## Assignment 6, ttk4215

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21st October

## Problem 4.10

 $\mathbf{c}$ 

We will modify the gradient algorithm to include projection. Before adding projection, we have the adaptive law

$$\dot{\theta} = \Gamma \epsilon \phi \tag{1}$$

To apply projection we need a function  $g(\theta)$  such that  $g(\theta) \leq 0$  when  $0 \leq \beta \leq 1$ ,  $k \geq 0.1$ , and  $m \geq 10$ .

I wasn't able to find a single function that defines the area we want.

To constrain m we can use  $g_1(m) = 10 - m$ , giving  $\nabla g_1(m) = -1$ . For  $\beta$ , we can use that  $g_2(\beta) = \beta(\beta - 1) \le 0$  in the are we are interested in. We then have  $\nabla g_2(\beta) = 2\beta - 1$ . To constrain k we can use  $g_3(k) = 0.1 - k$ , giving  $\nabla g_3(k) = -1$ .

Will try to use  $g(\theta) = g_1 + g_2 + g_3 = 10 - m + \beta(\beta - 1) + 0.1 - k$ , which is negative on the when  $\theta \in S$ , but is not positive everywhere outside so it doesn't satisfy the definition in (4.4.3).

We then have

$$\nabla g = \begin{bmatrix} -1 & 2\beta - 1 & -1 \end{bmatrix}$$

We can then update the adaptive law to use this information.

$$\dot{\theta} = \Pr(\Gamma \epsilon \phi) \tag{2}$$

 $\mathbf{d}$ 

## Problem 4.11

 $\mathbf{a}$ 

To create an on-line estimation scheme, I will develop a linear parametric form. We have  $(r - \theta_p)G_0(s) = \theta_p$ . This gives

$$(r - \theta_p)k_0\omega_0^2 = (s^2 + 2\xi_0\omega_0 s + \omega_0^2(1 - k_0))\theta_p$$
(3)

$$rk_0\omega_0^2 = (s^2 + 2\xi_0\omega_0 s + \omega_0^2)\theta_p \tag{4}$$

$$\frac{r}{\Lambda_1} = \left(\frac{1}{k_0 \omega_0^2} s^2 + \frac{2\xi_0 \omega_0}{k_0 \omega_0^2} s + \frac{1}{k_0}\right) \frac{\theta_p}{\Lambda_1}$$
 (5)

$$\frac{r}{\Lambda_1} = \left(\theta_1 s^2 + \theta_2 s + \theta_3\right) \frac{\theta_p}{\Lambda_1} \tag{6}$$

where  $\Lambda_1(s)$  is Hurwitz and at least of order 2.

Using  $z_1 = \frac{r(s)}{\Lambda_1(s)}$ ,  $\bar{\theta}_1 = \begin{bmatrix} \theta_1 & \theta_2 & \theta_3 \end{bmatrix}^T$ ,  $\phi_1 = \begin{bmatrix} s^2 & s & 1 \end{bmatrix}^T \frac{\theta_p}{\Lambda_1} = \frac{\alpha_2(s)^T \theta_p}{\Lambda_1}$ , we have written the system in linear parametric form. To convert  $\bar{\theta}_1$  to  $k_0$ ,  $\omega_0$ , and  $\xi_0$ , we would use

$$k_0 = \theta_3^{-1} \tag{7}$$

$$\omega_0 = \sqrt{\frac{\theta_3}{\theta_1}} \tag{8}$$

$$\xi_0 = \frac{1}{2} \frac{\theta_2}{\sqrt{\theta_1 \theta_3}} \tag{9}$$

To estimate the other set of parameters, we use  $\theta_p G_1(s) = \dot{\theta}$ . This gives

$$\theta_p k_1 \omega_1^2 = (s^2 + 2\xi_1 \omega_1 s + \omega_1^2) \dot{\theta}$$
 (10)

Which is essentially the same as eq. (4), so we can write in linear parametric form using  $z_2 = \frac{\theta_p}{\Lambda_2}$ ,  $\bar{\theta}_2 = \begin{bmatrix} \theta_4 & \theta_5 & \theta_6 \end{bmatrix}^T$ ,  $\phi_2 = \frac{\alpha_2(s)^T\dot{\theta}}{\Lambda_2}$ .

