

Appendix: some possibly useful formula

- Lagrange mechanics is built on the equations:

$$\frac{d}{dt} \frac{\partial \mathcal{L}}{\partial \dot{\mathbf{q}}} - \frac{\partial \mathcal{L}}{\partial \mathbf{q}} = \mathbf{Q}, \quad \mathcal{L}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{z}) = \mathcal{T} - \mathcal{V} - \mathbf{z}^\top \mathbf{C}, \quad \mathbf{C} = 0, \quad \langle \delta \mathbf{q}, \mathbf{Q} \rangle = \delta W, \forall \delta \mathbf{q} \quad (1)$$

The kinetic and potential energy of a point mass are given by:

$$\mathcal{T} = \frac{1}{2} m \dot{\mathbf{p}}^\top \dot{\mathbf{p}}, \quad \mathcal{V} = mg \mathbf{p}_3 \quad (2)$$

respectively, where $\mathbf{p} \in \mathbb{R}^3$ is the position of the mass in a cartesian reference frame having the third coordinate as the vertical axis pointing up. The generalized forces are identical to the external forces applied to a point mass if the position of that point is expressed in cartesian coordinates in the generalized coordinates \mathbf{q} .

- In the case $\mathcal{T} = \frac{1}{2} m \dot{\mathbf{q}}^\top W \dot{\mathbf{q}}$ with W constant $\mathcal{V} = \mathcal{V}(\mathbf{q})$ and $\mathbf{C} = \mathbf{C}(\mathbf{q})$, the Lagrange equations simplify to the dynamics in the semi-explicit index-3 DAE form:

$$\dot{\mathbf{p}} = \mathbf{v} \quad (3a)$$

$$W \dot{\mathbf{v}} + \frac{\partial \mathbf{C}^\top}{\partial \mathbf{q}} \mathbf{z} = \mathbf{Q} - \frac{\partial \mathcal{V}}{\partial \mathbf{q}} \quad (3b)$$

$$0 = \mathbf{C}(\mathbf{q}) \quad (3c)$$

- The Implicit Function Theorem (IFT) guarantees that a nonlinear set of equations

$$\mathbf{r}(\mathbf{y}, \mathbf{z}) = 0 \quad (4)$$

“can be solved” in terms of \mathbf{z} for a given \mathbf{y} iff the Jacobian $\frac{\partial \mathbf{r}(\mathbf{y}, \mathbf{z})}{\partial \mathbf{z}}$ is full rank at the solution. More specifically, it guarantees that there is a function $\phi(\mathbf{y})$ such that

$$\mathbf{r}(\mathbf{y}, \phi(\mathbf{y})) = 0 \quad (5)$$

holds in the neighborhood of the point \mathbf{y} where the Jacobian is evaluated. Furthermore, the IFT specifies that:

$$\frac{\partial \mathbf{z}}{\partial \mathbf{y}} = - \frac{\partial \mathbf{r}^{-1}}{\partial \mathbf{z}} \frac{\partial \mathbf{r}}{\partial \mathbf{y}} \quad (6)$$

- For solving a problem $\mathbf{r}(\mathbf{x}) = 0$, Newton iterates:

$$\mathbf{x} \leftarrow \mathbf{x} - \alpha \frac{\partial \mathbf{r}^{-1}}{\partial \mathbf{x}} \mathbf{r} \quad (7)$$

until $\mathbf{r}(\mathbf{x}) \approx 0$ where $\alpha \in [0, 1]$

- Runge-Kutta methods are described by:

c_1	a_{11}	\dots	a_{1s}	$\mathbf{K}_j = \mathbf{f} \left(\mathbf{x}_k + \Delta t \sum_{i=1}^s a_{ji} \mathbf{K}_i, \mathbf{u}(t_k + c_j \Delta t) \right), \quad j = 1, \dots, s$	(8a)
\vdots	\vdots		\vdots		
c_s	a_{s1}	\dots	a_{ss}		

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta t \sum_{i=1}^s b_i \mathbf{K}_i \quad (8b)$$

- For ERK methods, the relationship between the (minimum) number of stages s to the order o is given by:

s	1	2	3	4	6	7	9	11	...
o	1	2	3	4	5	6	7	8	...

Table 1: Stage to order of ERK methods

- Collocation methods use:

$$\dot{\mathbf{x}}(t_k + \Delta t \cdot \tau) \approx \dot{\hat{\mathbf{x}}}(t_k + \Delta t \cdot \tau) = \sum_{i=1}^s \mathbf{K}_i \ell_i(\tau), \quad \tau \in [0, 1] \quad (9)$$

$$\mathbf{x}(t_k + \Delta t \cdot \tau) \approx \hat{\mathbf{x}}(t_k + \Delta t \cdot \tau) = \mathbf{x}_k + \Delta t \sum_{i=1}^s \mathbf{K}_i L_i(\tau) \quad (10)$$

where the Lagrange polynomials are given by:

$$\ell_i(\tau) = \prod_{j=1, j \neq i}^s \frac{\tau - \tau_j}{\tau_i - \tau_j}, \quad \text{and} \quad L_i(\tau) = \int_0^\tau \ell_i(\xi) d\xi \quad (11)$$

