

Intelligent Systems and Control
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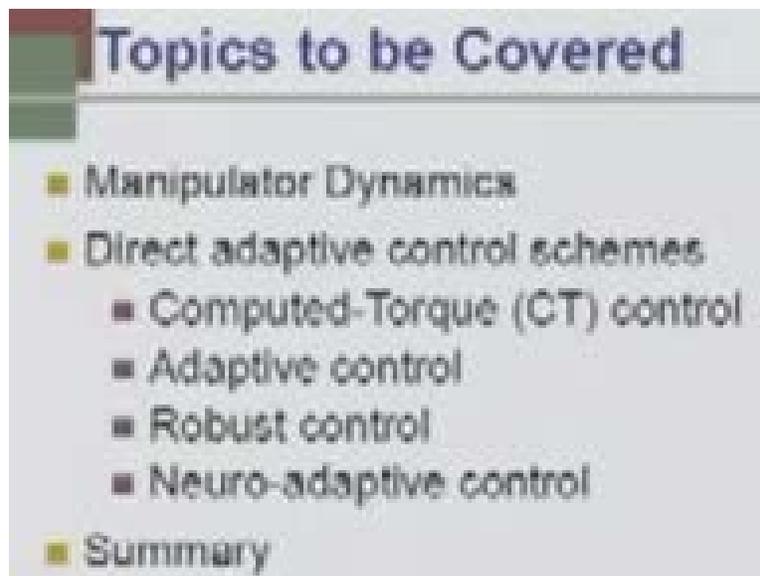
Lecture 9

Direct Adaptive Control of Manipulators: Introduction

Direct adaptive control of manipulators - introduction: This will be the topic we will discuss today. We discussed various control systems while discussing various aspects of neural control. From today the series of lectures that we will be delivering, they will be unidirectional –it means the focus would be application to manipulators.

And we have already discussed what direct adaptive control is. Now this direct adaptive control of manipulators this will be specific that means this physical system is fixed. So how do we design control schemes for manipulators? So we will go step by step today. The notion of direct adaptive control for manipulators that would lead to a neural network based direct adaptive control and then we will continue to back stepping and singular **perturbation** based neural network control.

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Topics that will be covered are: manipulator dynamics, direct adaptive control scheme, computed-torque control, adaptive control, robust control, neuro-adaptive control and summary.

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Manipulator Dynamics

Dynamics:

$$M(q)\ddot{q} + V_m(q, \dot{q})\dot{q} + F(q) + G(q) + \tau_d = \tau$$

Properties:

$$x^T (\dot{M} - 2V_m) x = 0$$

■ The inertia matrix $M(q)$ is symmetric, positive definite, and bounded so that $\mu_1 I \leq M(q) \leq \mu_2 I \quad \forall q(t)$.

■ Coriolis/centrifugal vector $V_m(q, \dot{q})\dot{q}$ is quadratic in \dot{q} . V_m is bounded so that $\|V_m \dot{q}\| \leq v_B \|\dot{q}\|^2$.

■ The Coriolis/centrifugal matrix can always be selected so that the matrix $S(q, \dot{q}) = \dot{M}(q) - 2V_m(q, \dot{q})$ is skew symmetric. Therefore, $x^T S x = 0$ for all vectors x .

Manipulator dynamics: we have already been talking about this dynamics for a long time, so the usual dynamics is $M(q)\ddot{q} + V_m(q, \dot{q})\dot{q} + F(q) + G(q) + \tau_d = \tau$. In this, the inertia matrix $M(q)$ this one is symmetric, positive definite and bounded. This is a property for all rigid link manipulator; this property is satisfied, so that $M(q)$ the inertial matrix can be written as less than $\mu_2 I$ and greater than $\mu_1 I$ for all q, t , q is angular position, \dot{q} is angular velocity and \ddot{q} is angular acceleration.

The second is Coriolis centripetal vector V_m is quadratic in \dot{q} ; v_B is bounded so that we can write $\|V_m \dot{q}\| \leq v_B \|\dot{q}\|^2$, so, here this $V_m \dot{q}$ is the total quantity. The Coriolis centripetal matrix can always be selected so that matrix $S(q, \dot{q}) = \dot{M}(q) - 2V_m(q, \dot{q})$ is skew symmetric. Skew symmetric means if a matrix is skew symmetric -if S is a skew symmetric matrix, then this condition is satisfied: $x^T S x = 0$. In this case, if you compute $\dot{M} - 2V_m$, this quantity and we multiply it by anything, it is 0.

This is called skew symmetric property

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Manipulator Dynamics

Properties:

- The friction term is bounded so that $\|F(q)\| \leq f_B \|\dot{q}\| + k_B$.
- The gravity vector is bounded so that $\|G(q)\| \leq g_B$.
- The disturbances are bounded so that $\|\tau_d(t)\| \leq d_B$.

It is often convenient to write the robot dynamics as

$$M(q)\ddot{q} + N(q, \dot{q}) + \tau_d = \tau$$

where $N(q, \dot{q}) = V_{cc}(q, \dot{q})\dot{q} + F(q) + G(q)$ represents a vector of nonlinear terms. It is assumed that $\tau_d = 0$.

The friction term is bounded; this is the friction term $F \dot{q}$ and it is bounded by this quantity f_B , which is some constant $q \dot{}$ plus k_B . The gravity vector is bounded, so that $G \dot{q}$ norm is less than or equal to g_B ; the disturbances τ_d - this is a disturbance term and this is a actual torque actuated at every joint, so disturbances are bounded so that this norm is less than d_B . It is often convenient to write the robot dynamics as $M(q) \ddot{q} + N(q, \dot{q}) + \tau_d = \tau$. For practical purpose, we will just not consider disturbance torque for the moment during the analysis. Of course in simulation, we will use τ_d , but in analysis we will just remove τ_d . So, in practical purpose $M(q) \ddot{q} + N = \tau$, where N is Coriolis force due to friction and the force due to gravity. So this represents a vector of non-linear terms; it is assumed that τ_d is 0.

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Manipulator Dynamics: State space models

Reconsider the robot dynamics

$$M(q)\ddot{q} + N(q, \dot{q}) = \tau$$

Position/velocity state-space form: Defining state vector as $x = [q^T \quad \dot{q}^T]^T$, we can rewrite robot dynamics as follows:

$$\begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix} = \begin{bmatrix} \dot{q} \\ -M^{-1}(q)N(q, \dot{q}) \end{bmatrix} + \begin{bmatrix} 0 \\ M^{-1}(q)\tau \end{bmatrix}$$

State space model $\dot{x} = Ax + B\tau$

Reconsider now the robot dynamics, which we said $M(q)\ddot{q} + N(q, \dot{q}) = \tau$ where N consists of Coriolis forces, gravitational forces and forces due to friction.

Now, let us define the state space x as the vector consisting of position angular position vector and angular velocity. We can rewrite robot dynamics as in the state space form; this is one state space form and state space model you can easily see \dot{x} is $\begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix}$; that is we can write here $\begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix}$, a vector. So \dot{x} is $\begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix}$, so the \dot{q} part I can put a line here. On the top line \dot{q} \ddot{q} 0 ; that is always true. The second part is, \ddot{q} you see the \ddot{q} is this one obviously minus $N(q)$ into M inverse. So M inverse minus $N(q)$ which is this one and plus M inverse into τ , thus very straight forward.

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Manipulator Dynamics: State space models

Brunovsky Canonical form: The above robot dynamics may be rewritten as

$$\ddot{q} = \underbrace{-M^{-1}N + M^{-1}\tau}_{u} \quad \checkmark$$

By defining a state vector $x = [q^T \quad \dot{q}^T]^T$, we get following state space model:

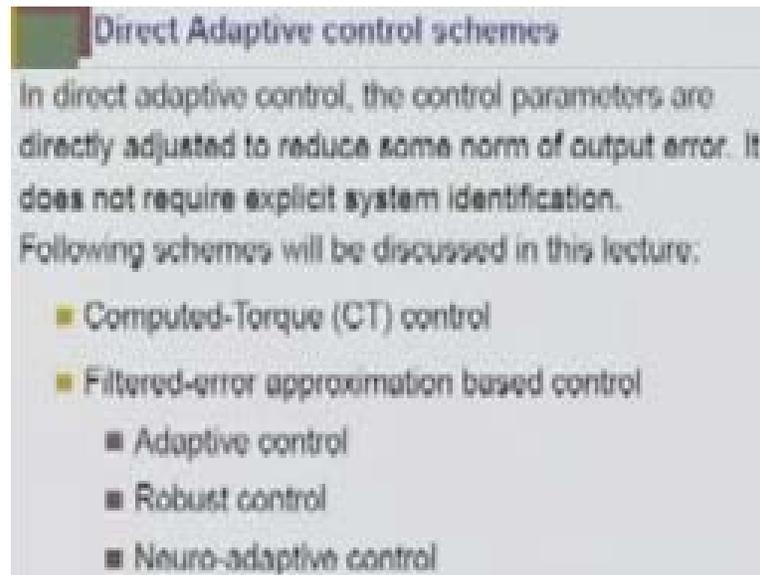
$$\begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix} = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} \begin{bmatrix} q \\ \dot{q} \end{bmatrix} + \begin{bmatrix} 0 \\ I \end{bmatrix} u$$

where $u = -M^{-1}(q)[N(q, \dot{q}) - \tau]$ Model II

There is another state space model, this is model 2. In this model the Brunovsky Canonical form the same robot dynamics can be written as q double dot minus M inverse N plus M inverse τ equal to u . This quantity, if I say u simply, then this is my input now. How do I write q double dot? x is q dot q double dot equal to u .

