

REU: Numerical optimal control

Hoang Nguyen
Note 1

May 24, 2018

0.1 Review

Euler-Lagrange equation

Let $S(y) = \int_a^b \mathcal{L}(x, y, y') dx$ where $y : [a, b] \subset \mathbb{R} \rightarrow X$ is a differentiable function and $y(a) = y_a, y(b) = y_b$. We have $S(y_0)$ reaches extrema if y satisfies:

$$\frac{d}{dx} \frac{\delta \mathcal{L}}{\delta y'} = \frac{\delta \mathcal{L}}{\delta y}$$

Generalization

We also have a generalization for higher order of derivation as following:

$$\sum_{i=0}^k (-1)^i \frac{d^i}{dx^i} \left(\frac{\delta \mathcal{L}}{\delta f^{(i)}} \right) = 0$$

Beltrami identity

Theorem. Given an Euler-Lagrange equation $\mathcal{L}(x, y, y')$ independent of x , we have:

$$\frac{d}{dx} \left(\mathcal{L} - y' \frac{\delta \mathcal{L}}{\delta y'} \right) = 0$$

Proof. From the Euler Lagrange equation, we have:

$$\begin{aligned} \frac{d}{dx} \frac{\delta \mathcal{L}}{\delta y'} &= \frac{\delta \mathcal{L}}{\delta y} \\ \Leftrightarrow y' \frac{d}{dx} \frac{\delta \mathcal{L}}{\delta y'} &= y' \frac{\delta \mathcal{L}}{\delta y} \\ \Leftrightarrow y' \frac{d}{dx} \frac{\delta \mathcal{L}}{\delta y'} &= y' \frac{\delta \mathcal{L}}{\delta y} \\ \Leftrightarrow y' \frac{\delta \mathcal{L}}{\delta y} &= \frac{d}{dx} \left(y' \frac{\delta \mathcal{L}}{\delta y'} \right) - y'' \frac{\delta \mathcal{L}}{\delta y'} \quad (1) \end{aligned}$$

On the other hand, from the chain rule we have:

$$\begin{aligned} \frac{d\mathcal{L}}{dx} &= \frac{\delta \mathcal{L}}{\delta x} + \frac{\delta \mathcal{L}}{\delta y} y' + \frac{\delta \mathcal{L}}{\delta y'} y'' \\ \Leftrightarrow \frac{\delta \mathcal{L}}{\delta y} y' &= \frac{d\mathcal{L}}{dx} - \frac{\delta \mathcal{L}}{\delta x} - \frac{\delta \mathcal{L}}{\delta y'} y'' \quad (2) \end{aligned}$$

From (1), (2), we have:

$$\begin{aligned}\frac{d}{dx} \left(y' \frac{\delta \mathcal{L}}{\delta y'} \right) - y'' \frac{\delta \mathcal{L}}{\delta y'} &= \frac{d\mathcal{L}}{dx} - \frac{\delta \mathcal{L}}{\delta x} - \frac{\delta \mathcal{L}}{y'} y'' \\ \Leftrightarrow \frac{d}{dx} \left(y' \frac{\delta \mathcal{L}}{\delta y'} \right) &= \frac{d\mathcal{L}}{dx} - \frac{\delta \mathcal{L}}{\delta x}\end{aligned}$$

Since \mathcal{L} is independent of x , hence $\frac{\delta \mathcal{L}}{\delta x} = 0$

$$\Rightarrow \frac{d}{dx} \left(\mathcal{L} - y' \frac{\delta \mathcal{L}}{\delta y'} \right) = 0$$

□

1 Task 1: One dimensional optimization problem

Problem 1

Let $q(t)$ be the position function of an object at time t , $u(t)$ be the energy function. We have: $\frac{\delta^2 q}{\delta t^2} = u$. Without the loss of generality, assume that the object begins the journey at coordinate 0 and arrives at 1 after 1 time unit, which means $q(0) = 0, q(1) = 1, q'(0) = 0$. Given these conditions, compute:

$$\min_u \int_0^1 u(t)^2 dt$$

Proof. Since $\frac{\delta^2 q}{\delta t^2} = u$, we have $S(t) = \int_0^1 u(t)^2 dt = \int_0^1 q''(t)^2 dt$ and $\mathcal{L}(t, q, q', q'') = q''(t)^2$.

