

June 2, 2024

HOMework — 2

You can check the code below.
https://github.com/JU-SUK/motion_planning-24spring

1 Sliding Mode control

(a)

$$\begin{aligned}
 (*) \quad & M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + F(\dot{q}) = \tau + \tau_d \\
 \Rightarrow \quad & \text{let } x_1 = q, \quad x_2 = \dot{q}, \quad u = \tau \\
 & \begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x) + g(x)u \end{cases} \\
 \text{where } & x(t) = \begin{Bmatrix} q \\ \dot{q} \end{Bmatrix}, \quad g = \begin{Bmatrix} 0 \\ I \end{Bmatrix}, \quad f(x, t) = M(q)^{-1} (\tau_d - C(q, \dot{q})\dot{q} - G(q) - F(\dot{q})), \quad g(x, t) = M(q)^{-1} \\
 \Rightarrow \quad & \text{sliding surface } s = \dot{e} + \lambda e \quad \text{where } e = q - q_d \\
 \Rightarrow \quad & \dot{s} = \ddot{e} + \lambda \dot{e} \\
 & = \ddot{q} - \ddot{q}_d + \lambda (\dot{q} - \dot{q}_d) \\
 \Rightarrow \quad & \text{output system dynamics } \ddot{q} = f(x) + g(x)u \quad \text{or } \mathbb{R}^2 \\
 & \dot{s} = f(x) + g(x)u - \ddot{q}_d + \lambda (\dot{q} - \dot{q}_d) \\
 \text{By sliding law, } & \dot{s} = -ks + \eta \text{sign}(s) \\
 \Rightarrow \quad & ks + \eta \text{sign}(s) = f(x) + g(x)u - \ddot{q}_d + \lambda (\dot{q} - \dot{q}_d) \\
 \Rightarrow \quad & g(x)u = -f(x) + \ddot{q}_d - \lambda (\dot{q} - \dot{q}_d) + ks + \eta \text{sign}(s) \\
 \Rightarrow \quad & u = \frac{1}{g} (-f + \ddot{q}_d - \lambda \dot{e} + ks + \eta \text{sign}(s)) \\
 \Rightarrow \quad & u = \frac{1}{g} (-f + \ddot{q}_d - \lambda \dot{e} + ks + \eta \text{sign}(s) + D \text{sign}(s)) \\
 \text{Let Lyapunov Function } & V = \frac{1}{2} s^2 \\
 & \dot{V} = s \dot{s} \\
 & = s (\ddot{e} + \lambda \dot{e}) \\
 \text{or } \ddot{e} = \ddot{q} - \ddot{q}_d = f(x) + g(x)u - \ddot{q}_d = ks + \lambda \dot{e} + (\eta + D) \text{sign}(s) \\
 \Rightarrow \quad & \dot{V} = s (ks + \lambda \dot{e} + (\eta + D) \text{sign}(s) + \lambda \dot{e}) \\
 & = ks^2 + (\lambda + \eta + D) s \dot{e} + (\eta + D) s^2 \\
 & = ks^2 + (\lambda + \eta) s^2 - (\lambda + \eta) \lambda e + (\eta + D) s^2 \\
 \Rightarrow \quad & (k + \lambda + \eta + D) s^2 - (\lambda + \eta) \lambda e \\
 \Rightarrow \quad & k + \lambda + \eta + D < 0
 \end{aligned}$$

Figure 1: (a)

(b)

matlab 예시 코드를 이용해서 simulation을 진행해보았다. 아래는 2개의 조인트에 대한 reference trajectory이다.

