

Motion Control of Robotic Manipulators

Dongjun Lee (이동준)

Department of Mechanical & Aerospace Engineering
Seoul National University

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Computed Torque Control

- Robot open-loop dynamics:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + f$$

where $\tau \in \mathbb{R}^n$ is the control torque and $f \in \mathbb{R}^n$ external force.

- Trajectory tracking control: design τ s.t., with $f \approx 0$,

$$(q(t), \dot{q}(t)) \rightarrow (q_d(t), \dot{q}_d(t))$$

where $q_d(t) \in \mathbb{R}^n$ is smooth joint trajectory (e.g., from IK: for WS, later).

- Computed torque control:** design τ s.t.,

$$\tau = M(q)[\ddot{q}_d - B(\dot{q} - \dot{q}_d) - K(q - q_d)] + C(q, \dot{q})\dot{q} + g(q)$$

so that the closed-loop dynamics becomes: with $e := q_d - q$,
exact dynamics cancelation

$$\ddot{e} + B\dot{e} + Ke = 0$$

implying that $(\dot{e}, e) \rightarrow 0$ exponentially, if $B, K \in \mathbb{R}^{n \times n}$ are positive-definite and symmetric (even for non-diagonal B, K).



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Stability of Second-Order LTI System

- Closed-loop error dynamics:

$$\ddot{e} + B\dot{e} + Ke = 0$$

- Define $x := (\dot{e}, e) \in \mathbb{R}^{2n}$. Then, the state-space representation:

$$\dot{x} = Ax = \begin{bmatrix} -B & -K \\ I & 0 \end{bmatrix} x = Ax$$

with all the **eigenvalues** $\lambda(A)$ in LHP, i.e., $x \rightarrow 0$ exponentially.

- Define $V = \frac{1}{2}\dot{e}^T\dot{e} + \frac{1}{2}e^Te = \frac{1}{2}x^Tx$. Then,

$$\dot{V} = \dot{e}^T[-B\dot{e} - Ke] + \dot{e}^TKe = -\dot{e}^TB\dot{e}$$

implying $\dot{e} \rightarrow 0$ likely (since $V \geq 0$); if so, $\ddot{e} \rightarrow 0$ likely and $e \rightarrow 0$ as well.

- This yet still implies that

$$\frac{1}{2}\|x(t)\|_2^2 = \frac{1}{2}\dot{e}^T\dot{e} + \frac{1}{2}e^Te = V(t) \leq V(0) = \frac{1}{2}\|x(0)\|_2^2$$

i.e., $\|x(t)\| \leq \|x(0)\| \Rightarrow$ starts close, stay close (stability?).

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Cross-Coupling Term

- Define $V = \frac{1}{2}\dot{e}^T\dot{e} + \epsilon e^T\dot{e} + \frac{1}{2}e^T[K + \epsilon B]e$. Then,

cross-coupling term

$$\dot{V} = -\dot{e}^T[B - \epsilon I]\dot{e} - \epsilon e^TKe$$

where $V \geq 0$ and $\dot{V} \leq 0$ with small-enough $\epsilon > 0$: likely $\dot{V} \rightarrow 0$, $e \rightarrow 0$.

- With cross-coupling $c > 0$, we have

$$V = \frac{1}{2} \begin{pmatrix} \dot{e} \\ e \end{pmatrix}^T \begin{bmatrix} I & \epsilon I \\ \epsilon I & K + \epsilon B \end{bmatrix} \begin{pmatrix} \dot{e} \\ e \end{pmatrix}, \quad \dot{V} = - \begin{pmatrix} \dot{e} \\ e \end{pmatrix}^T \begin{bmatrix} B - \epsilon I & 0 \\ 0 & \epsilon K \end{bmatrix} \begin{pmatrix} \dot{e} \\ e \end{pmatrix}$$

with $P, Q \in \mathbb{R}^{2n \times 2n}$ are positive-definite with small enough $\epsilon > 0$, from

$$\begin{bmatrix} A & B \\ B^* & C \end{bmatrix} > 0, \quad \text{if } A = A^* = \bar{A}^T > 0, C > B^*A^{-1}B$$

- Thus, with small-enough $\epsilon > 0$,

$$\dot{V} = -x^T Q x \leq -\lambda_{\min}[Q]\|x\|^2 \leq -\frac{\lambda_{\min}[Q]}{\lambda_{\max}[P]} V = -\gamma V$$

implying that $V(t) \leq V(0)e^{-\gamma t}$, i.e., $(\dot{e}, e) \rightarrow 0$ exponentially.

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Lyapunov Stability - Definition

Def. 2.1: Consider an **autonomous** system

$$\dot{x} = f(x), \quad f(0) = 0$$

$f : \mathcal{D} \rightarrow \mathbb{R}^n$ locally Lipschitz on \mathcal{D} and $0 \in \mathcal{D}$. Then, equilibrium $x = 0$ is

- **Lyapunov stable**, if, $\forall \epsilon > 0, \exists \delta(\epsilon) > 0$ s.t.,

$$\|x(0)\| < \delta \implies \|x(t)\| < \epsilon, \quad \forall t \geq 0$$

- **unstable**, if it is not stable

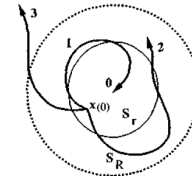
- **asymptotically stable**, if it is stable and we can find $\delta' > 0$ s.t.

$$\|x(0)\| < \delta' \implies \|x(t)\| \rightarrow 0$$

- **exponentially stable** if $\exists \alpha, \gamma, \delta' > 0$ s.t.,

$$\|x(0)\| < \delta' \implies \|x(t)\| \leq \alpha \|x(0)\| e^{-\gamma t}$$

- **globally asymptotically stable**, if asymptotically stable for any $\forall x(0) \in \mathbb{R}^n$.