So, q double dot equal to u , you see that if I put this line here, q double dot is simply u , which is q double dot is u and q dot is simply. This x is again q and q dot. Obviously, q dot is, you can easily see, 0 q is 0 and I q dot is q dot. So, q dot is this and 0 and the top 1 is 0 u is 0 , so q dot is q dot and q double dot is u . Simply by partitioning I can explain that this is and where u is this quantity, this is the virtual control u , this is the second model.

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Direct Adaptive control schemes

In direct adaptive control, the control parameters are directly adjusted to reduce some norm of output error. It does not require explicit system identification.

Following schemes will be discussed in this lecture:

- Computed-Torque (CT) control
- Filtered-error approximation based control
 - Adaptive control
 - Robust control
 - Neuro-adaptive control

Direct adaptive control schemes: In direct adaptive control, the control parameters are directly adjusted to reduce some norm of output error. It does not require explicit system identification, so we do not do explicit system identification direct adaptive control that what is the system model parameter exactly in the same subsystem identification -we do not do. We will first talk about computed torque control, which is non-adaptive control, an exact control. We assume that the all the parameters of the robot manipulators are known, what is the meaning of computed torque control? We will go from that, we are assuming – relaxing the condition that some of the parameters are unknown, and then we go to adaptive control. I will not really focus on a robust control, because that is not our topic today. But I will just give you a little idea about robust control and then I will from adaptive control I will go to neuro-adaptive control and the difference between these two, we will try to understand today in this class.

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Computed-Torque Control

It uses feedback-linearization technique. Define the tracking error as

$$e(t) = q_d(t) - q(t)$$

Differentiating twice we get

$$\ddot{e} = \ddot{q}_d - \ddot{q} = \ddot{q}_d - M^{-1}\tau + M^{-1}N = \ddot{q}_d + M^{-1}(N - \tau)$$

By choosing a state vector $x = [e^T \quad \dot{e}^T]^T$, we obtain the Brunovsky canonical form as

$$\frac{d}{dt} \begin{bmatrix} e \\ \dot{e} \end{bmatrix} = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ I \end{bmatrix} u$$

with $u(t) = \ddot{q}_d + M^{-1}(q)[N(q, \dot{q}) - \tau]$

closed loop error dynamics

Computed torque control: It uses feedback linearization technique, define the tracking error $e(t)$, it is a desired trajectory minus the actual trajectory. Differentiating this quantity twice, we get $\ddot{e} = \ddot{q}_d - \ddot{q}$ is $\ddot{q}_d - M^{-1}\tau$. So, \ddot{q}_d and \ddot{q} is, you know that \ddot{q} , writing properly here, we can write - we know that - the robot dynamics $M\ddot{q} + N = \tau$. This is our simplified form; so I can write $\ddot{q} = -M^{-1}N + M^{-1}\tau$. This is our simplified form; so I can write $\ddot{q} = -M^{-1}N + M^{-1}\tau$.

If I take this quantity and put it here instead of this, \ddot{q} is placed here, you get $\ddot{q}_d - M^{-1}N + \tau$. By choosing the state vector $x = [e \quad \dot{e}]^T$, we obtain the canonical form like this: $\dot{x} = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ I \end{bmatrix} u$. This is state closed error dynamics. This is normally we say, closed loop error dynamics where the control action u is $\ddot{q}_d + M^{-1}(N - \tau)$. This is virtual control action, but from here we can easily see the τ can be computed from this. You can see that, u is defined as this one, where the τ is computed.

What we have to see is that, now the objective would be what should be the u for which the system is stable. You take that u and put it here and then find out what is τ . This is the reverse process.

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Computed-Torque control

Now choose u to stabilize the error dynamics and then compute the required arm torques as

$$\tau = M(q)(\ddot{q}_d - u) + N(q, \dot{q})$$

Two forms of Computed-torque control are given below:

PD CT control $u = -k_{\dot{q}} \dot{e} - k_p e$

$$\tau = M(q)(\ddot{q}_d + k_{\dot{q}} \dot{e} + k_p e) + V_m(q, \dot{q})\dot{q} + F(q) + G(q)$$

PID CT control $e = \int e dt$

$$\tau = M(q)(\ddot{q}_d + k_{\dot{q}} \dot{e} + k_p e + k_i e) + V_m(q, \dot{q})\dot{q} + F(q) + G(q)$$

Now, choose u to stabilize the error dynamics, and then compute the required arm torque as τ is $M(q)\ddot{q}_d - u + N(q, \dot{q})$. If I write now here (Refer Slide Time 14:54), I want to compute τ , then I take $\ddot{q}_d - u$ this side and if I take the other side, $M(q)\ddot{q}_d - \tau + N(q, \dot{q})$, from there you find out τ is $M(q)\ddot{q}_d - u + N(q, \dot{q})$.

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Computed-Torque control

Now choose u to stabilize the error dynamics and then compute the required arm torques as

$$\tau = M(q)(\ddot{q}_d - u) + N(q, \dot{q})$$

Two forms of Computed-torque control are given below:

PD CT control $u = -k_{\dot{q}} \dot{e} - k_p e$

$$\tau = M(q)(\ddot{q}_d + k_{\dot{q}} \dot{e} + k_p e) + V_m(q, \dot{q})\dot{q} + F(q) + G(q)$$

PID CT control

$$e = \int e dt$$

$$\tau = M(q)(\ddot{q}_d + k_{\dot{q}} \dot{e} + k_p e + k_i e) + V_m(q, \dot{q})\dot{q} + F(q) + G(q)$$

Now what is this u ? If I want to stabilize this particular system using a PD controller, then my u is simply, u is minus $K_v \dot{e}$ minus $K_p e$, this is called PD controller, where my e is q_d minus q . This will stabilize the system. By plugging these values here, I get τ is $M q \ddot{q}_d$ plus $K_v \dot{e}$ plus $K_p e$ plus $N q \dot{q}$ is $V_m q \dot{q}$ plus $F q$ plus $G q$. But this control action I can actuate -provided all the parameters that is M , V_m , F , G all are known. The parameters that I had only designed are K_v and K_p . Similarly PID computed torque control would be, I just create another one for PID ϵ dot is e .

That is e d t integral, then your torque is this is my minus u . So $M q$ is this is minus u . So u is minus $K_v \dot{e}$ minus $K_p e$ plus minus $K_i \epsilon$. This is the integral term because ϵ is e d t. This implies ϵ is, so this is the integral action. This is the proportional action and this is the derivative action. This is the PID controller. The PID computed torque control is given by this function.

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CT control: Single link manipulator

Consider single-link manipulator dynamics given by

$$a\ddot{q} = b \sin q = \tau$$

where $a = ml^2$ and $b = mgl$. Differentiating tracking error $e = q_d - q$ twice, we get

$$\begin{aligned} \ddot{e} &= \ddot{q}_d - \ddot{q} \\ &= \ddot{q}_d + b \sin q - \tau = f(q) - \tau \end{aligned}$$

The computed torque control $\tau = f(q) + K_d \dot{e} + K_p e$ yields following closed loop error dynamics

$$\ddot{e} + K_d \dot{e} + K_p e = 0$$

which is stable and achieves trajectory tracking.

Now let us take a simple example: $a \ddot{q} + b \sin q = \tau$, which is a single link manipulator, a is ML squared, b is MGL . Now if I differentiate the tracking error e you get $a \ddot{e} = a \ddot{q}_d$ minus $a \ddot{q}$, which is $a \ddot{q}_d$ minus $b \sin q$ plus τ , which is $f(q)$ minus τ . So the computed torque control τ is obviously $f(q)$ plus, this is u term $K_d \dot{e}$ plus $K_p e$, yields the

following closed loop error dynamics. $\ddot{e} + K_d \dot{e} + K_p e = 0$, which is stable and achieve trajectory tracking. This is my closed loop error dynamics. Just like here we said that you select u put it here this u then this becomes closed loop error dynamics. So that is putting this u as a PD controller.