To convert to the system parameters, we use

$$k_1 = \theta_6^{-1} \tag{11}$$

$$\omega_1 = \sqrt{\frac{\theta_6}{\theta_4}}$$

$$\xi_1 = \frac{1}{2} \frac{\theta_5}{\sqrt{\theta_4 \theta_6}}$$

$$(12)$$

$$\xi_1 = \frac{1}{2} \frac{\theta_5}{\sqrt{\theta_4 \theta_6}} \tag{13}$$

To write the entire system in linear parametric form, we look at  $z = z_1 + z_2$ .

$$z = \frac{r}{\Lambda_1} + \frac{\theta_p}{\Lambda_2} \tag{14}$$

$$z = \frac{r}{\Lambda_1} + \frac{\theta_p}{\Lambda_2}$$

$$= \bar{\theta}_1^T \phi_1 + \bar{\theta}_2^T \phi_2 = \begin{bmatrix} \bar{\theta}_1 \\ \bar{\theta}_2 \end{bmatrix}^T \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \\ \theta_6 \end{bmatrix}^T \begin{bmatrix} \frac{s^2}{\Lambda_1} \theta_p \\ \frac{1}{\Lambda_1} \theta_p \\ \frac{s^2}{\Lambda_2} \dot{\theta} \\ \frac{s}{\Lambda_2} \dot{\theta} \\ \frac{1}{\Lambda_2} \dot{\theta} \end{bmatrix} = \theta^T \phi$$

$$(14)$$

To estimate  $\theta$ , we will use least-squares with forgetting factor, given below.

$$\hat{z} = \theta^T \phi \tag{16}$$

$$\epsilon = (z - \hat{z})/m^2 \tag{17}$$

$$\dot{\theta} = P\epsilon\phi \tag{18}$$

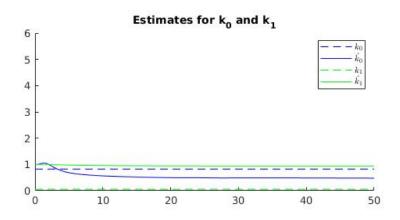
$$\dot{P} = \begin{cases} \beta P - P \frac{\phi \phi^T}{m^2} P & \text{if } ||P|| \le R_0 \\ 0 & \text{otherwise} \end{cases}$$
 (18)

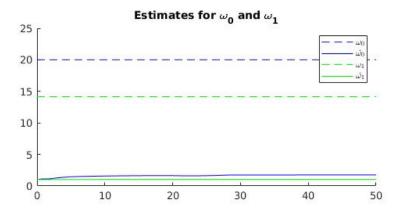
$$P(0) = P_0, \quad ||P_0|| \le R_0 \tag{20}$$

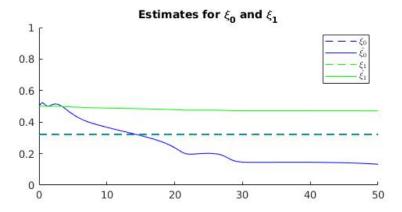
After experimenting a couple of hours with this, I was unable to get good convergence using this estimator.

i

With  $r=10\sin(0.2t)+8$  and  $V=20\mathrm{mph},$  the best I got was this

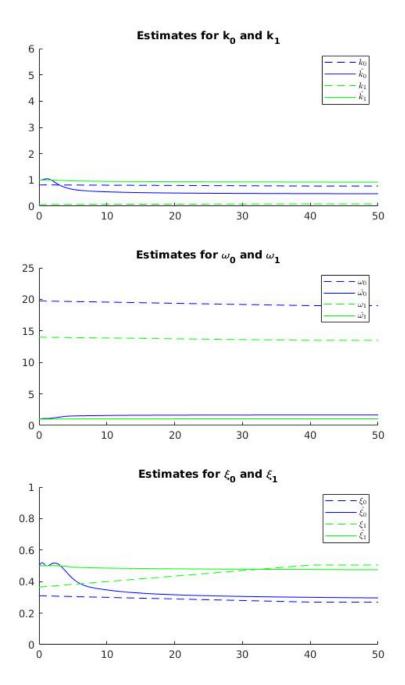






Unfortunately, the estimates don't seem to converge to the true value on any of the parameters.

With r=5 and V increasing from 30 to 60 in 40 seconds, I got this



The estimates seem to converge on  $k_i$  and  $\xi_i$ , but for  $\omega_i$  the estimates are really off.