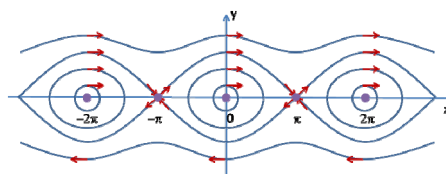
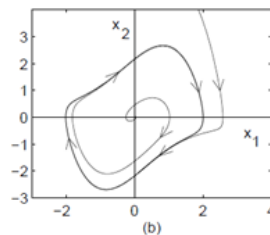
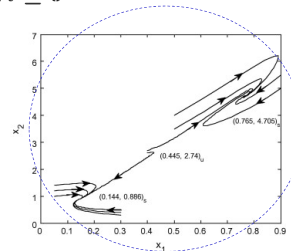
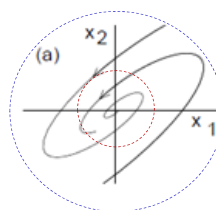
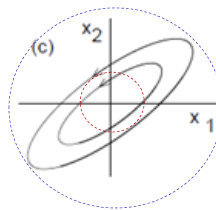
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Lyapunov Stability - Examples

Lyapunov stable, if, for any $\epsilon > 0$, there exists $\delta(\epsilon) > 0$ s.t.,

$$\|x(0)\| < \delta \implies \|x(t)\| < \epsilon, \quad \forall t \geq 0$$



satisfy definition: 1) for some ϵ or 2) $\forall \delta, \exists \epsilon$

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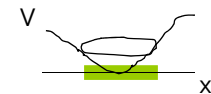
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Lyapunov Direct Theorem

Th. 2.1. (Lyapunov Direct): If we can find a Lyapunov function $V : \mathcal{D} \rightarrow \mathbb{R}$, which is continuously differentiable and satisfies

$$V(x) \geq 0 \text{ in } \mathcal{D}, \text{ with } V(x) = 0 \text{ iff } x = 0$$

negative semi-definite $\leftarrow \dot{V}(x) \leq 0$ in \mathcal{D} along the solution of $\dot{x} = f(x)$



then, $x = 0$ is **Lyapunov stable** (ex. $V = \frac{1}{2}x^T x$). Moreover, if

$$\dot{V}(x) \leq 0 \text{ in } \mathcal{D}, \text{ with } \dot{V}(x) = 0 \text{ iff } x = 0 \longrightarrow \text{negative-definite}$$

then, $x = 0$ is **asymptotically stable** (ex. $V = \frac{1}{2}x^T P x$). Furthermore, if

$$k_1 \|x\|^2 \leq V(x) \leq k_2 \|x\|^2, \quad \text{with} \quad \dot{V} \leq -k_3 \|x\|^2 \leq -\frac{k_3}{k_2} V$$

then, $x = 0$ is **exponentially stable** with $\|x(t)\| \leq \sqrt{\frac{V(0)}{k_1}} e^{-\frac{k_3}{2k_2} t} \rightarrow 0$.

- Here, $\dot{V}(x)$ is time differentiation of V along the solution $\dot{x} = f(x)$, i.e.,

$$\dot{V}(x) = \frac{\partial V}{\partial x} \dot{x} = \frac{\partial V}{\partial x} f(x) = \mathcal{L}_f V$$

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Lyapunov Stability – Non-autonomous System

Consider non-autonomous system

$$\dot{x} = f(t, x)$$

where $f : [0, \infty) \times \mathcal{D} \rightarrow \mathbb{R}^n$ piecewise continuous in t and locally Lipschitz in x , and $x = 0$ is an equilibrium at $t = t_o$, i.e.,

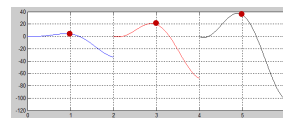
$$f(t, 0) = 0, \quad \forall t \geq t_o \geq 0$$

Def. 2.2: The equilibrium $x = 0$ of the non-autonomous system is

- stable, if, $\forall \epsilon > 0, \exists \delta(\epsilon, t_o) > 0$ s.t.

$$\|x(t_o)\| < \delta \Rightarrow \|x(t)\| < \epsilon, \quad \forall t \geq t_o \geq 0$$

- uniformly stable, if $\delta(\epsilon) > 0$ is independent of t_o .
- unstable, if not stable.



Ex) $\dot{x} = (6t \sin t - 2t)x$ with $t_o = 2n\pi$: $x(t) = e^{\int_{t_o}^t (6\tau \sin \tau - 2\tau) d\tau} x(t_o)$
 $x(t) = e^{6 \sin t - 6t \cos t - t^2 - 6 \sin t_o + 6t_o \cos t_o + t_o^2} x(t_o) \rightarrow 0$ as $t \rightarrow \infty$
 when evaluated at $t = t_o + \pi$: $|x(t_o + \pi)| = |x(t_o) e^{(4n+1)(6-\pi)\pi}| \leq \epsilon$
 $\delta(\epsilon, n) = \epsilon / e^{(4n+1)(6-\pi)\pi} \rightarrow 0$ as $n \rightarrow \infty$

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Lyapunov Direct Theorem

Th. 2.6: Consider non-autonomous system with equilibrium at $x = 0 \in \mathcal{D}$. Suppose we can find a continuously differentiable function $V(t, x)$ s.t.

$$\alpha_1(\|x\|) \leq V(t, x) \leq \alpha_2(\|x\|) \quad \text{decrecent condition}$$

$$\frac{dV}{dt} = \frac{\partial V}{\partial t} + \frac{\partial V}{\partial x} f(t, x) \leq 0$$

$\forall t \geq 0$ and $\forall x \in \mathcal{D}$, where $\alpha_i \in \mathcal{K}$ on \mathcal{D} . Then, $x = 0$ is **uniformly stable**. Moreover, if

$$\frac{\partial V}{\partial t} + \frac{\partial V}{\partial x} f(t, x) \leq -\alpha_3(\|x\|)$$

strictly-increasing with $\alpha(0)=0$

$\forall t \geq 0$ and $\forall x \in \mathcal{D}$, where $\alpha_3 \in \mathcal{K}$ on \mathcal{D} , $x = 0$ is **uniformly A.S.** Further, if

$$k_1\|x\|^2 \leq V(t, x) \leq k_2\|x\|^2, \quad \frac{\partial V}{\partial t} + \frac{\partial V}{\partial x} f(t, x) \leq -k_3\|x\|^2$$

$\forall t \geq 0$ and $\forall x \in \mathcal{D}$, where $k_i, a > 0$ are constants. Then, $x = 0$ is **U.E.S.**, i.e.,

$$\|x(t)\| \leq k\|x(t_0)\|e^{-\lambda(t-t_0)}$$

- Quadratic LF $V = x^T P x$ with $\dot{V} = -x^T Q x$ satisfies above conditions.

