

HW5: if only greeding 1 problem grade P2, else extra credit would be appreciated

1. Implement SQP to solve the following problem. Use  $\mathbf{x}_0 = (1, 1)^T$  as the initial guess. Use BFGS approximation for the Hessian of the Lagrangian. Use the merit function and Armijo Line Search to find the step size. Note: You can use an existing quadratic programming solver to solve the QP subproblem.

$$\begin{aligned} \min f &= x_1^2 + (x_2 - 3)^2 \\ \text{s.t. } g_1 &= x_2^2 - 2x_1 \leq 0 \\ g_2 &= (x_2 - 1)^2 + 5x_1 - 15 \leq 0 \end{aligned}$$

from lecture notes:

- ① initialize  $\mathbf{x}_0, \lambda_0 = 0, \mu_0 = 0, \omega = 1, k = 0, \epsilon = 10^{-3}$   
( $h(\mathbf{x}_0) = 0, f(\mathbf{x}_0) \leq 0$ ),  $\Lambda = \emptyset$
- ② calculate  $\nabla_x L = \nabla_x f + \lambda^T \nabla_x h + \mu^T \nabla_x g$
- ③ while  $|\nabla_x L| > \epsilon$  do
  - ③.1  $S_k, (\lambda_{k+1}, \mu_{k+1}) = \text{QP}(\mathbf{x}_k, \lambda_k, \mu_k, f, h, g, \Lambda, \omega_k)$
  - ③.2  $\alpha_k = \text{line Search}(S_k, \lambda_{k+1}, \mu_{k+1}, f, h, g, \Lambda)$
  - ③.3  $\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \cdot S_k$
  - ③.4  $\omega_{k+1} = \text{BFGS}(\omega_k, \alpha_k S_k, \mathbf{x}_k, \lambda_{k+1}, \mu_{k+1}, f, h, g, \Lambda)$
  - ③.5 calculate  $\nabla_x L$

$$\frac{\partial g_1}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \end{bmatrix} = \begin{bmatrix} -2 & 2x_2 \end{bmatrix}$$

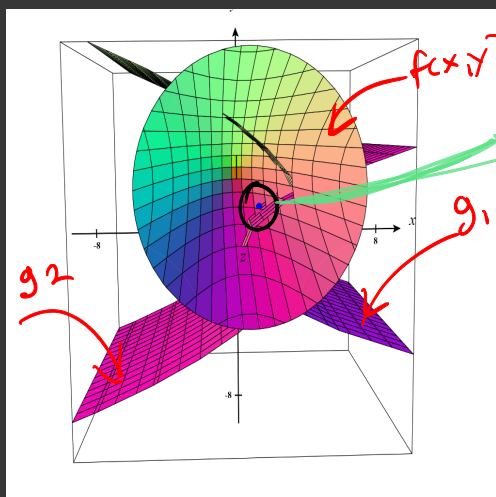
$$\frac{\partial g_2}{\partial \mathbf{x}} = \begin{bmatrix} 5 & 2(x_2 - 1) \end{bmatrix}$$

$$\frac{\partial g}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial g_1}{\partial \mathbf{x}} \\ \frac{\partial g_2}{\partial \mathbf{x}} \end{bmatrix}$$

$$\frac{\partial f}{\partial \mathbf{x}} = \begin{bmatrix} 2x_1 & 2(x_2 - 3) \end{bmatrix}$$

from code: Solution at  $\mathbf{x} = (1.06, 1.49)$

graphical solution



Point (1.06, 1.49)

Confirmed on graph  
& minimum value  
along f

code at:

<https://github.com/Davwittma/MAE-598-Design-Optimization/blob/main/Homework5.py>

2. Consider a moon lander with state  $[h, v, m]^T$  to have the following dynamics:

$$\begin{cases} \dot{h}(t) = v(t) \\ \dot{v}(t) = -g + \frac{a(t)}{m(t)} \\ \dot{m}(t) = -K a(t) \end{cases}$$

Here  $h$  is the altitude,  $v$  is the velocity, and  $m$  is the mass of the moon lander.  $a(t) \in [0, 1]$  is the thrust, and  $K$  is a constant fuel burning rate. Let the initial state be  $[h_0, v_0, m_0]^T$ , and the target be  $h(t^*) = 0$  and  $v(t^*) = 0$  at terminal time  $t^*$ . Derive the optimal control policy for minimal fuel consumption.