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CT control : 2-link Manipulator

Consider a planar 2-link manipulator in standard form

$$M(q)\ddot{q} + V(q, \dot{q}) + G(q) = \tau$$

Define

$$\alpha = (m_1 + m_2)a_1^2, \beta = m_2 a_2^2, \eta = m_2 a_1 a_2$$

and $e_1 = q_1/a_1$.

The dynamics may be re-written as

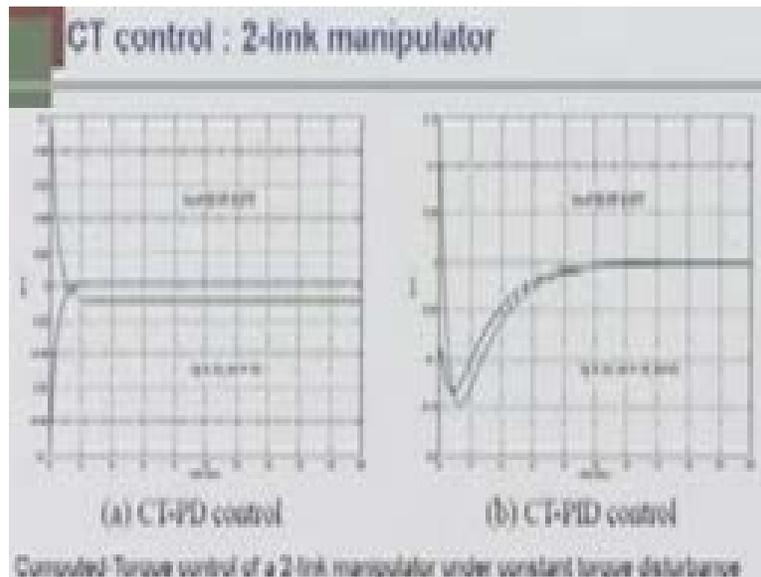
$$\begin{bmatrix} \alpha + \beta + 2\eta \cos q_2 & \beta + \eta \cos q_2 \\ \beta + \eta \cos q_2 & \beta \end{bmatrix} \begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix} + \begin{bmatrix} -\eta(\dot{q}_1 \dot{q}_2 + \dot{q}_2^2) \sin q_2 \\ \eta \dot{q}_1^2 \sin q_2 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}$$

$$\begin{bmatrix} \alpha_1 \cos q_1 + \eta_1 \cos(q_1 + q_2) \\ \eta_1 \cos(q_1 + q_2) \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}$$

For single link manipulator, the dynamics is a stable dynamics. The computed torque control, if I take a 2-link manipulator link 1 and link 2, actually this can be written as in the usual form - $M \ddot{q} + V \dot{q} + G = \tau$. In this, the \dot{q} term, this is actually $V_m \dot{q}$ is multiplied with V together is the total Coriolis force, the gravity force equal to torque, where if I define alpha, this quantity where a_1 is the link length 1 and a_2 link length 2, q_1 is the angle of link length 1 with the horizontal axis and q_2 is the link angle of link 2 aligned with link 1.

Then, if I define alpha beta eta as well as e_1 in this particular manner, the dynamics can be written in this form, so this is your M matrix (Refer Slide Time: 20:42), this is your V matrix, Coriolis force and this is your gravity force. This quantity is τ_1, τ_2 ; the τ_1 is actuated here and τ_2 is actuated here.

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You see that if you do the simulation if you give some small disturbance, then you see that the PD controller has some steady state error. It does not exactly go to 0 whereas the PID controller even if any disturbance it goes to 0. That is, the steady state error is eliminated in case of PID controller; in case of PD controller it is not eliminated, which is expected.

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The slide is titled "Approximation based controllers". It has a handwritten note "(approx)" in the top left. The main text consists of two bullet points: "Control torque control works very well when all dynamical parameters $M(q)$, $V_m(q, \dot{q})$, $F(q)$, $G(q)$ are accurately known. In case of robot manipulators, these parameters are not properly known or vary with time" and "The control objective is to achieve trajectory tracking under parameter uncertainty." Below this is the text "Two approaches:" followed by two bullet points: "Adaptive Control" and "Robust Control".

Now, computed torque control works very well when all dynamical parameters M , q , V , q , F , m , F , G are accurately known. In case of robot manipulators, these parameters are not properly known or vary with time. The control objective is to achieve trajectory tracking under parametric uncertainties. Two approaches that are normally followed are adaptive control and robust control.

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Filtered-error approximation based control

The filtered tracking error is defined as

$$\dot{r} = \dot{e} + \Lambda e$$

where $e = q_d - q$ is the tracking error and Λ is a positive definite design parameter matrix.

Taking Laplace transform, for a scalar case we get

$$E(s) = \frac{R(s)}{s + \lambda}$$

The tracking error can be obtained by passing the quantity r through a low-pass filter and hence the name.

This kind of error-representation leads to a simplified controller design owing to the reduction of system order.

What is adaptive control? I will first introduce what is filtered error approximation based control. The filtered tracking error defined as r , this is the filtered tracking error, which is \dot{e} plus the derivative of the error plus λe . So, λ is a matrix, r is a vector and e is error.

So, e is q_d minus q , you know that q is a vector. If I have a 2-link manipulator, q dimension is 2; if I have a n link manipulator, dimension of q is n . The error is a vector; r is also vector; this is a matrix, obviously. If e is 2 dimensional, the matrix is 2 by 2, e is n dimensional, matrix is n by n . So, taking Laplace transform for a scalar case, if it is a scalar thing, then we can write out $E(s)$ is $R(s)$ upon s plus λ . The tracking error can be obtained by passing the quantity r through a low pass filter, you can easily see this is a low pass filter, hence the name, this is filtered error tracking. This kind of error

representation leads to a simplified controller design owing to the reduction of the system order.

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Filtered-error approximation based control

- Boundedness of r ensures boundedness of e and \dot{e} .

$$|e| \leq \frac{|r|}{\sigma_m + m(\Lambda)}, \quad |\dot{e}| \leq |r|$$

- The desired trajectory is bounded so that

$$\begin{bmatrix} q_d(t) \\ \dot{q}_d(t) \\ \ddot{q}_d(t) \end{bmatrix} \leq q_B$$

Boundedness of r ensures boundedness of e and \dot{e} . This is just a certain idea, that if I know that r is bounded which is r is \dot{e} , as we saw λe , this is bounded. Then, it ensures that e is bounded as well as \dot{e} is bounded. So, boundedness is defined by this: e bounded is less than r bounded by σ_m , this quantity and the boundedness of \dot{e} is less than boundedness of r . The desired trajectory is bounded so that q_d , \dot{q}_d , \ddot{q}_d , this is less than q_B so always we define a boundedness of the desired trajectory.

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Filtered-error approximation based control

The robot dynamics can be expressed in terms of filtered error as:

$$M\dot{r} = -V_m r + f(x) - \tau$$

where the nonlinear robot function is defined as

$$f(x) = M(q)(\ddot{q}_d + \Lambda\dot{e}) + V_m(q, \dot{q})(\dot{q}_d + \Lambda e) + F(\dot{q}) + G(q)$$

and $x = [e^T \quad \dot{e}^T \quad \ddot{q}_d^T \quad \dot{q}_d^T \quad \ddot{q}_d^T]^T$. $f(x)$ contains all the potentially unknown robot arm parameters.

Handwritten notes:
 $r = \dot{e} + \Lambda e$
 $M\dot{r} + N = \tau$

The robot dynamics can be expressed in terms of filtered error. Once I define r as \dot{e} plus λe given that the robot dynamics $M \ddot{q} + N = \tau$. This can be written as $M \dot{r} = -V_m r + f(x) - \tau$, where the non-linear robot function is defined as $f(x)$ is $M(q)(\ddot{q}_d + \lambda \dot{e}) + V_m(q, \dot{q})(\dot{q}_d + \lambda e) + F(\dot{q}) + G(q)$. We can derive this equation. If I define r and given the robot dynamics, this is the filtered error dynamics where this x here $f(x)$ x is $[e^T \quad \dot{e}^T \quad \ddot{q}_d^T \quad \dot{q}_d^T \quad \ddot{q}_d^T]^T$. So, this state vector x in all known quantities because I know from the motion of the robot, I know the position and velocity.