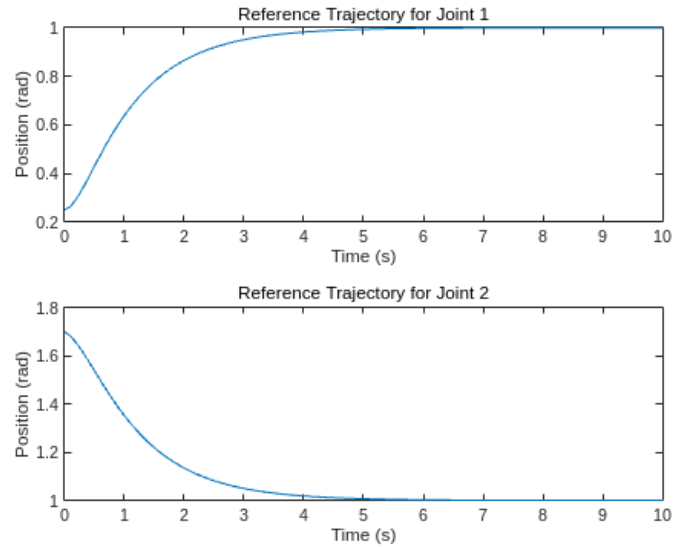


Figure 2: reference trajectory

아래의 sim1은 외부의 disturbance에 의해서 영향을 받지 않는다는 것을 보여주고, sim2은 model uncertainty에 대해서도 robust하다는 결과를 보여준다.

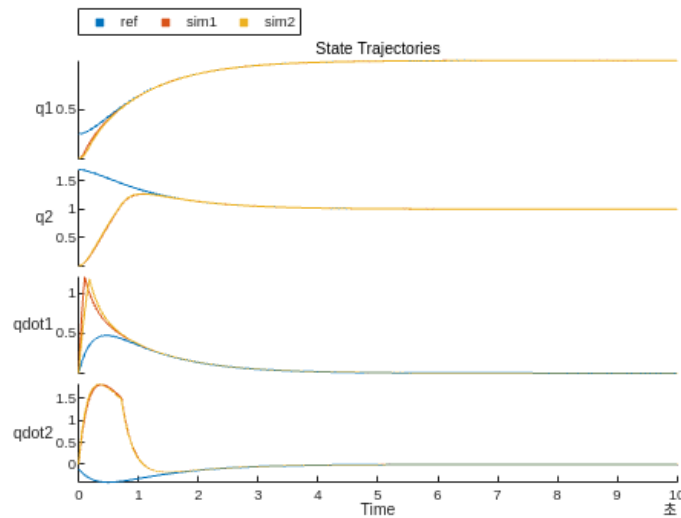


Figure 3: SMC with sign function

하지만 아래의 control input의 결과를 보면 sign function을 사용하였을 때 chattering이 발생한다는 것을 알 수 있다.

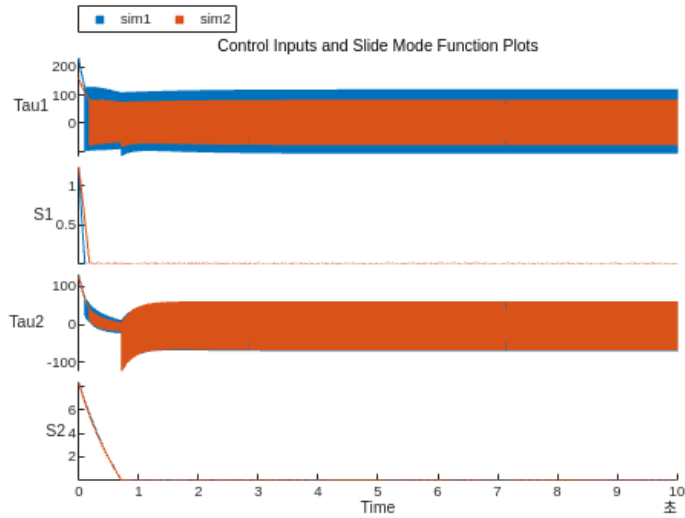


Figure 4: SMC with sign function

이제 control input chattering을 줄이기 위한 방법 중 하나인 sign function 대신에 saturation function을 사용해 보자. 아래 그림에서 sim3과 sim4가 saturation function을 쓴 결과이다. sim3은 마찬가지로 external disturbance에서 robust하다는 것을 보이고, sim4는 model uncertainty에 robust하다는 것을 보인다.

