

Adaptive and Variable Structure Control of Robot Manipulators

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Adaptive Control of Manipulators

References

Approximation Methods (1979-1985)

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Linear-parameterization Methods (1986-present)

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Non-linear-parameterization Methods

- [3] Y. Stepanenko and J. Yuan, "Robust adaptive control of a class of nonlinear mechanical systems with unbounded and fast-varying uncertainties," *Automatica*, vol. 28, pp. 265-276, 1992.
- [4] L. Fu, "Robust adaptive decentralized control of robot manipulators," *IEEE Trans. on Automatic Control*, vol. 37, pp. 106-110, 1992.
- [5] Y. Stepanenko, C.-Y. Su, and H. Hashimoto, "On the guaranteed stability based adaptive control of robotic manipulators: Continuity and Boundedness," *Proc. of the Workshop on Robust Control via Variable Structure & Lyapunov Techniques*, pp. 210-215, 1994.

Difficulty of Feedback Linearization (Computed Torque) Control

Dynamic equation

$$M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + G(\mathbf{q}) = \tau \quad (1)$$

where $\mathbf{q} \in R^n$ is the joint positions and $\tau \in R^n$ is the applied joint torques.

The feedback linearization (computed torque) control law is defined as

$$\tau = M(\mathbf{q})\mathbf{v} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + G(\mathbf{q}) \quad (2)$$

where vector \mathbf{v} is the outer loop control signals.

Since there are considerable uncertainties in all robot dynamic models, for example, model parameters such as link length, mass and inertia, variable payloads, etc, which are either impossible to know precisely or varying unpredictably, in this case, the feedback linearization method or the computed torque method cannot be directly used.

Adaptive Feedback Linearization (Computed Torque) Control of Manipulators

Objectives

Apply adaptive control methods in which controllers are designed to be adjustable so as to automatically compensate for these uncertainties.

Properties of Robotic Dynamics

- Positive definite

The inertia matrix $M(\mathbf{q})$ is symmetric, positive definite, and both $M(\mathbf{q})$ and $M(\mathbf{q})^{-1}$ are uniformly bounded as function of \mathbf{q} .

- Skew-symmetric

A suitable definition of $C(\mathbf{q}, \dot{\mathbf{q}})$ makes matrix $(\dot{M} - 2C)$ skew-symmetric. In particular, this is true if the elements of $B(\mathbf{q}, \dot{\mathbf{q}})$ are defined as

$$C_{ij} = \frac{1}{2}[\dot{\mathbf{q}}^T \frac{\partial M_{ij}}{\partial \mathbf{q}} + \sum_{k=1}^n (\frac{\partial M_{ik}}{\partial q_j} - \frac{\partial M_{jk}}{\partial q_i}) \dot{q}_k] \quad (3)$$

- Linear parameterization

$$M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + G(\mathbf{q}) = Y(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\theta \quad (4)$$

where $Y \in R^{n \times m}$ is a matrix of known functions, known as the regressor; $\theta \in R^m$ is a vector of the manipulator inertia parameters (masses, moments of inertia, etc.).

Control Objectives

For any given desired trajectory $\mathbf{q}_d \in R^n$, with some or all the manipulator parameters unknown, find τ so that

$$\lim_{t \rightarrow \infty} \|\mathbf{q}(t) - \mathbf{q}_d(t)\| = 0.$$

3. Adaptive Case

The adaptive implementation of the inverse dynamics control law is obtained by replacing M , C , and G by their estimates, i.e.,

$$\tau = \hat{M}(q)(\ddot{q}^d - K_v \dot{e} - K_p e) + \hat{C}(q, \dot{q})\dot{q} + \hat{G}(q). \quad (6)$$

We assume that \hat{M} , \hat{C} , and \hat{G} have the same functional form as M , C , G with estimated parameters $\hat{\theta}_1, \dots, \hat{\theta}_r$. Thus,

$$\hat{M}\ddot{q} + \hat{C}\dot{q} + \hat{G} = Y(q, \dot{q}, \ddot{q})\hat{\theta} \quad (7)$$

where $\hat{\theta}$ is the vector of estimated parameters.