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Passivity-Based Control

- Robot open-loop dynamics:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + f$$

which is passive, i.e., $\dot{M} - 2C$ is skew-symmetric, or, equivalently, $\forall T \geq 0$,

$$\int_0^T [\tau + f]^T \dot{q} dt = E(T) - E(0)$$

- Computed torque control:

$$\tau = M(q)[\ddot{q}_d - B(\dot{q} - \dot{q}_d) - K(q - q_d)] + C(q, \dot{q})\dot{q} + g(q)$$

which is not so robust and also cancels out nonlinear dynamics rather than utilizes it (as typical for any **feedback linearization**).

- **Passivity-based control:**

$$\tau = \hat{M}(q)\ddot{q}_d + \hat{C}(q, \dot{q})\dot{q}_d + \hat{g}(q) - K_d(\dot{q} - \dot{q}_d) - K_p(q - q_d)$$

with $\hat{\star}$ are estimates, $K_d, K_p \in \mathbb{R}^{n \times n}$ are symmetric and PD gain matrices.

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Passivity-Based Tracking Control

- Robot open-loop dynamics:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + f$$

with $f \approx 0$ and skew-symmetric $\dot{M} - 2C$.

- Passivity-based control:**

$$\tau = M(q)\ddot{q}_d + C(q, \dot{q})\dot{q}_d + g(q) - K_d(\dot{q} - \dot{q}_d) - K_p(q - q_d)$$

- Closed-loop error dynamics: with $e = q - q_d$,

$$M(q)\ddot{e} + C(q, \dot{q})\dot{e} + K_d\dot{e} + K_p e = 0 \quad \longrightarrow \text{dynamics utilized}$$

- Define energy-like Lyapunov function $V = \frac{1}{2}\dot{e}^T M \dot{e} + \frac{1}{2}e^T K_p e$. Then, from the skew-symmetry,

$$\dot{V} = \dot{e}^T M \ddot{e} + \frac{1}{2}\dot{e}^T \dot{M} \dot{e} + \dot{e}^T K_p e = -\dot{e}^T K_d \dot{e}$$

implying that $(\dot{e}, e) = 0$ is only Lyapunov stable. However, it is observed that $(\dot{e}, e) \rightarrow 0$ exponentially.

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Passivity-Based Stabilization

- Consider passivity-based stabilization control:

$$\tau = g(q) - K_d\dot{q} - K_p(q - q_d)$$

to achieve $(\dot{q}, q) \rightarrow (0, q_d)$.

- Then, the closed-loop dynamics becomes:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + K_d\dot{q} + K_p(q - q_d) = 0$$

which should satisfy $(\dot{q}, q) \rightarrow (0, q_d)$ as it's mass-spring-damper system.

- Yet, Lyapunov analysis is inconclusive even for this simple system, i.e, if we use total energy as Lyapunov function

$$V = \frac{1}{2}\dot{q}^T M \dot{q} + \frac{1}{2}e^T K_p e$$

we have

$$\dot{V} = -\dot{q}^T K_d \dot{q} \leq 0$$

- There may be better Lyapunov function, which, yet, in general, is difficult to find (i.e., not constructive approach) \Rightarrow invariance principle.

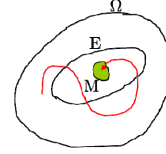
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Invariance Principle

- **LaSalle's Invariance Principle:** Consider autonomous system

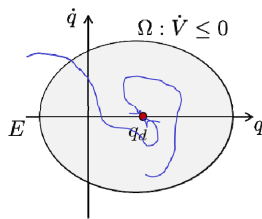
$$\dot{x} = f(x), \quad x \in \mathbb{R}^n, \quad f(0) = 0$$



Suppose \exists compact (i.e., bounded and closed) set $\Omega \in \mathbb{R}^n$ s.t., if $x(t) \in \Omega$, $x(t') \in \Omega \quad \forall t' \geq t$ (i.e., Ω positive invariant set). Suppose further \exists a continuously differentiable $V : \mathbb{R}^n \rightarrow \mathbb{R}$ s.t., $\dot{V}(x) \leq 0 \quad \forall x \in \Omega$. Define

$$E := \{x \in \Omega \mid \dot{V}(x) = 0\}$$

and $M \subset E \subset \Omega$ be the largest invariant set in E . Then, if $x(0) \in \Omega$, $x(t) \rightarrow M$.



1. Compact and positive-invariant set Ω :

$$\frac{1}{2} \lambda_{\min}[K_p] \|q - q_d\|^2 + \frac{1}{2} \lambda_{\min}[M] \|\dot{q}\|^2 \leq V(t) \leq V(0)$$

2. The set $E = \{(q, \dot{q}) \mid \dot{V} = 0\} = \{(q, \dot{q}) \mid \dot{q} = 0\}$.

3. If $\dot{q} = 0$ but $q \neq q_d$, $\ddot{q} \neq 0 \Rightarrow \dot{q} \neq 0$. Thus,

$$M = \{(q, \dot{q}) = (q_d, 0)\} \quad \text{i.e.,} \quad (q, \dot{q}) \rightarrow (q_d, 0)$$

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Passivity-Based Tracking Control

- Consider passivity-based trajectory tracking control:

$$\tau = M(q)\ddot{q}_d + C(q, \dot{q})\dot{q}_d + g(q) - K_d(\dot{q} - \dot{q}_d) - K_p(q - q_d)$$

- Then, the closed-loop error dynamics becomes: with $e = q - q_d$,

$$M(q)\ddot{e} + C(q, \dot{q})\dot{e} + K_d\dot{e} + K_p e = 0$$

- This closed-loop dynamics is **non-autonomous** system. Thus, LaSalle's invariance principle not applicable.
- Yet, with skew-symmetry of original dynamics, the closed-loop dynamics still behaves like mass-spring-damper system, i.e.,

$$V = \frac{1}{2} \dot{e}^T M \dot{e} + \frac{1}{2} e^T K_p e \quad \Rightarrow \quad \dot{V} = -\dot{e}^T K_d \dot{e}$$

which looks like damping dissipation.

