z_2) - k_2 z - W\hat{\mu}, \quad k_2 > 0$$



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$$= -k_1 \|x_1\|^2 + z^T [x_1 + W\mu + u + k_1 (p x_1 + z_2)] - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$u = -x_1 - k_1 (p x_1 + z_2) - k_2 z - W\hat{\mu}, \quad k_2 > 0$$

$$= -k_1 \|x_1\|^2 - k_2 \|z\|^2 + z^T W\hat{\mu} - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$= \hat{\mu}^T W^T z$$

choose, $\dot{\hat{\mu}} = \gamma W^T z$

$$= -k_1 \|x_1\|^2 - k_2 \|z\|^2 \leq 0$$



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$$= x_1^T (z - k_1 x_1) + z^T (\quad) - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$= -k_1 \|x_1\|^2 + z^T [x_1 + W\mu + u + k_1 (p x_1 + z_2)] - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$u = -x_1 - k_1 (p x_1 + z_2) - k_2 z - W\hat{\mu}, \quad k_2 > 0$$

$$= -k_1 \|x_1\|^2 - k_2 \|z\|^2 + z^T W\hat{\mu} - \frac{1}{\gamma} \hat{\mu}^T \dot{\hat{\mu}}$$

$$= \hat{\mu}^T W^T z$$

choose, $\dot{\hat{\mu}} = \gamma W^T z$

$$= -k_1 \|x_1\|^2 - k_2 \|z\|^2 \leq 0$$

$$\Rightarrow x_1 \rightarrow 0$$

$$z = x_2 + k_1 x_1 \rightarrow 0$$

$$\Rightarrow x_2 \rightarrow 0$$



So, let us do that. Let us do that. So, I am going to, let us say let us see if I can copy this whole thing. I believe I can copy and to move to the next page and simply paste it. I do not know what I copied somehow popping the whole thing, maybe I can still paste and delete it. That is fine. This is okay. So, what I will do is I will just erase this.

Great. So, now if I take my v dot here, what do I get? I will get V dot as V_1 dot, which is $\frac{1}{2} x_1^T x_1$. So, I will get $x_1^T x_1$ dot, which is again, p cross x_1 plus x_2 plus this guy, $\frac{1}{2} x_2^T x_2$ plus $k_1 x_1$ or I am going to just write this as z , $z^T z$ dot, which is x_2^T dot, which is W times μ plus u is x_2^T dot plus $k_1 x_1^T$ dot, which is $k_1 p$ cross x_1 plus x_2 plus just $\frac{1}{\gamma} \mu^T$ transpose μ , μ^T dot with the negative sign.

Because μ^T dot is just μ^T , great. So again, I know that this term amounts to nothing. So, I am going to write this as x_1^T times x_2 plus half z^T transpose this whole mess. Well, actually, you know what, I am going to make my life simpler. And I am going to write $x_1^T x_2$ in terms of z So, this is actually $z^T z$ minus $k_1 x_1^T$ plus half z^T transpose, this whole thing gets here and minus $\frac{1}{\gamma} \mu^T$ transpose μ dot.

Now, you can see that I have a minus k_1 norm x_1 squared from here, and sorry, I do not have a half here and forth, that is a mistake and plus z^T times i get a x_1 plus $W \mu$ plus $C u$ plus k_1 times p cross x_1 plus x_2 minus $\frac{1}{\gamma} \mu^T$ transpose μ dot. Again, just copying terms and moving this $z^T x_1$ to this term, I get this. Now, I am in a good position to design my control, this is an unknown, so I will just replace it with estimate.

So, my control will be just minus x_1 minus $k_1 p$ cross x_1 plus x_2 minus a good term which is $k_2 z^T z$ minus $W \mu^T$ and here k_2 is of course some positive quantity. So, what I have done? what have I done? I have cancelled this have cancelled this introduce the nice negative term and try to cancel it with my estimate. So, with this, my V will be minus k_1 norm x_1 squared minus k_2 norm z squared because of this guy.

And I we will be left with plus $z^T W \mu^T$ because I have a $W \mu$ here minus $W \mu^T$ from here I have a $W \mu^T$ and a minus $\frac{1}{\gamma} \mu^T$ transpose μ dot. Now, if you look at these 2 terms together I can take transpose here. So, this is equal to $\mu^T W^T z$ because these are all scalar quantities I can take as many transposes as I wish, no problem.

So, using that I choose $\hat{\mu}$ to be so that I cancel this guy. So, this will be $\gamma W^T z$, so if I do that, I end up with V as $-\|x_1\|^2 - k_2 \|z\|^2$, which is less than or equal to 0. And from here I can prove that x_1 goes to 0, z equal to $x_2 + a_1 x_1$ goes to 0. And this implies that x_2 goes to 0. So, this is what we want, we want, well, I mean, we did the stabilization problem.