Substituting (6) into (1) gives

$$M\ddot{q} + C\dot{q} + G = \hat{M}(\ddot{q}^d - K_v \dot{e} - K_p e) + \hat{C} + \hat{G} \quad (8)$$

Adding and subtracting $\hat{M}\ddot{q}$ on the left-hand side of (8) and using (7) we can write

$$\begin{aligned} \hat{M}(\ddot{e} + K_v \dot{e} + K_p e) &= \tilde{M}\ddot{q} + \hat{C}\dot{q} + \hat{G} \\ &= Y(q, \dot{q}, \ddot{q})\hat{\theta} \end{aligned} \quad (9)$$

where $(\cdot) := (\cdot) - (\cdot)$. Finally, the error dynamics may be written as

$$\ddot{e} + K_v \dot{e} + K_p e = \hat{M}^{-1} Y \hat{\theta} := \Phi \hat{\theta}. \quad (10)$$

We may write the system (10) in state space as

$$\dot{x} = Ax + B\Phi\hat{\theta} \quad (11)$$

where A is the Hurwitz matrix

$$A = \begin{bmatrix} 0 & I \\ -K_p & -K_v \end{bmatrix}; \text{ and } B = \begin{bmatrix} 0 \\ I \end{bmatrix}; x = \begin{bmatrix} e \\ \dot{e} \end{bmatrix}. \quad (12)$$

Theorem 1: Choose the update law

$$\dot{\hat{\theta}} = \dot{\hat{\theta}} = -\Gamma^{-1} \Phi^T B^T P x \quad (13)$$

where $\Gamma = \Gamma^T > 0$ and P is the unique symmetric positive definite solution to the Lyapunov equation

$$A^T P + P A + Q = 0 \quad (14)$$

for a given symmetric, positive definite Q . Under these conditions then, the solution x of (11) satisfies

$$x \rightarrow 0 \quad \text{as } T \rightarrow \infty \quad (15)$$

with all signals remaining bounded.

Assumptions:

1) \ddot{q}^d = acceleration is measurable

2) \hat{M}^{-1} is bounded.

Proof: Choose the Lyapunov function candidate

$$V = x^T P x + \bar{\theta}^T \Gamma \bar{\theta}. \quad (16)$$

The time derivative of V along trajectories of (11) is computed to be

$$\dot{V} = -x^T Q x + 2\bar{\theta}^T [\Phi^T B^T P x + \Gamma \dot{\bar{\theta}}]. \quad (17)$$

Using the parameter update law (11), this reduces to

$$\dot{V} = -x^T Q x \leq 0. \quad (18)$$

A New Adaptive Inverse Dynamics Scheme

The main drawback of the result in the previous section is the requirement that \hat{M} remain uniformly positive definite.

We choose an inverse dynamics control law of the form

$$\tau = M_0(q)(\dot{V} + \delta V) + C_0(q, \dot{q})\dot{q} + \zeta_0 \quad (20)$$

where $M_0 = M_0^T > 0$, C_0, ζ_0 are *a priori* estimates of M, C, ζ , respectively, with fixed parameters, V is given by (2), and δV is an additional outer loop control that compensates for the deviations $\Delta M, \Delta C, \Delta \zeta$, where $\Delta(\cdot) = (\cdot)_0 - (\cdot)$. In the present setup we will choose δV adaptively. It is important to note that the terms M_0, C_0, ζ_0 in (20) are not updated on-line, and hence the invertibility of M_0 is not an issue.

If we now combine (20) with (1) we have an equation similar to (9)

$$\begin{aligned} M_0(\ddot{e} + K_v \dot{e} + K_p e - \delta V) &= \Delta M \ddot{q} + \Delta C \dot{q} + \Delta \zeta \\ &= Y(q, \dot{q}, \ddot{q}) \Delta \theta \end{aligned} \quad (21)$$

where the last equality is obtained using Property 3 of linearity in the parameters. Note, in (21), that $\Delta \theta = \theta_0 - \theta$ is a fixed vector in \mathbb{R}^r and not a function of time, since the terms in (20) are fixed estimates. Finally, we write

$$\ddot{e} + K_v \dot{e} + K_p e = M_0^{-1} Y \Delta \theta + \delta V := \Phi_0 \Delta \theta + \delta V. \quad (22)$$

Choosing the control δV as

$$\delta V = -\Phi_0 \Delta \hat{\theta} \quad (23)$$

yields an equation identical to (11) with Φ replaced by Φ_0 . Note that $\Delta \hat{\theta} = \bar{\theta}$ and that now Φ_0 is not a function of the estimated parameters since M_0 is fixed. Choosing an update law for $\Delta \hat{\theta}$ according to

$$\Delta \dot{\hat{\theta}} = -\Gamma^{-1} \Phi_0^T B^T P x \quad (24)$$

where P satisfies (14), and choosing a Lyapunov function candidate

$$V = x^T P x + \Delta \bar{\theta}^T \Gamma \Delta \bar{\theta} = x^T P x + \bar{\theta}^T \Gamma \bar{\theta} \quad (25)$$

a proof identical to that of Theorem 1 shows that $x \rightarrow 0$ as $t \rightarrow \infty$, with all signals remaining bounded.