- This then would likely imply that $\dot{e} \rightarrow 0$ as V is lower-bounded by 0. Then, $e \rightarrow 0$? \Rightarrow **Barbalat's lemma**.

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Barbalat's Lemma

Lem. (Barbalat's) Suppose $f(t) \rightarrow c$. Then, $\dot{f}(t) \rightarrow 0$, if $\dot{f}(t)$ is uniformly continuous, i.e., $\forall \epsilon > 0, \exists \delta(\epsilon) > 0$ s.t.,

$$|t_1 - t_2| \leq \delta(\epsilon) \implies |\dot{f}(t_1) - \dot{f}(t_2)| \leq \epsilon, \quad \forall t_1, t_2 \geq 0.$$

- If $\ddot{f}(t)$ is uniformly bounded, $\dot{f}(t)$ is uniformly continuous (MVT)
- Applicable both to autonomous & non-autonomous systems
- $f \rightarrow c$, yet, not $\dot{f} \rightarrow 0$: $f(t) = e^{-t} \sin e^{2t}$, $\dot{f}(t) = e^{-t} \sin e^{2t} + 2e^t \cos e^{2t}$
- $\dot{f} \rightarrow 0$, yet, not $f \rightarrow c$: $f(t) = \sin(\ln t)$, $\dot{f}(t) = \frac{1}{t} \cos(\ln t)$

Corollary: Suppose $f(t)$ is square-integrable (i.e., $\int_0^\infty f^2(\tau) d\tau < \infty$) and $\dot{f}(t)$ is bounded. Then, $f(t) \rightarrow 0$.

(Proof) Define $g(t) = \int_0^t f^2(\sigma) d\sigma$. From the assumption, $\lim_{t \rightarrow \infty} g(t) = c$. Then, from Barbalat's, $\dot{g}(t) = f^2(t) \rightarrow 0$ if \dot{g} is UC or $\ddot{g} = 2\dot{f}f$ is bounded.
 - Here, 1) \dot{f} is assumed to be bounded; and 2) $f(t)$ cannot be unbounded, since, if so, $\int_0^t f^2(\sigma) d\sigma$ will also be unbounded (with \dot{f} bounded).
 - Thus, \ddot{g} is bounded $\implies \dot{g}$ is UC $\implies f \rightarrow 0$.

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Trajectory Tracking Convergence Proof

- The closed-loop error dynamics:

$$M(q)\ddot{e} + C(q, \dot{q})\dot{e} + K_d\dot{e} + K_p e = 0$$

- Using $V = \frac{1}{2}\dot{e}^T M\dot{e} + \frac{1}{2}e^T K_p e$, $\dot{V} = -\dot{e}^T K_d \dot{e}$, i.e., $V(t) - V(0) = -\int_0^t \dot{e}^T K_d \dot{e} d\tau$,
or,

$$0 \leq V(t) = V(0) - \int_0^t \dot{e}^T K_d \dot{e} d\tau \leq V(0)$$

implying that (\dot{e}, e) is bounded.

- From $\int_0^t \dot{e}^T K_d \dot{e} d\tau \leq V(0)$, \dot{e} is square integrable. Also, from the dynamics with bounded $(e, \dot{e}, q_d, \dot{q}_d)$, if $\frac{\partial m_{ij}}{\partial q_k}$ and $M \geq \lambda_{\min} I$, \ddot{e} will also be bounded, and $\dot{e} \rightarrow 0$ from the Corollary.
- Invoking BL again, with $\dot{e} \rightarrow 0$, $\ddot{e} \rightarrow 0$ if \ddot{e} is UC or \dddot{e} is bounded. This is true if $\frac{\partial^2 m_{ij}}{\partial q_p \partial q_r}$ is also bounded, since

$$M(q)\ddot{e} + \frac{dM(q)}{dt}\dot{e} + C\ddot{e} + \frac{dC(q, \dot{q})}{dt}\dot{e} + K_d\ddot{e} + K_p\dot{e} = 0$$

with $c_{kj} = \sum_i [\frac{\partial m_{kj}}{\partial q_i} + \frac{\partial m_{ki}}{\partial q_j} - \frac{\partial m_{ij}}{\partial q_k}] \dot{q}_i$. This then establish $e \rightarrow 0$ too.

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Trajectory Tracking Control - Theorem

Theorem: Consider robot dynamics with passivity-based tracking control as defined above. Then, if $q_d(t)$ is C^∞ -smooth, $\frac{\partial m_{ij}}{\partial q_k}$ and $\frac{\partial^2 m_{ij}}{\partial q_p \partial q_r}$ are bounded, and $\exists \lambda_{\min} > 0$ s.t., $\lambda_{\min} I \leq M(q)$, $(e, \dot{e}) \rightarrow 0$.