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Filtered-error approximation based control

The robot dynamics can be expressed in terms of filtered error as

$$M\dot{r} = -V_{wr} + f(x) - \tau$$

$$\tau = \ddot{e} + \Lambda \dot{e}$$

$$M\ddot{q} + N = \tau$$

where the nonlinear robot function is defined as

$$f(x) = M(q)(\ddot{q}_d + \Lambda \dot{e}) + V_m(q, \dot{q})(\dot{q}_d + \Lambda e) + F(\dot{q}) + G(q)$$

and $x = [e^T \quad \dot{e}^T \quad \underbrace{q_d^T \quad \dot{q}_d^T \quad \ddot{q}_d^T}_{\text{potentially unknown robot arm parameters}}]^T$. $f(x)$ contains all the potentially unknown robot arm parameters.

I know what e and \dot{e} are and the desired trajectories are already given, x is known this quantity is actually known. $f(x)$ - it is not an unknown quantity, provided all these quantities $M(q)$, $V_m F$ and G are known. So, $f(x)$ contains all the potentially unknown robot parameters, arm parameters - that is how we have separated - that in this $f(x)$, we have all these unknown parameters M , V_m , F and G .

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Filtered-error approximation based control

Approximation-based controller

$$\tau = \hat{f} + K_v r - \dot{v}(t)$$

where \hat{f} is an estimate of $f(x)$, $K_v r$ is an outer PD tracking loop and $\dot{v}(t)$ is a robustifying term.

$$M\ddot{q} + N = \tau$$

The closed loop error dynamics

$$M\dot{r} = -V_{wr} - K_v r + \hat{f} + \dot{v}(t)$$

where the function approximation error is $\tilde{f} = f - \hat{f}$.

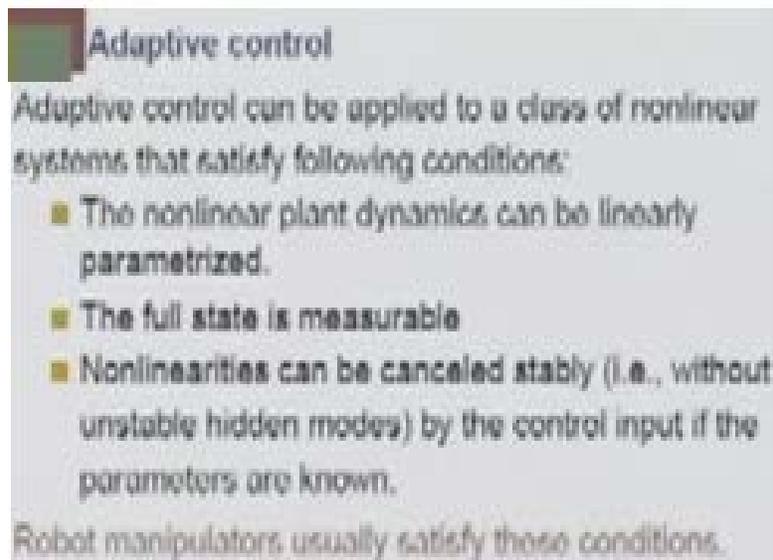
Controller Design problem

To select the estimate \hat{f} and $\dot{v}(t)$ in the above approximation based control law so that the closed-loop error dynamics is stable.

Approximation based controller: The previous one was $M \ddot{r} = -V_m \dot{r} + \dot{f}(x) - \tau$. So in that, τ is $\hat{f} + K_v \dot{r} - \dot{v}(t)$, where \hat{f} is an estimate of $f(x)$, K_v is an outer P D tracking loop and $v(t)$ is robust term, If I assume this as my control action and replace this action in my term which is $M \ddot{q} = \tau$.

If I put this here, that is in this $\tau = \hat{f} + K_v \dot{r} - \dot{v}(t)$, then we eventually reach this closed loop error dynamics, which is $M \ddot{r} = -V_m \dot{r} - K_v r + \tilde{f} + \dot{v}(t)$, where the function approximation error \tilde{f} is $f - \hat{f}$. Controller design problem is to select the estimate \hat{f} and this $v(t)$ in the above approximation based control law, so that the closed loop error dynamics is stable.

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Adaptive control can be applied to a class of non-linear systems that satisfy the following conditions: The non-linear- plant dynamics can be linearly parameterized, the full state is measurable; non-linearity can be cancelled stably. That is, without unstable hidden modes by the control input if the parameters are known, robot manipulator usually satisfies these conditions.

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Adaptive control of Robot manipulators

Rewriting the robot dynamics in terms of filtered error

$$M\dot{r} - V_{mr} = f(x) - \tau$$

where the nonlinear function $f(x)$ may be expressed as a linear function of unknown parameters as shown below:

$$f(x) = M(q)(\dot{q}_d + \Lambda r) + V_m(q, \dot{q})(\dot{q}_d + \Lambda r) + F(q) + G(q) = W(x)\phi$$

where $W(x)$ is a known regression matrix and ϕ is a vector of unknown parameters. One adaptive controller is given by Slotine (1988):

$$\begin{aligned} \tau &= W(x)\hat{\phi} + K_v r - \dot{f}(x) + K_p r \\ \dot{\hat{\phi}} &= \Gamma W^T(x)r \end{aligned}$$

where $\Gamma > 0$ is a tuning parameter matrix.

Adaptive control of robot manipulators rewriting the robot dynamics in terms of filtered error which is $M \dot{r}$ is minus V_{mr} plus $f(x)$ minus τ . This is the actual robot dynamics in terms of filtered error, where the non-linear function $f(x)$ may be expressed as a linear function of unknown parameters, as shown below. We have already shown this $f(x)$ and this can be written, if I can approximate this in terms of a regression matrix and an unknown parameter vector file.

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Adaptive control of Robot manipulators

Rewriting the robot dynamics in terms of filtered error

$$M\dot{r} - V_{mr} + \tau = f(x)$$

where the nonlinear function $f(x)$ may be expressed as a linear function of unknown parameters as shown below:

$$f(x) = M(q)(\dot{q}_d + \Lambda r) + V_m(q, \dot{q})(\dot{q}_d + \Lambda r) + F(q) + G(q) = W(x)\phi$$

where $W(x)$ is a known regression matrix and ϕ is a vector of unknown parameters. One adaptive controller is given by Slotine (1988):

Control law $\tau = W(x)\hat{\phi} + K_v r - \dot{f}(x) + K_p r$

parameter update law $\dot{\hat{\phi}} = \Gamma W^T(x)r$

where $\Gamma > 0$ is a tuning parameter matrix.

Handwritten notes:
 $a_j \dot{q}_j + b_k n_k = \tau$
 $\begin{bmatrix} a & b \end{bmatrix} \begin{bmatrix} \dot{q} \\ n \end{bmatrix} = \tau$

This is very important; I can show you what this $W(x)$ ϕ means. If I write a single link manipulator which is $\ddot{q} + b \sin q = \tau$. This particular theme can be written in $W(x)$ form, you see that $\ddot{q} \sin q$. This is my regression matrix and these are my parameters a and b is τ . This is the meaning of $W(x)$ and ϕ .

This $f(x)$, which we are talking about, is a non-linear function. This, in case of robot manipulator can be represented in terms of a regression matrix $W(x)$ and these are all known quantities provided if we, because \ddot{q} and normally it is in this $W \times \ddot{q}$ double dot will not be there, is not, in this x example it is \ddot{q} double dot. But, normally it is all quantities -this regression matrix would have all the quantities. Those are all measurable state vectors and we can compute them. So, where $W(x)$ is known as the regression matrix and τ is a vector of unknown parameters and in this case, unknown parameters are a and b . One adaptive controller which Slotine designed in 1998 is that control action τ is given by $W(x) \hat{\phi}$, the estimated parameter plus $K_v r$, very simple. This is kind of a P D kind of controller and this is our regression matrix into $\hat{\phi}$. This quantity is exactly $\hat{F} x + K_v r$. You can easily see that, if I do that here τ is exactly $\hat{F} x + K_v r$ when this system is stable. But, when it is \hat{F} , then the system stability is for we have to again have a law for $\hat{\phi}$, because we do not know what ϕ is. So, $\dot{\hat{\phi}}$ is $\Gamma^{-1} W^T (r - \hat{F} x)$ which is a positive definite matrix W^T transpose x into r . This is the parameter update law.

So, $\dot{\hat{\phi}}$, this is parameter update law and this is control law. You will always find adaptive control means, we will have a control law and then this control law consists of a term called unknown parameter $\hat{\phi}$ and that unknown parameter is computed using parameter update law, which is $\dot{\hat{\phi}} = \Gamma^{-1} W^T (r - \hat{F} x)$.