The Algorithm of Slotine and Li

Advantages:

- * Without measurement of the accelerations.
- * Without inversion of estimated inertia matrix.
- * The controller is globally stable.

Controller

$$\tau = \lambda \hat{1} \ddot{q}_r + \hat{C}(q, \dot{q}_r) \dot{q}_r + \hat{G}(q) - \underbrace{K_D S}_{\substack{\text{PD} \\ \text{Feed back} \\ \text{control} \\ \text{past.}}}$$

where

$$\dot{q}_r \triangleq \dot{q}_d - \Lambda \tilde{q}, \quad \Lambda = 1$$

Λ is a positive definite matrix

$\tilde{q} \triangleq q - q_d$; K_D is a uniformly positive matrix; S is defined as

$$S = \dot{q} - \dot{q}_r = \ddot{q} + \Lambda \tilde{q}$$

q_d = desired trajectory.

→ Unknown parameter.

$$\tau = Y(q, \dot{q}, \dot{q}_r, \ddot{q}_r) \hat{\theta} - K_D S$$

→ Using linearization property we can write this.

This suggests that choosing the adaptive law such that

$$\dot{Y}^T(q, \dot{q}, \ddot{q})S + \Gamma \dot{\hat{\Theta}} = 0$$

that is

$$\dot{\hat{\Theta}} = -\Gamma^{-1} Y^T S$$

$$(\dot{\hat{\Theta}} = \dot{\hat{\Theta}} \text{ since } \hat{\Theta} \text{ is constant})$$

The resulting expression of \dot{V} is

$$\dot{V} = -S^T K_p S < 0 \quad (16)$$

~~is~~ lemma:

Let $Y = H(s)X$, with $H(s)$ an $n \times m$ transfer matrix which is strictly proper and exponential stable.

Then if $x \in L_2^m$, we have

i) $y \in L_2^n \cap L_\infty^n$ and $\dot{y} \in L_2^n$

ii) y is continuous, and $y \rightarrow 0$ as $t \rightarrow \infty$

iii) if $x \rightarrow 0$, as $t \rightarrow \infty$, then $\dot{y} \rightarrow 0$

$$L^\infty \triangleq \sup |x|$$

Expression (16) imply that

$$S \in L_2^\infty \cap L_\infty^\infty,$$

Then

$$\text{Since } \tilde{q} = (S^* I - K_0)^{-1} S$$

By using lemma, we ~~can~~ can conclude that

$$\tilde{q} \in L_2^\infty \cap L_\infty^\infty$$

$$\tilde{q} \rightarrow 0 \text{ as } t \rightarrow \infty$$

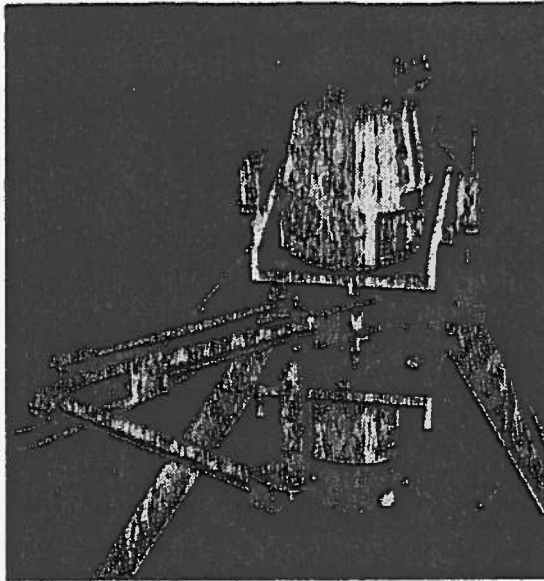


Fig. 2. The experimental two degree-of-freedom manipulator.