- The assumptions are always guaranteed for revolute joint robots.
- $(\dot{e}, e) \rightarrow 0$, yet, how fast is the convergence is not specified (may be extremely slow).
- Asymptotic stability may be fragile, that is, it may become divergent with a bit of disturbance, noise and/or uncertainty.
- Exponential convergence is always preferred to asymptotic convergence, as it automatically guarantees a level of **robustness** against external disturbances and parametric uncertainty (ultimately bounded).
- We can establish exponential convergence of the passivity-based tracking control with Lyapunov function with **cross-coupling** term as before:

$$V = \frac{1}{2} \dot{e}^T M \dot{e} + \epsilon \dot{e}^T M e + \frac{1}{2} e^T [K_p + \epsilon K_d] e$$

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Alternative Passivity-Based Control with r

- Consider again the robot dynamics:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + f, \quad f \approx 0$$

- Alternative passivity-based control with r -variable:

$$\tau = M[\ddot{q}_d - \Lambda \dot{e}] + C[\dot{q}_d - \Lambda e] + g(q) - K\dot{e} - K\Lambda e + \tau'$$

with $K, \Lambda \in \mathbb{R}^{n \times n}$ diagonal and positive-definite (i.e., $K\Lambda = \Lambda K$).

- The closed-loop dynamics becomes:

$$M(q)\dot{r} + C(q, \dot{q})r + Kr = \tau'$$

where $r := \dot{e} + \Lambda e$ serves now as velocity, defining new passivity input-output pair (τ', r) : with $V := \frac{1}{2} r^T M r$,

$$\dot{V} = r^T M \dot{r} + \frac{1}{2} r^T \dot{M} r = \tau'^T r - r^T K r$$

- With $\tau' = 0$, we have $\dot{V} = -r^T K r$ with $V = \frac{1}{2} r^T M r$, implying that $r = \dot{e} + \Lambda e \rightarrow 0$ exponentially (i.e., $(\dot{e}, e) \rightarrow 0$ exponentially too).

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Effect of Uncertainty - I

- Consider the robot dynamics:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + f, \quad f \approx 0$$

under passivity-based control with **parametric uncertainty**:

$$\tau_o = \hat{M}(q)[\ddot{q}_d - \Lambda \dot{e}] + \hat{C}(q, \dot{q})[\dot{q}_d - \Lambda e] + \hat{g}(q) - K\dot{e} - K\Lambda e$$

where $\hat{\star}$ is estimate of \star and $e = q - q_d$.

- From linearity in inertial parameters, $\forall y_1, y_2 \in \mathbb{R}^n$,

$$M(q)y_1 + C(q, \dot{q})y_2 + g(q) = Y(q, \dot{q}, y_1, y_2)\theta$$

where $Y \in \mathbb{R}^{n \times l}$ (known) regressor; $\theta \in \mathbb{R}^l$ (uncertain) inertia parameters.

- Since the estimated dynamics has the same structure,

$$\tau_o = Y(q, \dot{q}, \dot{\nu}, \nu)\hat{\theta} - K\dot{e} - K\Lambda e, \quad \nu = \dot{q}_d - \Lambda e$$

- Augment nominal control τ_o with $\delta\tau$ to address uncertainty:

$$\tau = \tau_o + \delta\tau$$

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Effect of Uncertainty - II

- Closed-loop dynamics:

$$M\ddot{q} + C\dot{q} + g = \hat{M}[\ddot{q}_d - \Lambda \dot{e}] + \hat{C}[\dot{q}_d - \Lambda e] + \hat{g} - K[\dot{e} + \Lambda e] + \delta\tau$$

- Subtracting $M[\ddot{q}_d - \Lambda \dot{e}] + C[\dot{q}_d - \Lambda e] + g$ from both sides, we obtain:

$$\begin{aligned} M[\ddot{e} + \Lambda \dot{e}] + C[\dot{e} + \Lambda e] + K[\dot{e} + \Lambda e] &= Y(q, \dot{q}, \nu, \dot{\nu})\hat{\theta} - Y(q, \dot{q}, \nu, \dot{\nu})\theta + \delta\tau \\ &= Y(q, \dot{q}, \nu, \dot{\nu})[\hat{\theta} - \theta] + \delta\tau \end{aligned}$$

or, using $r := \dot{e} + \Lambda e$,

$$M\dot{r} + Cr + Kr = Y[\hat{\theta} - \theta] + \delta\tau \rightarrow \text{matching uncertainty: appears in same channel with control}$$

- Define Lyapunov function as before: $V = \frac{1}{2}r^T M r$ (or $V = \frac{1}{2}r^T M r + e^T K \Lambda e$),

$$\frac{dV}{dt} = -r^T K r + r^T Y[\hat{\theta} - \hat{\theta}] + r^T \delta\tau$$

negative-definite as before want to make still negative even with uncertainty

- Robust control:** large-enough $\delta\tau$ to **absorb** the uncertainty effect
- Adaptive control:** adaptively change estimate $\hat{\theta}$ by seeing error r .

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Passivity-Based Robust Control

- Closed-loop dynamics: $M\dot{r} + Cr + Kr = Y[\hat{\theta} - \theta] + \delta\tau$.
- Using $V = \frac{1}{2}r^T Mr$, $\frac{dV}{dt} = -r^T Kr + r^T Y[\theta - \hat{\theta}] + r^T \delta\tau$. → matched uncertainty
- Suppose $\exists \rho \geq 0$ s.t., $\|\hat{\theta} - \theta\| \leq \rho$ (i.e., θ estimation error bounded). Then,

$$r^T Y(\theta - \hat{\theta}) + r^T \delta\tau \leq \|Y^T r\| \cdot \|\hat{\theta} - \theta\| + r^T \delta\tau \leq \|Y^T r\| \rho + r^T \delta\tau$$

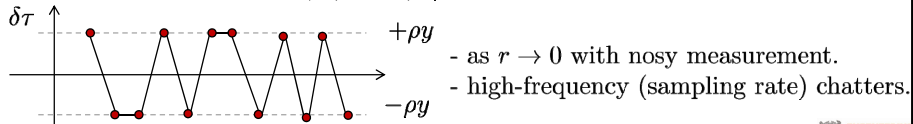
- Thus, if we choose the robust control term $\delta\tau := -\rho \frac{Y Y^T r}{\|Y^T r\|}$, we have

$$\frac{dV}{dt} \leq -r^T Kr + \|Y^T r\| \rho + r^T \left[-\rho \frac{Y Y^T r}{\|Y^T r\|} \right] \leq -r^T Kr$$

implying that $(e, \dot{e}) \rightarrow 0$ exponentially even under certainty.