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Adaptive control of robot manipulators

The estimate of nonlinear function is given by

Linearization property: $f(x) = W(x)\hat{\phi}$ $N \times 1 = T$

Due to LIP assumption one has

$$\tilde{f} = f - \hat{f} = W(x)\phi - W(x)\hat{\phi} = W(x)\tilde{\phi}$$

with $\tilde{\phi} = \phi - \hat{\phi}$ the parameter estimation error. The above adaptive control yields following closed loop filtered-error dynamics

$$M\dot{r} = -V_m r - K_v r + W(x)\tilde{\phi}$$

The estimate of non-linear function is given by $\hat{f}(x) = W(x)\hat{\phi}$ due to linearization property, this is linearization. Linearization property, as I told you earlier that robot dynamics can be written as a regression vector W into ϕ is τ . This is robot manipulator, any robot manipulator can be written in terms of ϕ is the vector of unknown parameter, W is the regression matrix. So, \tilde{f} is of course $W(x)\tilde{\phi}$, $\tilde{\phi}$ is ϕ minus $\hat{\phi}$, the parameter estimation error. The above adaptive control yields the following closed loop filtered error dynamics $M\dot{r} - V_m r - K_v r = W(x)\tilde{\phi}$. If I have this quantity $\tilde{\phi} = 0$ that means if I know the parameters, then this is stable dynamics, because M is a positive definite matrix. So \dot{r} is $V_m r + K_v r$. Now select the Lyapunov function. But the point is that we have this quantity, so select the Lyapunov function candidate. Actually whether the system is stable or not, when this quantity is not there, we can do Lyapunov function analysis again to show that, this is stable. We will take the total thing and we will show that the system is stable by giving the parameter adaptive control below.

(Refer Slide Time: 35:56)

Adaptive control of robot manipulators

Select the Lyapunov function candidate

$$L = \frac{1}{2} r^T M(q) r + \frac{1}{2} \tilde{\phi}^T \Gamma^{-1} \tilde{\phi}$$

with Γ a symmetric positive definite weighting matrix. On differentiating, we get

$$\dot{L} = \frac{1}{2} r^T \dot{M} r + r^T M \dot{r} + \tilde{\phi}^T \Gamma^{-1} \dot{\tilde{\phi}}$$

Substituting error dynamics yields

$$\dot{L} = \frac{1}{2} r^T \dot{M} r - r^T V_m r - r^T K_v r + r^T W(x) \tilde{\phi} + \tilde{\phi}^T \Gamma^{-1} \dot{\tilde{\phi}}$$

$$= \frac{1}{2} r^T (\dot{M} - 2V_m) r - r^T K_v r + \tilde{\phi}^T (\Gamma^{-1} \dot{\tilde{\phi}} + W^T(x) r)$$

$M \dot{r} = -V_m r - K_v r + N(x) \tilde{\phi}$

This is the Lyapunov function which is $r^T M r$ plus half $\tilde{\phi}^T \Gamma^{-1} \tilde{\phi}$. If I take the rate derivative of this Lyapunov function \dot{L} , I get this quantity $r^T \dot{M} r$ plus $r^T M \dot{r}$ and then $\tilde{\phi}^T \Gamma^{-1} \dot{\tilde{\phi}}$. This is direct. Substituting the error dynamics \dot{r} and what is error dynamics that is $M \dot{r}$ is minus $V_m r$ minus $K_v r$ plus f tilde, which is here $W x$ tilde, that is same actually; $W x$ $\tilde{\phi}$, this is same as F tilde. If you look at now, this is my \dot{r} . If I replace \dot{r} here, M inverse also comes there and putting this quantity \dot{r} , we get \dot{L} is this quantity.

You know that, robot dynamics has a skew symmetric property. That means $\dot{M} - 2V_m$ is skew symmetric and hence r^T transpose this quantity into r , this goes to 0 due to skew symmetric and then \dot{L} is minus $r^T K_v r$. This is negative definite. This \dot{L} can be made negative definite if I say this is 0.

From here, I get the parameter update law $\dot{\tilde{\phi}}$ is minus equal to minus $\Gamma W^T x r$ and $\tilde{\phi} \dot{\tilde{\phi}}$ is minus $\tilde{\phi} \hat{\phi}$. **That is how we got...**

(Refer Slide Time: 38:29)

Adaptive control of robot manipulators

Because of Skew-symmetry property of $(M - 2V_m)$, we have

$$r^T (M(q) - 2V_m(q, \dot{q}))r = 0$$

Now select following parameter update dynamics

$$\dot{\theta} = -\hat{\theta} - \Gamma W^T(r)r \quad (\text{obviously})$$

Substituting these values into \dot{L} , we get

$$\dot{L} = -r^T K_v r \leq 0$$

Hence, r and $\hat{\theta}$ are bounded according Lyapunov's theorem. In order to show that $r(t) \rightarrow 0$ as $t \rightarrow \infty$, one may use Barbalat's Lemma to show that \dot{L} goes to zero with t .

Because of skew symmetric property, this quantity is 0. Selecting the parameter update law $\dot{\theta}$ which I said minus $\hat{\theta}$ dot is minus $\gamma W^T r$. obviously; my parameter update law was $\dot{\theta}$ is $\gamma W^T r$.

If this is the parameter update law and this is my control action, we proved that system is Lyapunov stable. So, \dot{L} is a negative term. Hence r and $\hat{\theta}$ are bounded according to Lyapunov's theorem. In order to show that $r(t)$ tends to 0 as t tends to infinity, one may use Barbalat's Lemma to show that \dot{L} goes to 0 with t . So, with that r goes to 0, that means obviously e and \dot{e} goes to 0. Differential at Lyapunov function once again, you get $\ddot{L} = 2r^T K_v \dot{r}$.

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Adaptive control of robot manipulators

Differentiate Lyapunov function once again to get

$$\dot{L} = -2r^T K_v r$$

Substitute the error dynamics to obtain

$$\dot{L} = -2r^T K_v M^{-1} [-V_m r - K_v r + W(x) \tilde{\theta}]$$

The right hand side is bounded because of bounding assumptions of manipulator for $V_m(q, \dot{q})$, $M(q)$ etc. and demonstrated boundedness of r and $\tilde{\theta}$. Hence \dot{L} is bounded, implying that L is uniformly continuous and by Barbalat's Lemma $\dot{L} \rightarrow 0$ as $t \rightarrow \infty$. Thus, $r(t) \rightarrow 0$ as $t \rightarrow \infty$.

However this does not ensure parameter convergence.

Direct adaptive control ensures tracking convergence but not parameter convergence

Substitute the error dynamics to obtain this quantity, the right hand side is bounded because of the bounding assumptions of the manipulator and demonstrated the boundedness of r and $\tilde{\theta}$. Hence, \dot{L} is bounded implying that L is uniformly continuous. By Barbalat's Lemma, \dot{L} tends to 0 as t tends to infinity thus r tends to 0 as t tends to infinity. However, this does not ensure parameter convergence. The direct adaptive control, as we have been saying that in direct adaptive control, the objective is not to, parameter update law will give you the exact parameter, but always the tracking error will go to 0. What we finally said that direct adaptive controller ensures tracking convergence but not parameter convergence.

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Adaptive control: Example

Consider the same 2-link manipulator as before with $m_1 = m_2 = 1 \text{ kg}$, $m_0 = 0.5$, $m_2 = 2.3 \text{ kg}$. The desired trajectory was selected as $q_{d1} = \sin t$, $q_{d2} = \cos t$. The control parameters were selected as

$$K_v = \text{diag}(20, 20), \quad \Gamma = \text{diag}(10, 10), \quad \Lambda = \text{diag}(5, 5)$$

$$= \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix}, \quad = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}, \quad \Gamma < \Delta + \Lambda \Phi$$

The elements of 2×2 regression matrix and gain are

$$W_{11} = \alpha_1^2 (\dot{q}_{d1} + \lambda_1 q_1) + \alpha_{12} \sin q_2$$

$$W_{12} = (\alpha_1^2 + 2\alpha_1 \alpha_2 \sin q_2 + \alpha_2^2) (\dot{q}_{d1} + \lambda_1 q_1) + (\alpha_1^2 + \alpha_2 \alpha_2 \sin q_2) (\dot{q}_{d2} + \lambda_2 q_2) \\ - \alpha_1 \alpha_2 \dot{q}_{d2} \sin q_2 + \alpha_2 (\dot{q}_{d1} + \lambda_1 q_1) + \alpha_2 (\dot{q}_{d2} + \lambda_2 q_2) \\ + \alpha_{12} \sin(q_1 + q_2) + \alpha_{12} \sin q_1$$