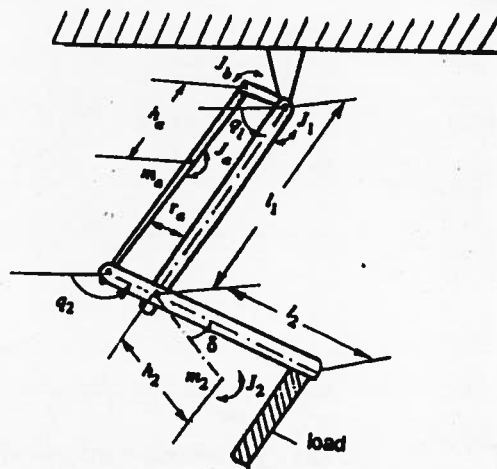


Fig. 3. The schematic structure of the manipulator.

B. Dynamic Model and Adaptive Controller Design

The dynamic model of the manipulator can be derived from Lagrange's equations to be

$$a_1 \ddot{q}_1 + (a_3 c_{21} + a_4 s_{21}) \ddot{q}_2 - a_3 s_{21} \dot{q}_2^2 + a_4 c_{21} \dot{q}_2^2 = \tau_1 \quad (9-a)$$

$$(a_3 c_{21} + a_4 s_{21}) \ddot{q}_1 + a_2 \ddot{q}_2 + a_3 s_{21} \dot{q}_1^2 - a_4 c_{21} \dot{q}_1^2 = \tau_2 \quad (9-b)$$

where $c_{21} = \cos(q_2 - q_1)$, $s_{21} = \sin(q_2 - q_1)$. It is clearly linear in terms of the four parameters a_1, a_2, a_3, a_4 , which are related to the physical parameters of the links in Fig. 3 through

$$\begin{aligned} a_1 &= J_1 + J_a + m_2 l_1^2 + m_a h_a^2 & a_2 &= J_2 + J_b + m(2)h_2^2 + m_a r_a^2 \\ a_3 &= m_2 h_2 l_1 \cos \delta - m_a h_a r_a & a_4 &= m_2 h_2 l_1 \sin \delta \end{aligned} \quad (10)$$

with the load treated as part of the second link. Defining the components of the matrix C as

$$C(1, 1) = C(2, 2) = 0$$

$$C(1, 2) = (a_4 c_{21} - a_3 s_{21}) \dot{q}_2 \quad C(2, 1) = (a_3 s_{21} - a_4 c_{21}) \dot{q}_1$$

the skew-symmetry of $\dot{H} - 2C$ can also be confirmed easily.

For simplicity, the feedback gain matrix K_D and the adaptation gain matrix Γ in the controller design are chosen to be diagonal

$$K_D = \text{diag}(k_{d1}, k_{d2}) \quad \Gamma = \text{diag}(\gamma_1, \gamma_2, \gamma_3, \gamma_4).$$

The explicit form of the control law $\tau = \hat{H}\ddot{q}_r + \hat{C}\dot{q}_r - K_D s$ in terms of the parameter vector a is

$$\tau_1 = Y_{11}a_1 + Y_{13}a_3 + Y_{14}a_4 - k_{d1}s_1 \quad (11-a)$$

$$\tau_2 = Y_{22}a_2 + Y_{23}a_3 + Y_{24}a_4 - k_{d2}s_2 \quad (11-b)$$

where

$$Y_{11} = \ddot{q}_{r1} \quad Y_{13} = c_{21} \ddot{q}_{r2} - s_{21} \dot{q}_2 \dot{q}_{r2} \quad Y_{14} = s_{21} \ddot{q}_{r2} + c_{21} \dot{q}_2 \dot{q}_{r2}$$

$$Y_{22} = \ddot{q}_{r2} \quad Y_{23} = c_{21} \ddot{q}_{r1} + s_{21} \dot{q}_1 \dot{q}_{r1} \quad Y_{24} = s_{21} \ddot{q}_{r1} - c_{21} \dot{q}_1 \dot{q}_{r1}$$