- **Chattering:** control pushes $r \rightarrow 0$, yet, as $r \rightarrow 0$, $\delta\tau$ becomes un-defined.

For scalar case, $\delta\tau = -\rho \frac{y^2 r}{|yr|} = \rho y \frac{yr}{|yr|} = -\rho y \operatorname{sgn}(yr)$



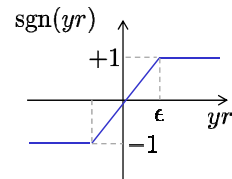
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Boundary-Layer Approximation

- To avoid chattering problem, instead of discontinuous control $\delta\tau = -\rho \frac{Y Y^T r}{\|Y^T r\|}$, we use its **boundary-layer approximation**:

$$\delta\tau = \begin{cases} -\rho Y \frac{Y^T r}{\|Y^T r\|} & \text{if } \|Y^T r\| > \epsilon \\ -\rho Y \frac{Y^T r}{\epsilon} & \text{if } \|Y^T r\| \leq \epsilon \end{cases}$$



- Then, if $\|Y^T r\| > \epsilon$, $\frac{dV}{dt} \leq -r^T Kr$. Also, if $\|Y^T r\| \leq \epsilon$,

$$\begin{aligned} \frac{dV}{dt} &\leq -r^T Kr + \rho \|Y^T r\| - \rho \frac{r^T Y Y^T r}{\epsilon} \\ &= -r^T Kr + \rho \|Y^T r\| - \rho \frac{\|Y^T r\|^2}{\epsilon} \\ &= -r^T Kr - \frac{\rho}{\epsilon} \left[\|Y^T r\| - \frac{\epsilon}{2} \right]^2 + \frac{\rho\epsilon}{4} \leq -r^T Kr + \frac{\rho\epsilon}{4} \rightarrow \text{hold for all } t \end{aligned}$$

- Here, if $\|r\|$ increases, \dot{V} will become negative $\rightarrow \|r\|$ starts to decrease $\rightarrow V$ will be bounded. In other words,

$$\frac{dV}{dt} \leq -\lambda_{\min}[K] \|r\|^2 + \frac{\rho\epsilon}{4} \leq -\frac{\lambda_{\min}[K]}{\lambda_{\max}[M]} V + \frac{\rho\epsilon}{4}$$

i.e., $V(t)$ is ultimately bounded by $\frac{\lambda_{\max}[M]}{\lambda_{\min}[K]} \frac{\rho\epsilon}{4}$.



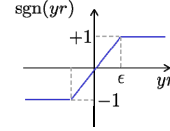
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Ultimate Boundedness

- To avoid chattering problem, instead of discontinuous control $\delta\tau = -\rho \frac{Y Y^T r}{\|Y^T r\|}$, we use its **boundary-layer approximation**:

$$\delta\tau = \begin{cases} -\rho Y \frac{Y^T r}{\|Y^T r\|} & \text{if } \|Y^T r\| > \epsilon \\ -\rho Y \frac{Y^T r}{\epsilon} & \text{if } \|Y^T r\| \leq \epsilon \end{cases}$$

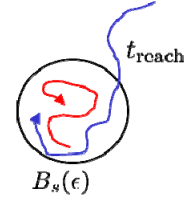


- $V(t)$ is **ultimately bounded** by $\frac{\lambda_{\max}[M]}{\lambda_{\min}[K]} \frac{\rho\epsilon}{4}$, since

$$\frac{dV}{dt} \leq -\lambda_{\min}[K] \|r\|^2 + \frac{\rho\epsilon}{4} \leq -\frac{\lambda_{\min}[K]}{\lambda_{\max}[M]} V + \frac{\rho\epsilon}{4}$$

- $r(t)$ eventually enters into the bounded set

$$B_s := \{r \mid \|r\| \leq \sqrt{\frac{\lambda_{\max}[M]}{\lambda_{\min}[M]\lambda_{\min}[K]} \frac{\rho\epsilon}{4}}\}$$



- U.B. set B_s gets smaller if ρ is small (i.e., good estimation of θ) or ϵ is small (i.e., tighter approximation) or $\lambda_{\min}[K]$ is large (i.e., large feedback gain).
- Note that B_s is positive-invariant, i.e., $r(t)$ may start outside, yet, eventually enters into it, and, once in it, $r(t)$ will stay in B_s afterward.

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Passivity-Based Adaptive Control

- Robot dynamics: $M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + f$, $f \approx 0$.
- Tracking control: $\tau = \hat{M}(q)[\ddot{q}_d - \Lambda\dot{e}] + \hat{C}(q, \dot{q})[\dot{q}_d - \Lambda e] + \hat{g}(q) - K\dot{e} - K\Lambda e$. Here, we **adaptively change** $\hat{\theta}(t)$ instead of large-action $\delta\tau$.
- Closed-loop dynamics:

$$M\dot{r} + Cr + Kr = Y[\hat{\theta} - \theta] = Y\tilde{\theta}$$

where $\tilde{\theta} = \hat{\theta}(t) - \theta$ is parameter estimation error for constant θ . Note that $\hat{\theta}$ constitutes another state vector, since it has its own dynamics.

- Define $V = \frac{1}{2}r^T M r + \frac{1}{2}\tilde{\theta}^T \Gamma \tilde{\theta}$ with symmetric and pd $\Gamma \in \mathbb{R}^{l \times l}$. Then,

$$\frac{dV}{dt} = -r^T K r + r^T Y \tilde{\theta} + \tilde{\theta}^T \Gamma \tilde{\theta} = -r^T K r + \tilde{\theta}^T [Y^T r + \Gamma \dot{\tilde{\theta}}]$$

passivity (cf. CLF)

- This then suggests the following adaptation law

$$\dot{\tilde{\theta}} = \frac{d\hat{\theta}}{dt} = \Gamma^{-1} Y^T (q, \dot{q}, \nu, \dot{\nu}) r(t), \quad \nu = \dot{q}_d(t) - \Lambda e(t)$$

with which we have $\frac{dV}{dt} = -r^T K r$, i.e., $(r, \tilde{\theta})$ is Lyapunov stable.