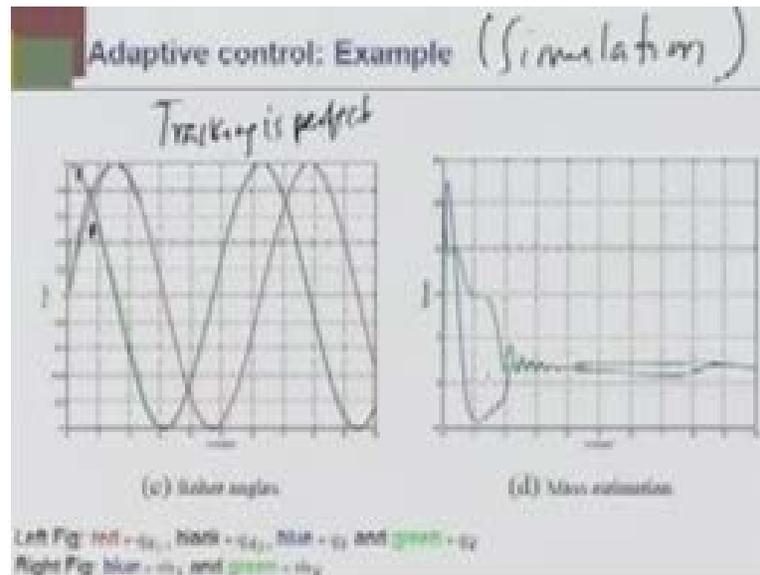
$$W_{21} = 0$$

$$W_{22} = (\alpha_2^2 + \alpha_1 \alpha_2 \sin q_2) (\dot{q}_{d1} + \lambda_1 q_1) + \alpha_2^2 (\dot{q}_{d2} + \lambda_2 q_2) \\ + \alpha_1 \alpha_2 (\dot{q}_{d1} + \lambda_1 q_1) \sin q_2 + \alpha_{22} \sin(q_1 + q_2)$$

We will take an example of adaptive control; consider the same second link manipulator that we showed earlier. The parameters are taken as follows: The desired trajectory was selected as the first desired trajectory for link 1 as sine t and desired trajectory for a link 2 as cos t.

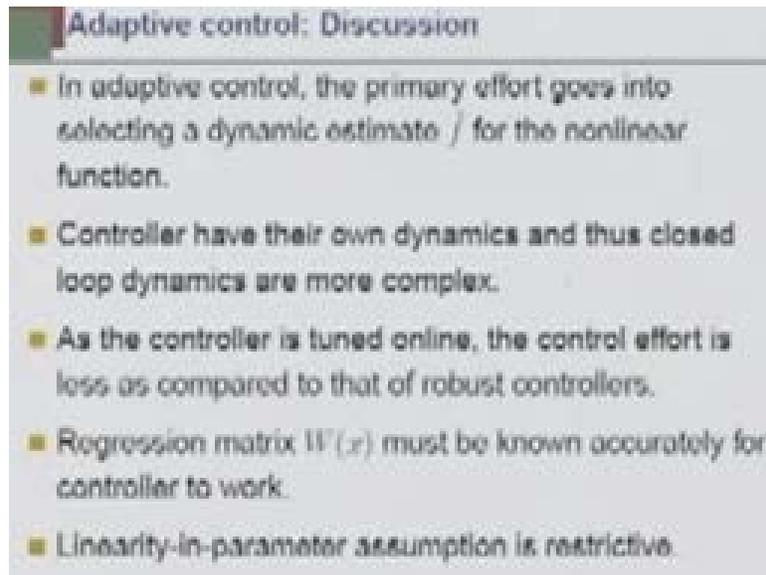
The P D parameters K_v is 20 diagonal 20, that means this is 20 0 0 20 and the parameter update law requires the vector matrix gamma, which is again 10 0 0 10 and this is a filtered tracking error which is e dot plus gamma e, so where gamma is diagonal phi. The elements of 2 by 2 regression matrix are given as W_{11} is given this, W_{12} this quantity, W_{21} you will find it to be 0, W_{22} is given by this quantity. For a 2-link manipulator, this regression matrix is quite involved.

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If you implement this in simulation - this is actually simulation not experiment - the red is the desired $q_d 1$ and blue is the actual $q 1$. In the beginning red and blue don't match; after sometime the tracking is perfect, very perfect. Similarly, the desired trajectory in link 2 is $q_d 2$ which is black and the green is the actual one. In the beginning, there is a lot of discrepancy which is obvious, but as time progresses green and black converge and there is no tracking error. Tracking is perfect or accurate and that the estimation of mass which is m_1 and m_2 , these two things we assumed to be not known, the actual mass is point 8 and 2 point 3, but here you see they do not -point 8 and 2 point 3 do not converge and actually they have become same here. The estimated quantities do not converge with the actual quantities but tracking is perfect. That is the objective of adaptive control.

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Adaptive control: Discussion

- In adaptive control, the primary effort goes into selecting a dynamic estimate \hat{f} for the nonlinear function.
- Controller have their own dynamics and thus closed loop dynamics are more complex.
- As the controller is tuned online, the control effort is less as compared to that of robust controllers.
- Regression matrix $W(x)$ must be known accurately for controller to work.
- Linearity-in-parameter assumption is restrictive.

Finally, going back to the discussion on adaptive control; in adaptive control, the primary effort goes into selecting a dynamic estimate \hat{f} for the non-linear function. Controller has its own dynamics and thus closed loop dynamics are more complex. As a controller is tuned online, the control effort is less as compared to as that of robust controllers. Regression matrix $W(x)$ must be known accurately for controller to work, linearization property assumption is restrictive, because this type of controller that we talked about is only valid for robot manipulator, because that follows linearization property and this linearization property is not valid for all kind of non-linear system. That is why, whatever we will be discussing- in the following lectures they are only meant for robot manipulators, because there is a certain advantage but in general, it is not true.

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Adaptive control and computed-torque control

The computed torque control for robot manipulators, can be expressed in terms of filtered error as

$$\tau = f(x) + K_v r$$

where the nonlinear function f is given by

$$f(x) = M(q)\ddot{q} + V_m(q, \dot{q})\dot{q} + F(q) + G(q)$$

The adaptive control has a similar form given by

$$\tau = \hat{f}(x) + K_v r$$

where $\hat{f}(x) = W(x)\hat{\phi}$.

Hence, Adaptive control is an approximated computed-torque control where $f(\cdot)$ is replaced by $\hat{f}(\cdot)$.

The computed torque control robot manipulator can be expressed in terms of filtered tracking error as $f(x) + K_v r$ where $f(x)$ is this quantity and adaptive control is $\hat{f}(x) + K_v r$. This is my computed torque control and this is my adaptive control, where $f(x)$ is replaced by \hat{f} . Adaptive control is an approximated computed torque control where the actual f is replaced by the estimated \hat{f} and for that, we have a parameter update law that is given by $\dot{\hat{\phi}} = \gamma W^T r$.

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Robust control

- It is seen that adaptive controllers are complex because of additional estimator dynamics.
- Simpler controllers can be designed if bound on uncertain nonlinear term $f(\cdot)$ is known.

In robust control, an additional robust term $v(t)$ is added to the computed-torque control as follows:

$$\tau = \hat{f}(x) + K_v r + v(t)$$

The primary design effort goes into selecting the robust term.

It is seen that adaptive controllers are complex because of additional estimator dynamics. Simpler controllers can be designed if bound on uncertain non-linear term f is known. In robust control, an additional robust term $v(t)$ is added to the computed torque control as follows. This is the connection, this was our adaptive controller and then we found out. But here, we add a robust term minus v t. Primary design effort goes into selecting this robust term v t, so that the system is stable.

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Robust control of Robot manipulators

Robust Saturation Controller

$$\tau = \hat{f} + K_v \dot{e} + e$$

$$v = \begin{cases} -\frac{F(x)}{\epsilon}, & |v| \geq \epsilon \\ -\frac{F(x)}{\epsilon}, & |v| < \epsilon \end{cases}$$

where \hat{f} is an estimate of $f(x)$ that is not changed on-line. $F(x)$ is a bound on uncertainties $f = \hat{f} + f$ so that

$$|f| \leq F(x)$$

The intent is that $F(x)$ is a simplified function that can be computed using bounding properties of robot manipulator even if the exact value of complicated nonlinear function $f(x)$ is unknown.

This is our controller action, this is my v and \hat{f} is an estimate of $f(x)$ that is not changed online. $F(x)$ is a bound on certain uncertainties. If I know this bound on uncertainties -the intent is that $F(x)$ is a simplified function that can be computed using bounding properties of robot manipulator even if the exact value of complicated non-linear function $f(x)$ is unknown.