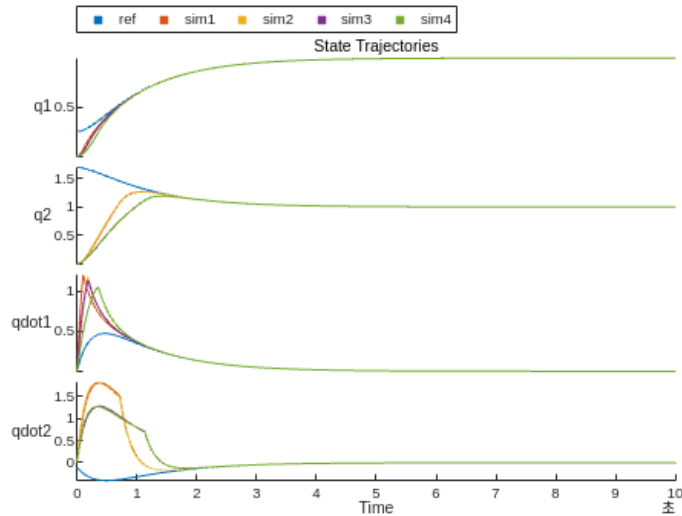


Figure 5: SMC with saturation function

또한 control input chattering을 보면 sign function을 썼을 때보다 확연하게 줄어든 것을 볼 수 있다.

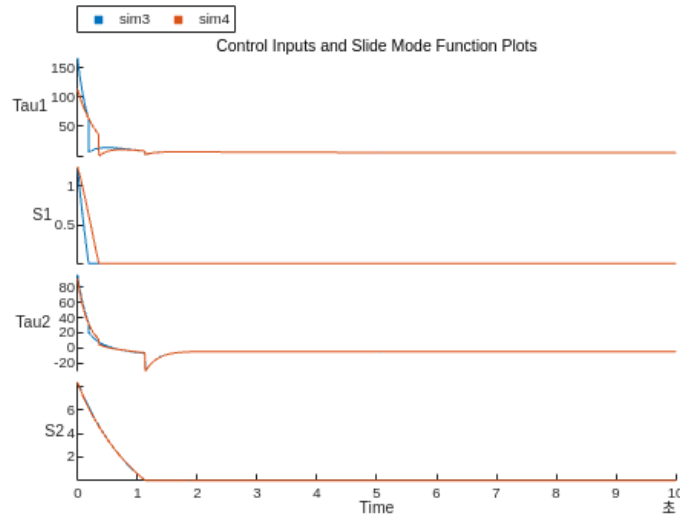
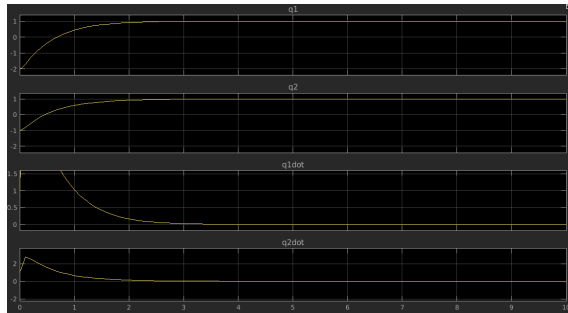