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Convergence Proof

- Closed-loop dynamics: $M\dot{r} + Cr + Kr = Y[\hat{\theta} - \theta] = Y\tilde{\theta}$.
- Define $V = \frac{1}{2}r^T Mr + \frac{1}{2}\tilde{\theta}^T \Gamma \tilde{\theta}$. Then, with adaptation law $\frac{d\hat{\theta}}{dt} = \Gamma^{-1}Y^T r$, we have $\frac{dV}{dt} = -r^T K r$, i.e., $(r, \tilde{\theta}) = 0$ is only Lyapunov stable.
- Integrating this, we have, $\forall T \geq 0$,

$$V(T) = V(0) - \int_0^T r^T K r dt \leq V(0)$$

implying that $r \in \mathcal{L}_2$. Also, if $|\frac{\partial m_{ij}}{\partial q_k}|$ is bounded, $\dot{r} \in \mathcal{L}_\infty$. Then, from the Corollary of Barbalat's lemma, $r \rightarrow 0$.

- We now have $(e, \dot{e}) \rightarrow 0$. Then, $\tilde{\theta}(t) = \hat{\theta}(t) - \theta \rightarrow 0$ as well? When this parameter convergence possible? \Rightarrow **persistency of excitation**.
- With $r \rightarrow 0$, we have $\dot{\tilde{\theta}} \rightarrow 0$ from adaptation. We also have $Y^T \tilde{\theta} \rightarrow 0$ from C.L. dynamics. This then collectively defines LTV dynamics

$$\dot{\tilde{\theta}} = 0, \quad y = Y^T(q, \dot{q}, \nu, \dot{\nu})\tilde{\theta} = Y^T(q_d, \dot{q}_d, \ddot{q}_d)\tilde{\theta}$$

with the output $y \rightarrow 0$. Does this then also implies $\tilde{\theta} \rightarrow 0$?

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Observability of LTV Systems

- LTV dynamics of parameter estimation error $\tilde{\theta}$:

$$\dot{\tilde{\theta}} = 0, \quad y = Y^T(q_d, \dot{q}_d, \ddot{q}_d)\tilde{\theta}$$

with the output $y \rightarrow 0$. If $Y \in \mathbb{R}^{n \times l}$ is rich enough (e.g., non-singular square), $y \rightarrow 0$ would imply $\tilde{\theta} \rightarrow 0$. However, if Y is not rich enough (e.g., constant fat), $y \rightarrow 0$ wouldn't imply $\tilde{\theta} \rightarrow 0$.

- **Definition:** A LTV system $\dot{x} = A(t)x$, $y = C(t)x$ is **observable** if, $\forall t' > 0$, the initial state $x(0)$ is uniquely determined by $y(t)$, $t = [0, t']$.

- **Theorem:** LTV system $\dot{x} = A(t)x$, $y = C(t)x$ is **observable** on $[t_o, t_f]$ iff

$$W_o(t_o, t_f) = \int_{t_o}^{t_f} \Phi(t, t_o) C^T(t) C(t) \Phi(t, t_o) dt \geq \sigma_o I$$

where $\sigma_o > 0$, $\Phi(t, t_o)$ is the transition matrix with $x(t) = \Phi(t, t_o)x(0)$, and W_o is **observability grammian**.

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Observability Grammian

- **Theorem:** LTV system $\dot{x} = A(t)x$, $y = C(t)x$ is **observable** on $[t_o, t_f]$ iff

$$W_o(t_o, t_f) = \int_{t_o}^{t_f} \Phi(t, t_o) C^T(t) C(t) \Phi(t, t_o) dt \geq \sigma_o I$$

where $\sigma_o > 0$, $\Phi(t, t_o)$ is the transition matrix with $x(t) = \Phi(t, t_o)x(0)$, and W_o is **observability grammian**.

(Proof) From $y = C(t)x = C(t)\Phi(t, t_o)x(0)$, we have

$$\int_{t_o}^{t_f} \Phi^T(t, t_o) C^T(t) y(t) dt = \int_{t_o}^{t_f} \Phi^T(t, t_o) C^T(t) C(t) \Phi(t, t_o) dt \cdot x(0)$$

thus, if the above condition holds, $x(0)$ is uniquely determined by

$$x(0) = W_o^{-1}(t_o, t_f) \int_{t_o}^{t_f} \Phi^T(t, t_o) C^T(t) y(t) dt$$

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Persistency of Excitation

- **Theorem:** LTV system $\dot{x} = A(t)x$, $y = C(t)x$ is **observable** on $[t_o, t_f]$ iff

$$W_o(t_o, t_f) = \int_{t_o}^{t_f} \Phi(t, t_o) C^T(t) C(t) \Phi(t, t_o) dt \geq \sigma_o I$$

with

$$x(0) = W_o^{-1}(t_o, t_f) \int_{t_o}^{t_f} \Phi^T(t, t_o) C^T(t) y(t) dt$$

- Consider the LTV dynamics of parameter estimation error $\tilde{\theta}$:

$$\dot{\tilde{\theta}} = 0, \quad y = Y^T(q_d, \dot{q}_d, \ddot{q}_d) \tilde{\theta}$$

with $\Phi(t_o, t_f) = I$. Then, with the output $y \rightarrow 0$, we will have $\tilde{\theta} \rightarrow 0$, if

$$W_o(t+T, t) = \int_t^{t+T} Y^T(q_d, \dot{q}_d, \ddot{q}_d) Y(q_d, \dot{q}_d, \ddot{q}_d) dt \geq \sigma_o I, \quad \forall t \geq 0$$

for some positive constants $T > 0$ and $\sigma_o > 0$.

- This condition is referred to (uniform) **persistency of excitation**, i.e., the signal q_d is rich enough and persistently exciting the system so that $Y^T(q_d, \dot{q}_d, \ddot{q}_d) \tilde{\theta} \rightarrow 0$ should necessarily imply $\tilde{\theta} \rightarrow 0$ as well.