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Robust control of Robot manipulators

Rewrite the robot dynamics in terms of filtered-error

$$M\dot{r} = -V_m r + f(r) - \tau$$

Substituting the above proposed controller into this yields

$$M\dot{r} = -V_m r - K_v r + \dot{f} + v$$

with $\|\dot{f}\| < F(r)$ the known function. Select following Lyapunov function candidate

$$L = \frac{1}{2} r^T M(q) r$$

Rewrite the robot dynamics in terms of filtered error, we have already shown that and substituting the above proposed controller into this, we get this closed loop error dynamics and taking the Lyapunov function is half r transpose M(q) r.

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Robust control of Robot manipulators

Differentiate to get

$$\dot{L} = \frac{1}{2} r^T \dot{M} r + r^T M(q) \dot{r}$$

Substituting error dynamics yields

$$\begin{aligned} \dot{L} &= \frac{1}{2} r^T \dot{M} r - r^T V_m r - r^T K_v r + r^T (\dot{f} + v) \\ &= \frac{1}{2} r^T (\dot{M} - 2V_m) r - r^T K_v r + r^T (\dot{f} + v) \end{aligned}$$

Because of skew-symmetry property of $(\dot{M} - 2V_m)$, we get

$$\dot{L} = -r^T K_v r + r^T (\dot{f} + v)$$

When differentiating, you will get this quantity because of skew symmetric property goes to 0. From here, we can find out what is V?

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Robust control of Robot manipulators

Using the norm property $\sigma_{\max}(K_v)\|r\|^2 \leq r^T K_v r$, we get

$$\dot{L} = -\sigma_{\min}(K_v)\|r\|^2 + |r|\dot{\epsilon} + r^T v$$

$$\dot{L} = -\sigma_{\min}(K_v)\|r\|^2 + |r|\{F(r) + r^T v\}$$

There are two cases to consider

Case 1. $|r| \geq \epsilon$. According to the definition of robust control term $v(r)$, one has

$$\begin{aligned} \dot{L} &\leq -\sigma_{\min}(K_v)\|r\|^2 + |r|\{F(r) - |r|^2 \frac{F(r)}{|r|}\} \\ &\leq -\sigma_{\min}(K_v)\|r\|^2 + |r|\{F(r) - |r|F(r)\} \\ \dot{L} &\leq -\sigma_{\min}(K_v)\|r\|^2 \end{aligned}$$

\dot{L} is negative definite in terms of $|r|$. Hence, L decreases in the region and $|r|$ decreases to ϵ .

Using the norm property, we get L dot is this quantity and this quantity. There are two cases to consider. I am just going little faster because I have to go to the neural network based controller. There are two cases to consider, the boundedness r is greater than equal to epsilon.

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Robust control of Robot manipulators

Using the norm property $\|K_v\| \leq r^2 K_v$, we get

$$\dot{L} = -\sigma_{\min}(K_v)\|r\|^2 + \|r\|\dot{\|r\|} + r^2 \dot{v}$$

$$\dot{L} = -\sigma_{\min}(K_v)\|r\|^2 + \|r\|F(r) + r^2 \dot{v}$$

There are two cases to consider:

Case 1. $\|r\| > \epsilon$. According to the definition of robust control term $v(t)$, one has

$$\dot{L} \leq -\sigma_{\min}(K_v)\|r\|^2 + \|r\|F(r) - \|r\|^2 \frac{F(r)}{\|r\|}$$

$$\leq -\sigma_{\min}(K_v)\|r\|^2 + \|r\|F(r) - \|r\|F(r)$$

$$\dot{L} \leq -\sigma_{\min}(K_v)\|r\|^2$$

\dot{L} is negative definite in terms of $\|r\|$; hence, \dot{L} decreases in the region and $\|r\|$ decreases towards ϵ .

According to the definition, robust control term $v(t)$ has \dot{L} , is this quantity which is less than this quantity, this is same this is same and this is replaced by simply $r f(x)$. This cancels out, so this \dot{L} is only this quantity which is negative definite

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Robust control of Robot manipulators

Case 2. $\|r\| < \epsilon$. In this case, according to the definition of robust control term $v(t)$ one has

$$\dot{L} \leq -\sigma_{\min}(K_v)\|r\|^2 + \|r\|F(r) - \|r\|^2 \frac{F(r)}{\epsilon}$$

$$\leq -\sigma_{\min}(K_v)\|r\|^2 + \|r\|F(r) \left(1 - \frac{\|r\|}{\epsilon}\right)$$

Last term is generally positive in this region and so nothing can be said about whether \dot{L} is increasing or decreasing. In general, \dot{L} may be increasing in this region so that $\|r\|$ increases towards ϵ .

Case 2: When it is less than epsilon, in this case according to definition of robust control term $v(t)$ has again this quantity, which is this quantity plus $r f(x) \left(1 - \frac{r}{\epsilon}\right)$

epsilon. Last term is generally positive, this quantity and this region and nothing can be said about whether L is increasing or decreasing. In general L may be increasing in this region so that r increases towards epsilon.

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Robust Control: Example

Consider the same 2-link manipulator as discussed earlier. The control parameters are selected as

$$K_v = \text{diag}\{20, 20\} \quad \Lambda = \text{diag}\{5, 5\}, \quad \epsilon = 0.1.$$

For a robust PD control we take $f = G(q)$ and the control input is given by $\tau = K_v \dot{r} + G(q) - v$. This yields

$$\dot{f} = f(r) - f = M(q)(\ddot{q}_d + \Lambda \dot{q}) + V_m(q, \dot{q})(\dot{q}_d + \Lambda \dot{q}) + F(q)$$

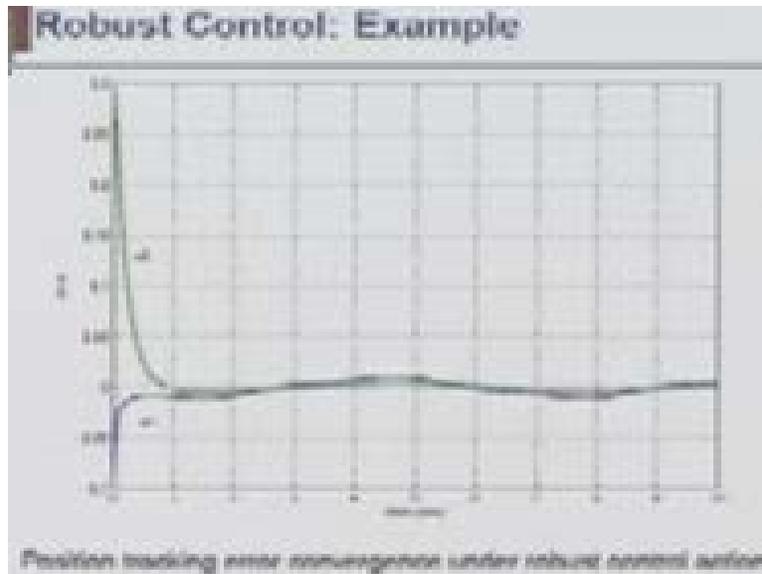
Using norm inequalities and bounding properties of manipulator, it can be shown that

$$\begin{aligned} \|\dot{f}\| &\leq \|M\| \|\ddot{q}_d + \Lambda \dot{q}\| + \|V_m(q, \dot{q})\| \|\dot{q}_d + \Lambda \dot{q}\| + \|F(q)\| \\ &\leq \mu_2 \|\ddot{q}_d + \Lambda \dot{q}\| + v_B \|\dot{q}_d + \Lambda \dot{q}\| + f_B \|\dot{q}_d + \Lambda \dot{q}\| + k_B = P(r) \end{aligned}$$

where $\mu_2 = (m_1 + m_2) \alpha^2 + 2m_2 \alpha$ and $v_B = m_2 \alpha_1 \alpha_2$.

Robust controller example: Consider the same 2-link manipulator as discussed earlier. The control parameters are selected as with epsilon as point 1; for a robust PD controller we take f equal to G q; control input is given as this quantity. If you implement it, given an initial trajectory disturbance finally, this converges to 0.

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Position tracking error convergence under robust control action.

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- ### Robust control: Summary
- The primary design effort goes into selecting the robust term v in torque equation.
 - Robust controller don't have dynamics of their own and hence simpler to implement.
 - It is necessary to compute the *bounding function* $F(x)$ for uncertainties.
 - More control effort is required as the controller is not tuned online.

The primary design effort goes into selecting the robust term v in torque equation, robust controllers do not have dynamics of their own and hence simpler to implement. It is necessary to compute the bonding function $F(x)$ for uncertainties. More control effort is required as the controller is not tuned online.