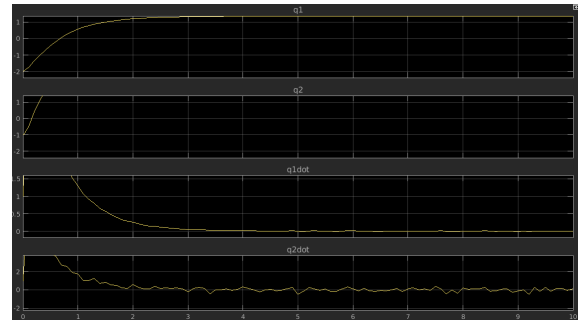
Figure 6: SMC with saturation function

2 Nonlinear model predictive controller

1번 문제에서의 robot manipulator dynamics를 이용해서 nonlinear model predictive controller를 design해 보자. matlab example을 이용해서 disturbance가 존재할 때($\tau_D \neq 0$)와 존재하지 않을 때($\tau_d = 0$)를 비교하자. target state는 $[1, 1, 0, 0]$ 인 constant 값이고, 초기값은 $[-2, -1, 1, 1]$ 이다. 이때 disturbance는 평균이 400, 분산이 100인 gaussian distribution으로 주었다.



(a) States without disturbance



(b) States with disturbance

Figure 7: Simulation Results

위의 결과를 보면 disturbance가 없을 때는 target state로 수렴을 하는 것을 확인할 수 있었다. 하지만 disturbance를 주었을 때는 q_2 의 값을 제외하고 잘 수렴하는 것을 확인할 수 있다. 하지만 q_2 의 값은 target인 1이 아니라 4 근처로 수렴하였다.

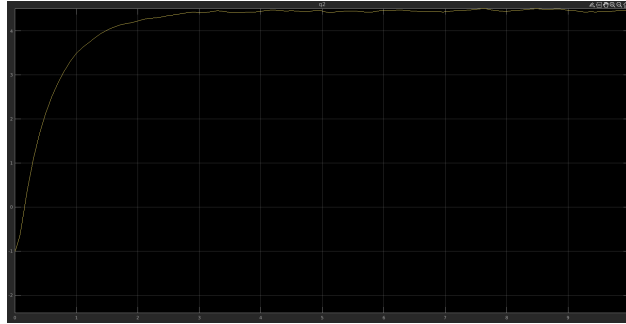


Figure 8: q2 state with disturbance

3 Backstepping control

(a)

$$\begin{aligned}
 (*) \quad & \text{let } \alpha=1 \\
 & \text{then } \begin{cases} \dot{x} = x - x^3 + \xi \\ \dot{\xi} = u \end{cases} \\
 \Rightarrow \quad & \text{let } x = x_1, \xi = z_2 \quad \begin{cases} \dot{x}_1 = x_1 - x_1^3 + x_2 \\ \dot{x}_2 = u \end{cases} \\
 \Rightarrow \quad & x_2 = \alpha(x_1) = -x_1 \\
 \Rightarrow \quad & \text{let } x_1 = z_1 \\
 & V = \frac{1}{2} z_1^2 \rightarrow \dot{V} = z_1 \dot{z}_1 = z_1 (-z_1^3) = -z_1^4 < 0 \quad \text{따라서 stabilize.} \\
 \Rightarrow \quad & \text{let } z_2 = x_2 - \alpha(x_1) \\
 \Rightarrow \quad & \dot{z}_1 = z_1 - x_1^3 + z_2 + \alpha(x_1) = -z_1^3 + z_2 \\
 & \dot{z}_2 = u - \dot{\alpha}(x_1) = V \\
 \Rightarrow \quad & V_2 = \frac{1}{2} z_1^2 + \frac{1}{2} z_2^2 \\
 & \dot{V}_2 = z_1 \dot{z}_1 + z_2 \dot{z}_2 \\
 & = -z_1^4 + z_2 (u - \dot{\alpha}(x_1)) \\
 \text{따라서 } & u = \dot{\alpha}(x_1) - z_2 z_1 \quad \text{하면 } \dot{V}_2 = -z_1^4 - z_2^2 < 0 \quad \text{오직 stabilize.} \\
 \text{즉, } & u = -\dot{x}_1 - (z_2 + x_1) = -\dot{x}_1 - x_2 - x_1
 \end{aligned}$$

Figure 9: (a)