But again, the tracking problem is exactly the same. No problem. So, we this is what we want, this is what we get, we get a nice update law here, we get this nice update law here. And similarly, we get a control law here. So, we get an update on the controller just like we want and this is a standard adaptive controller. And you can see that dealing with the vector case did not significantly complicate things or anything, it was quite okay, it was quite okay.

So anyway, so let us, so this is how you do the design for the matched case that is where the unknown is θ . And p is in fact known. And p is in fact known. Great. Now, let us look at an example for an unmatched case. So, I will try to construct an example.

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unmatched case :

$$\dot{x}_1 = f(x_1)p + x_2$$

$$\dot{x}_2 = \omega \times x_2 + u$$

$x_1, x_2, u, \omega \in \mathbb{R}^3$; $f(x_1) \in \mathbb{R}^{3 \times 3}$

$p \in \mathbb{R}^3$ ω is known.

p is unknown

$$V_1 = \frac{1}{2} \|x_1\|^2 + \frac{1}{2\gamma} \|\tilde{p}\|^2$$

$$\tilde{p} = p - \hat{p}$$

assuming $x_2 = x_{2d}$

$$\dot{V}_1 = x_1^T (f(x_1)p - f(x_1)\hat{p} - k_1 x_1) + \frac{1}{\gamma} \tilde{p}^T \dot{\tilde{p}}$$

$$= -k_1 \|x_1\|^2 + x_1^T f(x_1) \tilde{p} - \frac{1}{\gamma} \tilde{p}^T \dot{\tilde{p}}$$

choose $\dot{\tilde{p}} = \gamma f(x_1)^T x_1$

$$\dot{V}_1 = -k_1 \|x_1\|^2 \leq 0$$

So, let us look at the unmatched case and see what happens. So, what I want to do is to have a similar system. So, here I will have not p cross x_1 because that will not be interesting enough. So, I will do something like \dot{x}_1 is definitely something like $f(x_1)$ times a p plus x_2 and \dot{x}_2 is ω cross x_2 plus a control. Where again, x_1, x_2, u, ω in \mathbb{R}^3 f of x_1 belongs to \mathbb{R}^3 by 3. That is a 3 by 3 matrix and p of course belongs to \mathbb{R}^3 , p is unknown.

ω is known. So, this is the system. So, now this becomes an unmatched case. Because I have unknowns here. So, let us try to do this with the standard integrator backstepping type design. So, what would I do? I am directly dealing with the unknown case, of course, so, we will see what we will do and so, I will take my... So, I will first take my first set of dynamics, I will want to do V_1 as $\frac{1}{2}$ norm x_1 squared plus $\frac{1}{2\gamma}$ p tilde squared, where p tilde is p minus p cap and x_2 is assumed to be the control.

So, x_2 desired is of course $-f(x_1)p$ cap minus $k_1 x_1$ for some positive k_1 . So, with this what would I get? I will get \dot{V}_1 as $x_1^T \dot{x}_1$ I mean this is again assume this \dot{V}_1 dot is assuming x_2 is x_{2d} you will get $x_1^T \dot{x}_1$ which is $f(x_1)p$ minus $f(x_1)p$ cap minus $k_1 x_1$ plus $\frac{1}{\gamma} \tilde{p}^T \dot{\tilde{p}}$ I apologize this should have been a norm also because p is in \mathbb{R}^3 and so, this will be $\frac{1}{\gamma} \tilde{p}^T \dot{\tilde{p}}$ and this is just $-\frac{1}{\gamma} \tilde{p}^T \dot{\tilde{p}}$ plus $x_1^T f(x_1) \tilde{p}$ minus $\frac{1}{\gamma} \tilde{p}^T \dot{\tilde{p}}$ dot p cap dot I am simply reproducing this step here by just combining terms carefully.

So, now, if I choose p cap dot as $f^T x_1$ transpose x_1 times γ then I have \dot{V}_1 dot is minus k_1 norm x_1 squared which is negative semi definite and I am good this is essentially what I want it in our standard adaptive integrator backstepping design so, I have a first estimate first Lyapunov candidate, I have a first estimate I have first Lyapunov candidate.

I have a first estimate I have first Lyapunov candidate and we are good. And we also have an x_2 desired of course, we also have our x_2 desired right here we also have an x_2 desired right here, great. So now, what do we want to do? We want to, of course create our backstepping variable. So, we want to create a backstepping variable. And how do we do that? It is pretty straightforward.