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NN based simple adaptive control

Consider a Single-link Manipulator:

$$a\ddot{q} + b\sin(q) = \tau \quad (\text{affine form})$$

Let's define $e = q_d - q$, $\dot{e} = \dot{q}_d - \dot{q}$ and $r = \dot{e} + \lambda e$, then we have

$$\begin{aligned} \dot{r} &= (\ddot{q}_d + \lambda\dot{e}) + \frac{b}{a}\sin(q) - \frac{\tau}{a} \\ &= F(\ddot{q}_d, \dot{q}, \ddot{q}, \dot{e}) - u \end{aligned}$$

A NN can be used to approximate this nonlinear function.

$$F = \underbrace{W\phi}_{NN} + \epsilon \quad \text{and suppose } F = W\phi$$

This is the final part of this lecture. We will be talking about neural network based adaptive controller, so that how we can do the same direct adaptive control using neural network. Take a simple example a q double dot plus b sine q is τ , which is a single link manipulator defined as usual e is q_d minus q , \dot{e} is \dot{q}_d minus \dot{q} and the tracking filtered tracking error r is \dot{e} plus λe

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NN based simple adaptive control

Consider a Single-link Manipulator:

$$a\ddot{q} + b\sin(q) = \tau \quad (\text{affine form})$$

Let's define $e = q_d - q$, $\dot{e} = \dot{q}_d - \dot{q}$ and $r = \dot{e} + \lambda e$, then we have

$$\begin{aligned} \dot{r} &= (\ddot{q}_d + \lambda\dot{e}) + \frac{b}{a}\sin(q) - \frac{\tau}{a} \\ &= F(\ddot{q}_d, \dot{q}, \ddot{q}, \dot{e}) - u \end{aligned}$$

A NN can be used to approximate this nonlinear function.

$$F = \underbrace{W\phi}_{NN} + \epsilon \quad \text{and suppose } F = W\phi$$

We have \dot{r} is q_d double dot plus λe dot plus b upon a sin q minus τ upon a which is my regression matrix F minus u . So the NN can be used to approximate this

non-linear function this F can be written as $W^T \phi + \epsilon$ and suppose F is $W^T \phi$.

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NN based simple adaptive control

By choosing a control $u = F + Kr$, the closed loop error dynamics can be written as

$$\dot{r} = \tilde{W}^T \phi - Kr \text{ where } \tilde{W} = W - \hat{W}$$

Consider a Lyapunov function

$$V = \frac{1}{2} r^T r + \frac{1}{2} \text{tr}(\tilde{W}^T \Gamma^{-1} \tilde{W})$$

The time derivative of the Lyapunov function

$$\dot{V} = -r^T Kr + \text{tr}(\tilde{W}^T \phi r^T - \tilde{W}^T \Gamma^{-1} \dot{\tilde{W}})$$

By choosing a control law, u is F hat plus Kr the closed loop error dynamics can be written as \dot{r} is $\tilde{W}^T \phi$ minus Kr . What I am saying here is that this non-linear function is represented by a neural network. That is very simple, because W is the weight of the neural network and ϕ is the input to the neural network. The closed loop error dynamics can be written as \dot{r} is $\tilde{W}^T \phi$ minus Kr . If I now take Lyapunov function V in this form, which is $r^T r$ plus $\tilde{W}^T \Gamma^{-1} \tilde{W}$, time derivative of Lyapunov function is $-r^T Kr$ and then this is trace of this quantity. We can make \dot{V} is minus $r^T Kr$, provided this term is m - with 0.

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NN based simple adaptive control

Choosing a weight update law

$$\dot{W} = \Gamma \phi r^T$$

we get

$$\dot{V} = -r^T K r \leq 0$$

Since $V > 0$ and $\dot{V} \leq 0$, above weight update law ensures stability in the sense of Lyapunov, so that r and \dot{W} are bounded.

Again $\dot{V} = -2r^T K r = -2r^T K W^T \phi + 2r^T K^2 r$. Since r and \dot{W} are bounded, \dot{V} is also bounded. By Barbalat's lemma, $V \rightarrow 0$ as $t \rightarrow \infty$. Hence r vanishes with time.

That can be achieved \dot{W} is $\gamma \phi r^T$ which you can easily see.

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NN based simple adaptive control

By choosing a control $u = -\dot{r} + K_r r$, the closed loop error dynamics can be written as

$$\dot{r} = \tilde{W}^T \phi - K_r r \text{ where } \tilde{W} = W - \hat{W}$$

Consider a Lyapunov function

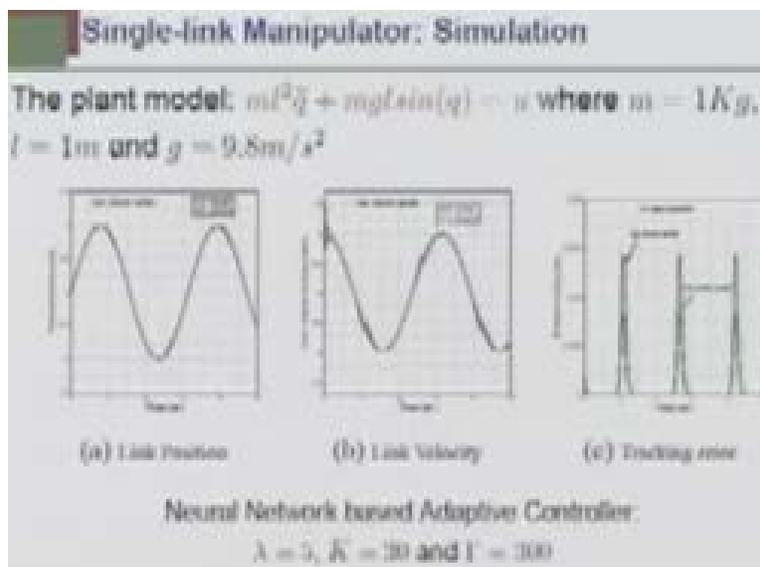
$$V = \frac{1}{2} r^T r + \frac{1}{2} \text{tr}(\tilde{W}^T \Gamma^{-1} \tilde{W})$$

The time derivative of the Lyapunov function

$$\dot{V} = -r^T K_r r + \text{tr}(\tilde{W}^T \dot{\phi} r^T - \tilde{W}^T \Gamma^{-1} \dot{\tilde{W}})$$

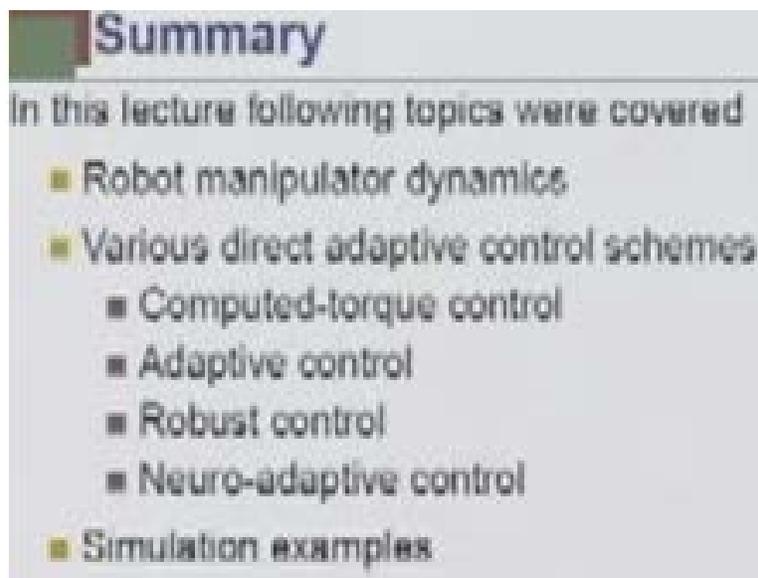
I can take this $\gamma \tilde{W}^T \phi r^T$ is minus γ inverse \tilde{W} dot. So, \tilde{W} dot is $\gamma \phi r^T$, which is this one. This is the weight update law for neural networks. Using that we saw \dot{V} is negative definite \ddot{V} is this quantity and since r and \tilde{W} are bounded, \ddot{V} is also bounded by Barbalat's lemma. \dot{V} tends to 0 as t tends to ∞ ; hence r vanishes with time. As r vanishes with time, so is the derivative of error.

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If we now do the simulation taking a neural network based adaptive controller, where the neural network represents this quantity, $\hat{\phi}$. Taking the single link manipulator, we see that actual and desired very closely following and the velocity actual and desired also following and tracking error is very small, point 0 0 means N to the power minus 3 order. Taking these parameters, we got these simulation results. This is control input in the link and this is the function approximation, this is a PD controller. Finally the summary in this lecture. Following topics were covered.

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Robot manipulator dynamics, various direct adaptive control schemes, computed torque control adaptive control, robust control, neuro-adaptive control, simulation examples

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Summary

In this lecture following topics were covered

- Robot manipulator dynamics
- Various direct adaptive control schemes
 - Computed-torque control
 - Adaptive control
 - Robust control
 - Neuro-adaptive control
- Simulation examples