(b)

$$\begin{aligned}
 & b) \begin{cases} \dot{z}_1 = az_1 - z_1^3 + z_2 \\ \dot{z}_2 = u \end{cases} \\
 & \Rightarrow z_2 = \alpha(z_1) = -az_1 \\
 & \Rightarrow \text{let } z_1 = \bar{z}_1 \text{ then } V_1 = \frac{1}{2} \bar{z}_1^2 = \bar{z}_1 \dot{\bar{z}}_1 = \bar{z}_1 (-\bar{z}_1^3) = -\bar{z}_1^4 < 0 \\
 & \text{하지만 } \alpha(z_1) \text{ is unknown Value.} \\
 & \bar{z}_2 = z_2 - \hat{\alpha}_1(z_1) = z_2 - (-\hat{a}z_1) = z_2 + \hat{a}z_1 \\
 & V_2 = \frac{1}{2} \bar{z}_1^2 + \frac{1}{2} \bar{z}_2^2 \Rightarrow \dot{V}_2 = \bar{z}_1 \dot{\bar{z}}_1 + \bar{z}_2 \dot{\bar{z}}_2 = -\bar{z}_1^4 + \bar{z}_2 (u + \hat{a}\bar{z}_1 + \hat{a}\dot{\bar{z}}_1) \\
 & V_3 = \frac{1}{2} \bar{z}_1^2 + \frac{1}{2} \bar{z}_2^2 + \frac{1}{2} \tilde{a}^2 \quad \text{where } \tilde{a} = \hat{a} - a \\
 & \dot{V}_3 = \bar{z}_1 \dot{\bar{z}}_1 + \bar{z}_2 \dot{\bar{z}}_2 + \tilde{a} \dot{\tilde{a}} \\
 & \quad = -\bar{z}_1^4 + \bar{z}_2 (u + \hat{a}\bar{z}_1 + \hat{a}\dot{\bar{z}}_1) + \tilde{a} \dot{\tilde{a}} \\
 & \Rightarrow u = -\bar{z}_2 - \hat{a}\bar{z}_1 - \hat{a}\dot{\bar{z}}_1 \\
 & \quad \hat{a} = -\sigma z_1 e
 \end{aligned}$$

Figure 10: (b)

(c)

x_d 를 \sin 함수로 주었다. 이렇게 했을 때 adaptive backstepping control을 이용해 추종을 하는지 simulation했다.

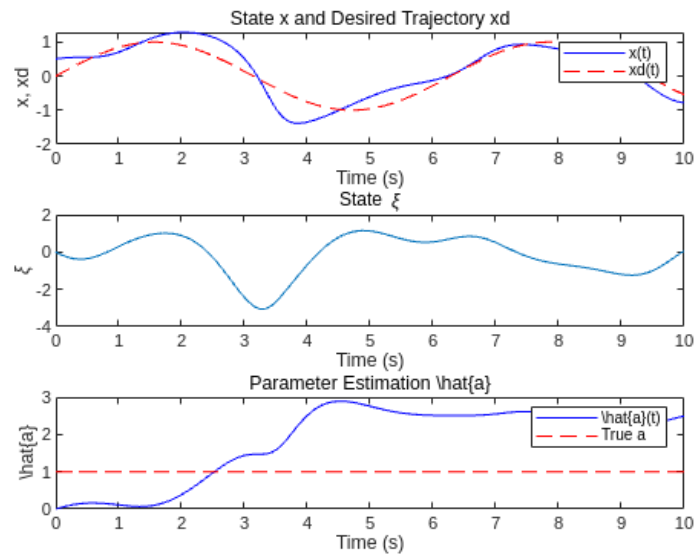


Figure 11: (c)

4 Nonlinear System

(a), (b), (c)

(a) $y = x_1 - x_2$
 $\dot{y} = \dot{x}_1 - \dot{x}_2 = x_1 + x_1 x_2 - x_2^2 + u - x_1 x_2 + x_2^2 - u$
 $\dot{y} = \dot{x}_1 = x_1 + x_1 x_2 - x_2^2 + u$
 \Rightarrow Relative degree = 2