The adaptation law can be explicitly written as

$$\dot{\hat{a}}_1 = -\gamma_1 Y_{11} s_1 \quad (12-a)$$

$$\dot{\hat{a}}_2 = -\gamma_2 Y_{22} s_2 \quad (12-b)$$

$$\dot{\hat{a}}_3 = -\gamma_3 (Y_{13} s_1 + Y_{23} s_2) \quad (12-c)$$

$$\dot{\hat{a}}_4 = -\gamma_4 (Y_{14} s_1 + Y_{24} s_2). \quad (12-d)$$

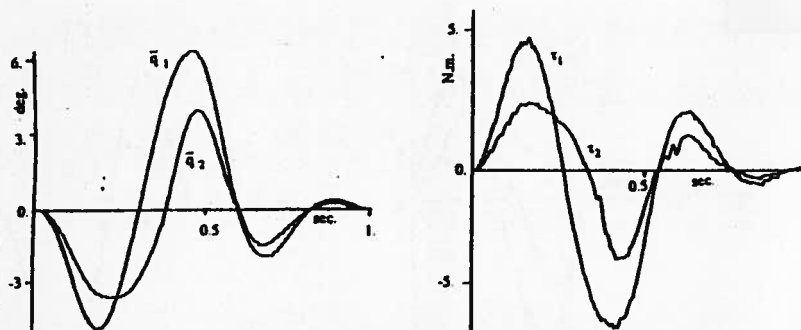


Fig. 5. PD control without load.

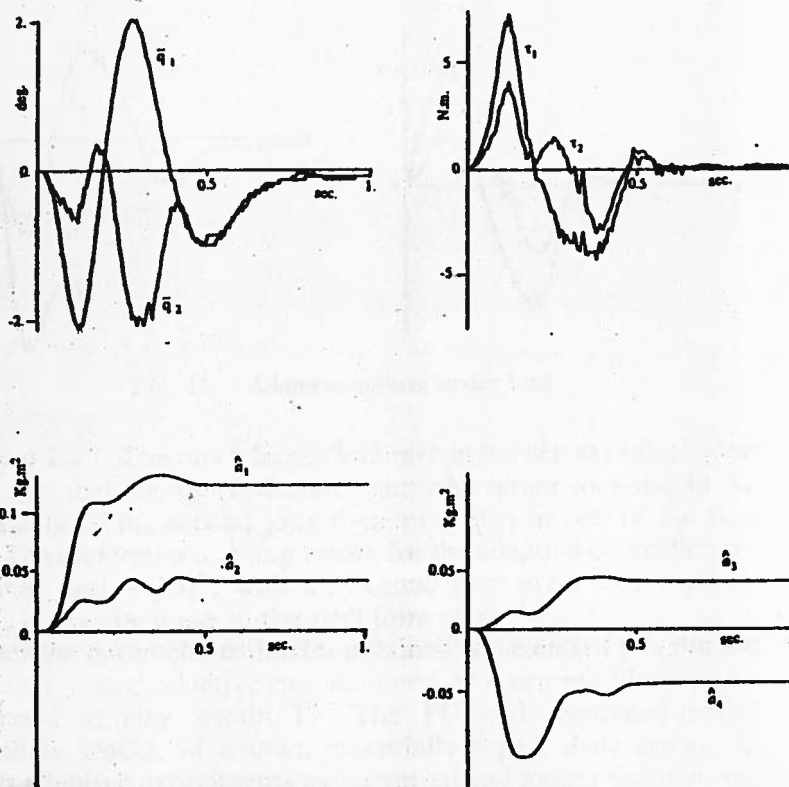


Fig. 6. Adaptive control starting from zero estimates.

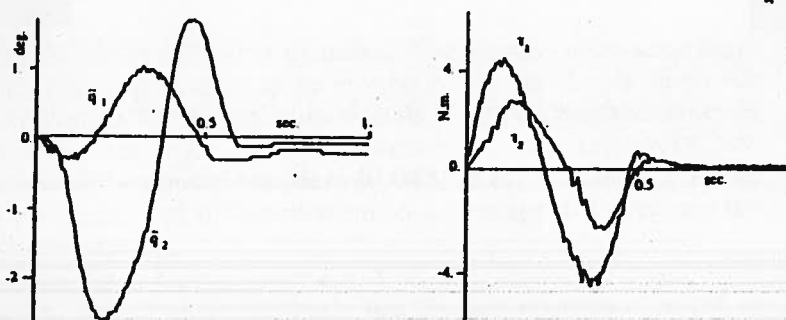


Fig. 7. Computed torque control.