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Workspace EF Control

Consider the robot dynamics

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + \tau_e$$

where $q \in \mathbb{R}^n$ is joint configuration and $\tau_e \in \mathbb{R}^n$ is external wrench effect.

- In most applications, tasks are specified for the end-effector $x \in f(q) \in \mathbb{R}^m$, not for the joint configuration $q \in \mathbb{R}^n$, thus, want to control x directly.
- Let $f(q) \in \mathbb{R}^m$ be a minimal representation of EF motion for the task. Assume $n = m$ and $J(q) = \frac{\partial f}{\partial q} \in \mathbb{R}^{n \times n}$ locally full-rank (i.e., f also locally invertible).
- For instance, $(x, y, z, \phi, \theta, \psi)$ for EF in SE(3) with $\tau_e = J^T(q)f_e$, where $f_e \in \mathfrak{se}^*(3)$ is wrench, i.e., force and torque.
- We then have the following kinematics relations:

$$\begin{aligned} \dot{x} &= \frac{\partial f}{\partial q} \dot{q} = J(q)\dot{q} \quad \rightarrow \quad \dot{q} = J^{-1}(q)\dot{x} \\ \ddot{q} &= \frac{d}{dt}[J^{-1}(q)\dot{x}] = \frac{dJ^{-1}(q)}{dt}\dot{x} + J^{-1}(q)\ddot{x} \end{aligned}$$

where $\frac{d}{dt}[J^{-1}(q)] = -J^{-1}(q)\dot{J}(q)J^{-1}(q)$.



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Workspace Dynamics

- The robot dynamics in joint-space

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + J^T(q)f_e$$

- Using $\dot{q} = J^{-1}(q)\dot{x}$ and $\ddot{q} = \frac{dJ^{-1}}{dt}\dot{x} + J^{-1}(q)\ddot{x}$, can rewrite joint-space dynamics:

$$\begin{aligned} M(q)[J^{-1}\ddot{x} + \frac{dJ^{-1}}{dt}\dot{x}] + C(q, \dot{q})J^{-1}\dot{x} + g(q) &= \tau + J^T f_e \\ \Rightarrow J^{-T}M(q)J^{-1}\ddot{x} + J^{-T}[M(q)\frac{dJ^{-1}}{dt} + C(q, \dot{q})J^{-1}]\dot{x} + J^{-T}g(q) &= J^{-T}\tau + f_e \end{aligned}$$

from which we can obtain the **robot workspace dynamics**:

$$D(x)\ddot{x} + Q(x, \dot{x})\dot{x} + g_x(x) = u + f_e$$

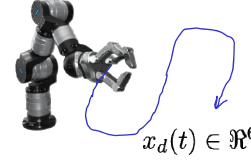
- $D(x) = J^{-T}M(q)J^{-1} \in \mathbb{R}^{n \times n}$ is symmetric and positive-definite.
- $Q(x, \dot{x}) = J^{-T}[M(q)\frac{dJ^{-1}}{dt} + C(q, \dot{q})J^{-1}]$ is workspace Coriolis matrix.
- $\dot{D}(x) - 2Q(x, \dot{x})$ is skew-symmetric.
- $g_x(x) = J^{-T}g(q)$ is workspace gravity.
- $u = J^{-T}\tau$ is workspace control.
- $J(q)$ is analytic Jacobian with representation singularity.



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Workspace Control



- Consider the robot workspace dynamics:

$$D(x)\ddot{x} + Q(x, \dot{x})\dot{x} + g_x(x) = u + f_e$$

- Workspace EF trajectory tracking control objective:

$$(x(t), \dot{x}(t)) \rightarrow (x_d(t), \dot{x}_d(t))$$

- Passivity-based trajectory tracking control with r -variable:

$$u = D[\ddot{x}_d - \Lambda(\dot{x} - \dot{x}_d)] + Q[\dot{x}_d - \Lambda(x - x_d)] - K(\dot{x} - \dot{x}_d) - K\Lambda(x - x_d) + g_x - f_e$$

which results in exponentially-stable system

$$D(x)\dot{r} + Q(x, \dot{x})r + Kr = 0, \quad r := \dot{e} + \Lambda e, \quad e = x - x_d$$

- Real joint torque control: with $e = x(q(t)) - x_d(t)$,

$$\tau = J^T u = J^T(q) \cdot [D(q)(\ddot{x}_d - \Lambda\dot{e}) + Q(q, \dot{q})(\dot{x}_d - \Lambda e) - Kr] + g(q) - J^T(q)f_e$$

wrench sensing

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Workspace Control: Example

- Robot workspace dynamics:

$$D(q)\ddot{x} + Q(q, \dot{q})\dot{x} + g_x(q) = u$$

where $q = (\theta_1, \theta_2)$.

- We want to control the EF position in plane. Then,

$$f(q) = \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} l_1 c_1 + l_2 c_{12} \\ l_1 s_1 + l_2 s_{12} \end{pmatrix} \in \mathbb{R}^2$$

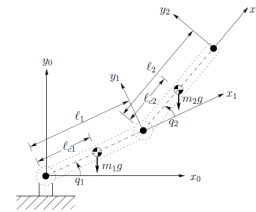
- Jacobian relation

$$\frac{df(q)}{dt} = J(q)\dot{q} = \begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = \begin{bmatrix} -l_1 s_1 - l_2 s_{12} & -l_2 s_{12} \\ l_1 c_1 + l_2 c_{12} & l_2 c_{12} \end{bmatrix} \begin{pmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{pmatrix}$$

with $J(q) \in \mathbb{R}^{2 \times 2}$ is full-rank if $\theta_2 \neq n\pi$.

- Workspace trajectory tracking control: with $e = x(q) - x_d(t)$,

$$\tau = J^T(q) \cdot [D(q)(\ddot{x}_d - \Lambda\dot{e}) + Q(q, \dot{q})(\dot{x}_d - \Lambda e) - Kr] + g(q)$$



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