$$\min_{\alpha(t)} C(\alpha) = \int_0^T \alpha(t) dt, \quad h(T) = 0, \quad v(T) = 0$$

Using Pontryagin's Maximum principle to solve the optimal control prob.

initial state:

$$\begin{cases} \dot{h}(0) = h_0 \\ \dot{v}(0) = v_0 \\ \dot{m}(0) = m_0 \end{cases}$$

$$f = \begin{bmatrix} v \\ -g + \frac{\alpha(t)}{m(t)} \\ -K \alpha(t) \end{bmatrix} \quad \ell = \alpha$$

$$H = -\ell + \lambda^T f = -\alpha + \lambda_1 v + \lambda_2 \left(-g + \frac{\alpha(t)}{m(t)}\right) + \lambda_3 (-K \alpha(t))$$

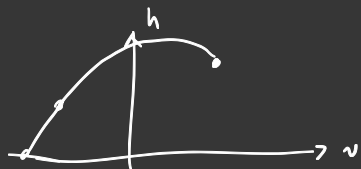
$$\alpha^* = \arg \max_{\alpha \in [0, 1]} H = \arg \max_{\alpha \in [0, 1]} \left( -\alpha + \lambda_1 v + \lambda_2 \left(-g + \frac{\alpha(t)}{m(t)}\right) + \lambda_3 (-K \alpha(t)) \right)$$

$$\text{for } \alpha \in [0, 1] = \arg \max_{\alpha \in [0, 1]} \left( v \lambda_1 - g \lambda_2 + \alpha \left( \frac{\lambda_2}{m(t)} - \lambda_3 K \right) \right)$$

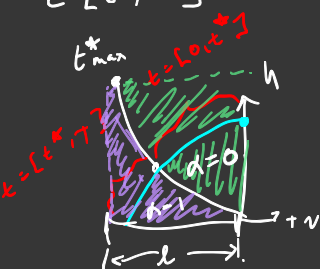
$$\alpha^* = \begin{cases} 0 & b \leq 0 \\ 1 & b > 0 \end{cases}$$

policy  $\alpha^* = 0$  for  $[0, t^*]$   
 $\alpha^* = 1$  for  $[t^*, T]$

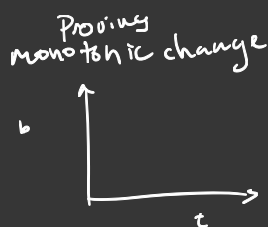
at  $t \in [0, t^*]$   $f = \begin{bmatrix} v \\ -g \\ 0 \end{bmatrix}$   $\begin{cases} \dot{h} = v \\ \dot{v} = -g \\ \dot{m} = 0 \end{cases}$



$t \in [t^*, T]$   $f = \begin{bmatrix} v \\ -g + \frac{1}{m} \\ -K \end{bmatrix}$   $\begin{cases} \dot{h} = v \\ \dot{v} = -g + \frac{1}{m} \\ \dot{m} = -K \end{cases}$  for  $\alpha = 1$



aside:  $\int_0^T f \begin{bmatrix} v \\ -g + \frac{1}{m} \\ -K \end{bmatrix} dv \leq m_{fuel}$



if  $b$  is continuous and differentiable between

$$t \in [0, t^*]$$

and

$$t \in [t^*, T]$$

the monotonic change is expressed as:

$$\frac{db}{dt} \Big|_0 \neq \frac{db}{dt} \Big|_{t^*}$$

$$\text{and } b = \frac{\lambda_2}{m(t)} - 1 - \lambda_3 K$$

$$\text{thus } \frac{db}{dt} = \frac{\lambda_2}{m}$$

where  $\dot{m} = 0$  because there is no thrust between  $\alpha \in [0, t^*]$  or for  $\alpha \in [t^*, T]$   $\dot{m} = -K \alpha(t)$  where  $K$  is constant acceleration change from a negative # to a less negative number, thus this can be approximated between both  $t \in [0, t^*]$  &  $t \in [t^*, T]$  as monotonic decrease into monotonic inc

this makes sense when thinking about landing with  $v(T) = 0$  at  $h(T) = 0$