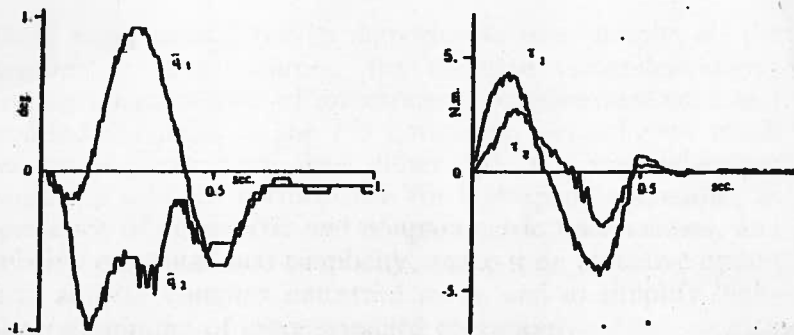


Fig. 8. Adaptive control starting with nonzero estimates.

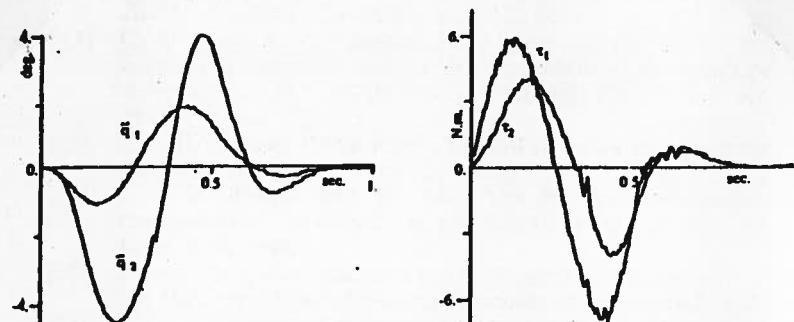


Fig. 10. Computed torque control under large load.

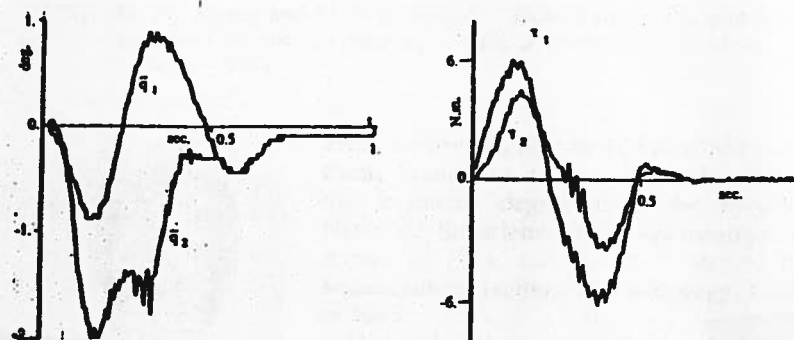


Fig. 11. Adaptive control under load.

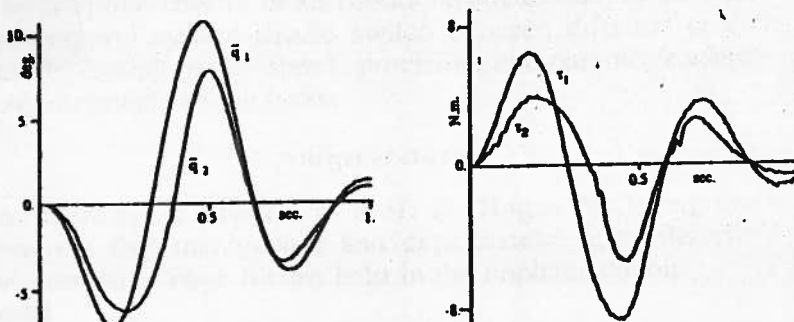


Fig. 9. PD control under load.

Algorithm of Slotine and Li

$$\tau = Y(q, \dot{q}, q_r, \dot{q}_r) \hat{z} - K_D S \quad (*)$$

$$\dot{\hat{z}} = -\Gamma Y^T S \quad \rightarrow \text{The only parameter we can change here.}$$

where $Y(q, \dot{q}, q_r, \dot{q}_r)$ is defined as

or

$$M \ddot{q}_r + C \dot{q}_r + G = Y(q, \dot{q}, q_r, \ddot{q}_r) \alpha$$

$$S \triangleq q - q_r = \tilde{q} + \lambda \tilde{q}$$

$$\dot{q}_r = \dot{q} - \lambda \tilde{q}$$

Objective:

Design a variable structure control by using the controller structure of (*) without estimating the parameters.

$$\tau = Y(q, \dot{q}, q_r, \dot{q}_r) \psi - K_D S \quad (2)$$

where ψ is switching function designed according to the variable structure theory.