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$$z = x_2 - x_{2d} = x_2 + f(x_1)\hat{p} + k_1 x_1$$

$$\dot{z} = \omega x_2 + u + \left(\frac{\partial f}{\partial x_1} + k_1\right) [f(x_1)\hat{p} + x_2] + \frac{f(x_1)\dot{\hat{p}}}{\sigma f(x_1)f(x_1)^T x_1}$$

design new estimate \hat{p} for this term

$$V = V_1(x_1, \hat{p}) + \frac{1}{2} \|z\|^2 + \frac{1}{2\delta} \|(p - \hat{p})\|^2$$

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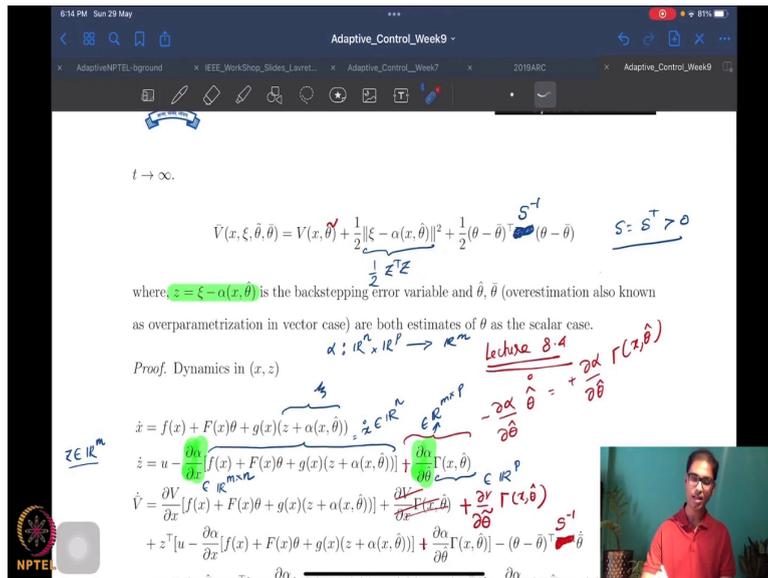
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$$\dot{z} = \omega x_2 + u + \left(\frac{\partial f}{\partial x_1} + k_1\right) [f(x_1)\hat{p} + x_2] + \frac{f(x_1)\dot{\hat{p}}}{\sigma f(x_1)f(x_1)^T x_1}$$

design new estimate \hat{p} for this term

$$V = V_1(x_1, \hat{p}) + \frac{1}{2} \|z\|^2 + \frac{1}{2\delta} \|(p - \hat{p})\|^2, \quad \underline{\underline{\delta \geq 0}}$$

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We design our z which is equal to x_2 minus x_2 desired. I am going to explicitly write this up and what is x_2 desired? x_2 desired is this guy minus $f x_1$ plus $k_1 x_1$. So, this is plus $f x_1$ plus $k_1 x_1$. This is what is my z .

And so, so what happens now, if I actually compute my \dot{z} , which is what I will do that compute my \dot{z} , I get \dot{x}_2 , which is ω cross x_2 plus u plus this which is partial of f with respect to x_1 plus k_1 times \dot{x}_1 and \dot{x}_1 is what \dot{x}_1 is $f x_1$ times p plus x_2 and then I get $f x_1$ plus p dot p dot is already specified, so p dot is this $\gamma f x_1$.

So, this is actually equal to $f x_1$ times $\gamma f x_1$ transpose x_1 , so this is what is this term. And now, what do we do? We sort of try to of course, we want to try to specify the control, we want to try to specify the control. But now we are little bit of a soup why? This is what happens in this adaptive integrated term, there is another unknown appearing here.

And because we have already come up with a \hat{p} dot we cannot replace use \hat{p} again and the control, so what do we do? We use a new estimate \bar{p} . So, we designed the control as minus but anyway we of course, I will just not design the control right now. Design new estimate \bar{p} for this term. Because we already have a \hat{p} .

And we already have an update law for \hat{p} . So, we cannot use this earlier estimate \hat{p} , so, we need to create a new estimate. And that is what we call \bar{p} . Now, once we know this, we define our complete Lyapunov function as V_1 which is a function of your x_1 and \hat{p} and add to it are backstepping error terms which is standard and then a term in the new parameter error and then a term in the new parameter error that is p minus \bar{p} squared.

So, this is what we have been doing, I mean, if you look at this, how we did not the extended design but this guy. So, if you look at this, what was it, it was the original V , then the term in the square term in the backstepping error, then a quadratic in the new parameter error. That is exactly what I did I just instead of having a matrix, instead of having a matrix S inverse, have taken just a delta, just as some delta positive.

And with this, my plan is to design the \bar{p} dot. So, that is what we do, great. So, what I will do is I will continue with this in the subsequent lecture. So, we look at it very carefully. So, what did we do today was we have already seen all the methods for design of parameter update laws for matched and unmatched control via adaptive integrator backstepping. And of course, the extended matching design.

What I wanted to do was to take up an example. So, that is what we did for the match design, we took our vector example and we showed how to design a control and then estimation law or update law for the parameter. And similarly, we are now doing the same for a vector example for the unmatched case and we are first trying to do the design using the adaptive integrator backstepping.

And subsequently we will use the extended matchings. So, this is so that we get some exposure to vector system adaptive control design. So, that is the idea. Excellent, so this is where we will stop and we will continue with this example in the next session. Thank You.