The Lagrange polynomials satisfy the conditions of

$$\text{Orthogonality:} \quad \int_0^1 \ell_i(\tau) \ell_j(\tau) d\tau = 0 \quad \text{for} \quad i \neq j \quad (12a)$$

$$\text{Punctuality:} \quad \ell_i(\tau_j) = \begin{cases} 1 & \text{if } j = i \\ 0 & \text{if } j \neq i \end{cases} \quad (12b)$$

and enforce the collocation equations (for $j = 1, \dots, s$):

$$\dot{\hat{\mathbf{x}}}(t_k + \Delta t \cdot \tau_j) = \mathbf{f}(\hat{\mathbf{x}}(t_k + \Delta t \cdot \tau_j), \mathbf{u}(t_k + \Delta t \cdot \tau_j)), \quad \text{in the explicit ODE case} \quad (13a)$$

$$\mathbf{F}(\dot{\hat{\mathbf{x}}}(t_k + \Delta t \cdot \tau_j), \hat{\mathbf{x}}(t_k + \Delta t \cdot \tau_j), \mathbf{u}(t_k + \Delta t \cdot \tau_j)) = 0, \quad \text{in the implicit ODE case} \quad (13b)$$

$$\mathbf{F}(\dot{\hat{\mathbf{x}}}(t_k + \Delta t \cdot \tau_j), \hat{\mathbf{z}}_j, \hat{\mathbf{x}}(t_k + \Delta t \cdot \tau_j), \mathbf{u}(t_k + \Delta t \cdot \tau_j)) = 0, \quad \text{in the fully-implicit DAE case} \quad (13c)$$

- Gauss-Legendre collocation methods select the set of points τ_1, \dots, τ_s as the zeros of the (shifted) Legendre polynomial:

$$P_s(\tau) = \frac{1}{s!} \frac{d^s}{d\tau^s} [(\tau^2 - \tau)^s] \quad (14)$$

They achieve the order $\|\mathbf{x}_N - \mathbf{x}(t_f)\| = \mathcal{O}(\Delta t^{2s})$.

- Maximum-likelihood estimation is based on

$$\max_{\boldsymbol{\theta}} \quad \mathbb{P}[e_k = y_k - \hat{y}_k \quad \text{for} \quad k = 1, \dots, N \mid \boldsymbol{\theta}] \quad (15)$$

If the noise sequence is uncorrelated, then

$$\mathbb{P}[e_k = y_k - \hat{y}_k \quad \text{for} \quad k = 0, \dots, N \mid \boldsymbol{\theta}] = \prod_{k=1}^N \mathbb{P}[e_k = y_k - \hat{y}_k \mid \boldsymbol{\theta}] \quad (16)$$

- The solution of a linear least-squares problem

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \frac{1}{2} \|A\boldsymbol{\theta} - \mathbf{y}\|_{\Sigma_e^{-1}}^2 \quad (17)$$

reads as:

$$\hat{\boldsymbol{\theta}} = (A^\top \Sigma_e^{-1} A)^{-1} A^\top \Sigma_e^{-1} \mathbf{y} \quad (18)$$

and the covariance of the parameter estimation based is given by the formula:

$$\Sigma_{\hat{\boldsymbol{\theta}}} = (A^\top \Sigma_e^{-1} A)^{-1} \quad (19)$$

- In system identification, given the a plant $G(z)$ and a noise $H(z)$ model description, the one-step-ahead predictor $\hat{y}(k|k-1)$ can be retrieved with

$$H(z)\hat{y}(z) = G(z)u(z) + (H(z) - 1)y(z) \quad (20)$$

- The Gauss-Newton approximation in an optimization problem

$$\min_{\mathbf{x}} J(\mathbf{x}) = \frac{1}{2} \|\mathbf{R}(\mathbf{x})\|^2 \quad (21)$$

uses the approximation:

$$\frac{\partial^2 J}{\partial \mathbf{x}^2} \approx \frac{\partial \mathbf{R}}{\partial \mathbf{x}}^\top \frac{\partial \mathbf{R}}{\partial \mathbf{x}} \quad (22)$$

- The solution to an LTI system $\dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u}$ is given by:

$$\mathbf{x}(t) = e^{At}\mathbf{x}(0) + \int_0^t e^{A(t-\tau)} B\mathbf{u}(\tau) d\tau \quad (23)$$

and the transformation state-space to transfer function is given by:

$$G(s) = C(sI - A)^{-1} B + D \quad (24)$$

- $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$, $\det(A) = ad - bc$
- $A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$, $\det(A) = a.\det\left(\begin{bmatrix} e & f \\ h & i \end{bmatrix}\right) - b.\det\left(\begin{bmatrix} d & f \\ g & i \end{bmatrix}\right) + c.\det\left(\begin{bmatrix} d & e \\ g & h \end{bmatrix}\right)$
- $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$, $\det(A) = ad - bc$, $A^{-1} = \frac{1}{\det(A)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$
- $\alpha = \mathbf{x}^T A \mathbf{x}$, where A is a symmetric matrix and \mathbf{x} is $n \times 1$, A is $n \times n$, and A does not depend on \mathbf{x} , then, $\frac{\partial \alpha}{\partial \mathbf{x}} = 2\mathbf{x}^T A$.