Since $M \dot{S} = M \ddot{q} - M \ddot{q}_r$

$$= \tau - C(q, \dot{q}) \dot{q} - G - M \ddot{q}_r$$

$$= \tau - C(q, \dot{q}) \dot{q}_r - G - M \ddot{q}_r - C(q, \dot{q}) S$$

General approach to robot control

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

$$\begin{aligned}
&= \tau - \gamma(q, \dot{q}, q_r, \dot{q}_r) \alpha - c(q, \dot{q}) s \\
&= \gamma(q, \dot{q}, q_r, \dot{q}_r) \psi - \gamma(q, \dot{q}, q_r, \dot{q}_r) \alpha \\
&\quad - c(q, \dot{q}) s - K_D s \quad (3)
\end{aligned}$$

The generalized Lyapunov function

$$V = \frac{1}{2} s^T M s$$

{ original Lyapunov function was

$$V = \frac{1}{2} s^T M s + \tilde{\alpha}^T \tilde{\Gamma} \tilde{\alpha}; \text{ since we cannot estimate } \tilde{\alpha} \text{ we just take the first part}$$

Differentiating with respect to time yields,

$$\dot{V} = s^T M \dot{s} + \frac{1}{2} s^T \dot{M} s$$

$$= s^T (\gamma \psi - \gamma \alpha - K_D s) + \frac{1}{2} s^T \underbrace{(\dot{M} - 2c)}_0 s$$

(Using
skew
symmetric
property.)

$$= s^T (\gamma \psi - \gamma \alpha - K_D s) \quad (4)$$

Now choosing

$$\psi_i' = -\tilde{\alpha}_i \operatorname{sgn} \left(\sum_{j=1}^n S_j' Y_{ji} \right)$$

where $\tilde{\alpha}_i \gg |\alpha_i|, \forall i$

then,

$$\begin{aligned} \dot{V} &= -S^T K_D S - \sum_{i=1}^m \tilde{\alpha}_i \left| \sum_{j=1}^n S_j' Y_{ji} \right| \\ &= -\sum_{i=1}^m \alpha_i \sum_{j=1}^n S_j' Y_{ji} \leq -S^T K_D S \end{aligned} \quad (5)$$

Therefore,

$\|S\| \rightarrow 0$ at least exponentially
converges to zero which implies
that $\ddot{q} \rightarrow 0$ as $t \rightarrow \infty$

Remarks:

(1) In sliding mode, the resulting system equation $\Lambda = \text{a positive constant matrix.}$

$$\ddot{\tilde{q}} = -\Lambda \tilde{q} \quad (6)$$

Equation (6) represents n uncoupled first order linear system and the system only depends on the parameter

$\dot{S} = \ddot{q} + \Lambda \dot{q} = 0$

1.

Clearly the robustness to the uncertainty is guaranteed.

(2) It differs from adaptive control in that no learning mechanism is used, and has the advantage of prescribed transient response in sliding mode.

Estimating $\hat{\alpha}$ parameters

$$\hat{\alpha}_i = \eta_i / \left| \sum_{j=1}^n s_j y_{ji} \right|, \quad i = 1, \dots, n$$

where, η_i are arbitrary constants.
Consider a Lyapunov function

$$V = \frac{1}{2} S^T M S + \frac{1}{2} \sum_{i=1}^m (\alpha_i - \hat{\alpha}_i)^2 / \eta_i$$

\Downarrow
 $Y\alpha$

~~Minimize~~

The time derivative is given by

$$\dot{V} = S^T M \dot{S} + \frac{1}{2} S^T M S + \sum_{i=1}^m (\alpha_i - \hat{\alpha}_i) \frac{(-\dot{\hat{\alpha}}_i)}{\eta_i}$$

$$= S^T (Y\psi - Y\alpha - K_0 S) - \sum_{i=1}^m (\alpha_i - \hat{\alpha}_i) \frac{\dot{\hat{\alpha}}_i}{\eta_i} + \sum_{i=1}^m \hat{\alpha}_i \frac{\dot{\hat{\alpha}}_i}{\eta_i}$$

$$\left| \sum_{j=1}^n s_j y_{ji} \right| \leq -S^T K_0 S$$