(b) Let's define the internal variable
 $\begin{cases} z_1 = y = x_1 - x_2 \\ z_2 = \dot{y} = \dot{x}_1 \end{cases}$
 $\Rightarrow \begin{cases} \dot{z}_1 = z_2 = x_1 \\ \dot{z}_2 = \dot{x}_1 = x_1 + x_1 x_2 - x_2^2 + u \end{cases}$
 or $\begin{cases} z_2 = x_1 \\ z_1 = x_1 - x_2 \end{cases} \longrightarrow x_2 = x_1 - z_1 = z_2 - z_1$
 $\Rightarrow \begin{cases} \dot{z}_1 = z_2 \\ \dot{z}_2 = z_2 + z_2(z_2 - z_1) - (z_2 - z_1)^2 + u \end{cases}$
 \Rightarrow Internal variable $\eta = z_3$
 $\dot{\eta} = x_1 + x_1 x_2 - x_2^2 - (x_2 - x_1)^3 + u$
 $= z_2 + z_2(z_2 - z_1) - (z_2 - z_1)^2 - (\eta - z_2)^3 + u$
 \Rightarrow Normal form
 $\begin{cases} \dot{z}_1 = z_2 \\ \dot{z}_2 = z_2 + z_2(z_2 - z_1) - (z_2 - z_1)^2 + u \\ \dot{\eta} = z_2 + z_2(z_2 - z_1) - (z_2 - z_1)^2 - (\eta - z_2)^3 + u \end{cases}$

(c) To find the zero dynamics, $z_1 = z_2 = 0$
 $\Rightarrow x_1 = x_2, x_2 = 0 \longrightarrow x_1 = 0 \text{ \& } x_2 = 0$
 $\Rightarrow \dot{\eta} = -\eta^3$
 \Rightarrow Let Lyapunov function $V(\eta) = \frac{1}{2} \eta^2$; positive-definite
 $\dot{V}(\eta) = \eta \dot{\eta} = -\eta^4 < 0$; negative-definite
 \Rightarrow globally asymptotically stable

Figure 12: (a), (b), (c)

(d)

(d) let control law

$$u = -k_1 \bar{z}_1 - k_2 \bar{z}_2 \quad \text{where } \dot{y} = \bar{z}_1, \dot{\bar{y}} = \bar{z}_2$$

Lyapunov function

$$V = \frac{1}{2} \bar{z}_1^2 + \frac{1}{2} \bar{z}_2^2 + \frac{1}{2} \eta^2$$
$$\begin{aligned} \dot{V} &= \bar{z}_1 \dot{\bar{z}}_1 + \bar{z}_2 \dot{\bar{z}}_2 + \eta \dot{\eta} \\ &= \bar{z}_1 \bar{z}_2 + \bar{z}_2^2 + \bar{z}_2^3 - \bar{z}_2^2 \bar{z}_1 - \bar{z}_2 (\bar{z}_2^3 - 2\bar{z}_1 \bar{z}_2 + \bar{z}_1^2) - k_1 \bar{z}_1 \bar{z}_2 - k_2 \bar{z}_2^2 \\ &\quad - \eta^4 \\ &= \bar{z}_1 \bar{z}_2 + \bar{z}_2^2 (1 - 3\bar{z}_1 - k_2) - \bar{z}_1^2 \bar{z}_2 - k_1 \bar{z}_1 \bar{z}_2 \\ &= (1 - k_1) \bar{z}_1 \bar{z}_2 + (1 - k_2) \bar{z}_2^2 - 3\bar{z}_1 \bar{z}_2^2 - \bar{z}_1^2 \bar{z}_2 \end{aligned}$$

$\Rightarrow k_1 < 1, k_2 < 1$

$\Rightarrow u = -k_1 \bar{z}_1 - k_2 \bar{z}_2 \quad \text{where } k_1 < 1, k_2 < 1$

Figure 13: (d)

Submitted by Jusuk Lee on June 2, 2024.