Apply the generalized result for higher order of derivation of the Euler-Lagrange equation, we have:

$$\begin{aligned}\sum_{i=0}^2 (-1)^i \frac{d^i}{dt^i} \left(\frac{\delta \mathcal{L}}{\delta q^{(i)}} \right) &= 0 \\ \Leftrightarrow \frac{\delta \mathcal{L}}{\delta q} - \frac{d}{dt} \frac{\delta \mathcal{L}}{\delta q'} + \frac{d^2}{dt^2} \frac{\delta \mathcal{L}}{\delta q''} &= 0\end{aligned}$$

Since \mathcal{L} is independent of t and y' , we have:

$$\begin{aligned}\Leftrightarrow \frac{d}{dt} \frac{\delta \mathcal{L}}{\delta q'} - \frac{d^2}{dt^2} \frac{\delta \mathcal{L}}{\delta q''} &= 0 \\ \Leftrightarrow \frac{d}{dt} \left(\frac{\delta \mathcal{L}}{\delta q'} - \frac{d}{dt} \frac{\delta \mathcal{L}}{\delta q''} \right) &= 0 \\ \Leftrightarrow -\frac{\delta \mathcal{L}}{\delta q'} + \frac{d}{dt} \frac{\delta \mathcal{L}}{\delta q''} &= A \\ \Leftrightarrow \frac{d}{dt} \frac{\delta \mathcal{L}}{\delta q''} &= A \\ \Leftrightarrow 2q'' &= At + B\end{aligned}$$

Where A, B are constants

$$\Leftrightarrow q = C_0 + C_1 t + C_2 t^2 + C_3 t^3$$

From $q(0) = 0, q(1) = 1, q'(0) = 0$, we have: $\begin{cases} C_0 = 0 \\ C_1 = 0 \\ C_2 + C_3 = 1 \end{cases}$ Let $C_3 = w$, we have $q(t, w) = wt^3 + (1-w)t^2 \Rightarrow$

$q''(t, w) = 2(3wt + 1 - w)$. The original function now becomes

$$S(t) = \int_0^1 u(t)^2 dt = \int_0^1 q''(t)^2 dt = 4 \int_0^1 (3wt + 1 - w)^2 dt = 4(w^2 + w + 1) \geq 3$$

The equality holds when $w = \frac{-1}{2}, q(t) = \frac{3t^2 - t^3}{2}$

□

2 Gradient descent

2.1 Algorithm

The algorithm is the following recursion:

$$x_{k+1} = x_k - \epsilon \nabla f(x_k)$$

2.2 Extensions

2.2.1 Line search algorithm

One problem with the gradient descent is that we don't know the optimal ϵ value and the sequence might overshoot the optimal point. Thus, we will attempt to apply a method similar to binary search to find it. Let $h(\alpha) = f(x + \alpha \nabla f(x))$, the optimal α such that $h'(\alpha) = 0$ is also the optimal *epsilon*.

In a convex optimization problem, $f(x)$ convex means that $h'(\alpha)$ would be monotonic, which means that if we know $a < b$ such that $h(a)h(b) < 0$, we can find the root in logarithmic time.

2.3 Accelerated gradient descent

Nesterov's accelerated gradient descent is the double recursion:

$$\begin{aligned} x_{k+1} &= y_k - \epsilon \nabla f(y_k) \\ y_k &= x_k + \frac{k-1}{k+2}(x_k - x_{k-1}) \end{aligned}$$

This algorithm drops the monotonic property of the objective sequence and converges faster than the original algorithm.

3 Appendix

Reference

- [1] <https://en.wikipedia.org/wiki/Euler>
- [2] <https://math.stackexchange.com/questions/881053/explanation-of-lagrange-equation-with-chain-rule>
- [3] <http://math.mit.edu/classes/18.086/2006/am72.pdf>
- [4] <http://blog.mrtz.org/2013/09/07/the-zen-of-gradient-descent.html>
- [5] <http://www.stronglyconvex.com/blog/accelerated-gradient-descent.html>
- [6] <http://awibisono.github.io/2016/06/20/accelerated-gradient-descent.html>