

Numerical Methods for PDE-Constrained Optimization of Particle Dynamics

Jonna Roden

University of Edinburgh/MIGSAA

Joint work with Ben Goddard and John Pearson

12th July 2021

Structure of the Talk

- ▶ The Optimization Problem
- ▶ Numerical Methods
 - ▶ Pseudospectral and Spectral Element Methods
 - ▶ Fixed Point Algorithm
 - ▶ Newton-Krylov Algorithm
- ▶ Results

The Optimization Problem

$$\min_{\rho, \vec{w}} \quad \frac{1}{2} \|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2} \|\vec{w}\|_{L_2(\Sigma)}^2$$

subject to:

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \quad \text{in } \Sigma$$

BC and IC:

$$\frac{\partial \rho}{\partial n} - \rho \vec{w} \cdot \vec{n} + \rho \frac{\partial V_{\text{ext}}}{\partial n} + \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \frac{\partial V_2}{\partial n}(|\vec{x} - \vec{x}'|) d\vec{x}' = 0 \quad \text{on } \partial \Sigma$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x})$$

The Optimization Problem

The (first-order) optimality system

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\partial_t q = -\nabla^2 q - \nabla q \cdot \vec{w} + \nabla q \cdot \nabla V_{\text{ext}} + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\vec{w} = -\frac{1}{\beta} \rho \nabla q$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x}), \quad q(T, \vec{x}) = 0, \quad +\text{BCs}$$

Numerical Methods

- ▶ Challenge 1: Particle interaction term is nonlinear and nonlocal (+ nonlocal BCs). How to avoid shortcomings of standard methods (FEM/FDM)?

- ⇒ **Pseudospectral Method**

- AND

- ⇒ **Spectral Element Method**

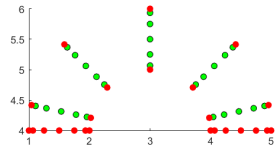
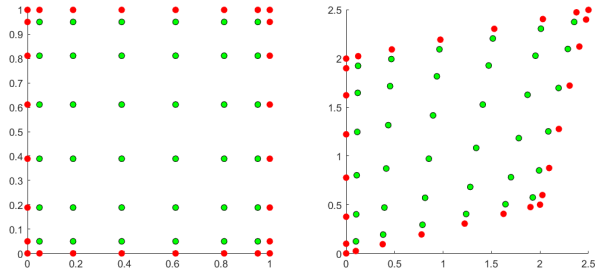
- ▶ Challenge 2: One PDE has an initial, the other a final time condition. The Laplacians have opposite signs. How to do time stepping?

- ⇒ **Fixed Point Algorithm**

- OR

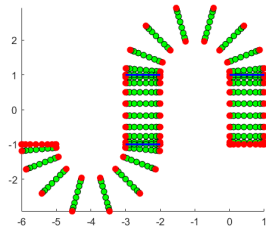
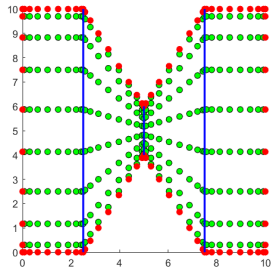
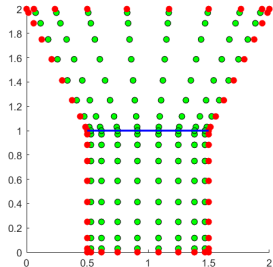
- ⇒ **Newton-Krylov Algorithm**

Pseudospectral Method



- ▶ Reduce both PDEs to systems of ODEs.
- ▶ Discretize time (accurate interpolation).
- ▶ Equations can now be solved using the Fixed Point Algorithm (with DAE solvers) or the Newton-Krylov Algorithm.

Spectral Element Method



- Discretize PDE on each element using pseudospectral methods.
- Match solution and flux between elements.

Fixed Point Algorithm

The (first-order) optimality system

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\partial_t q = -\nabla^2 q - \nabla q \cdot \vec{w} + \nabla q \cdot \nabla V_{\text{ext}} + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\vec{w} = -\frac{1}{\beta} \rho \nabla q$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x}), \quad q(T, \vec{x}) = 0, \quad +\text{BCs}$$

Fixed Point Algorithm

Initialize with guess $\vec{w}^{(0)}$.

1. Solve

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}^{(i)}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'.$$

2. Solve $\partial_{\tau} q = \nabla^2 q + \nabla q \cdot \vec{w}^{(i)} - \nabla q \cdot \nabla V_{\text{ext}}$

$$- \int_{\Omega} \rho^{(i)}(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'.$$

3. Solve $\vec{w}_g^{(i)} = -\frac{1}{\beta} \rho^{(i)} \nabla q^{(i)}.$

4. Measure the error: $\mathcal{E} = \|\vec{w}^{(i)} - \vec{w}_g^{(i)}\|.$

5. Update control, with $\lambda \in [0, 1]$: $\vec{w}^{(i+1)} = (1 - \lambda) \vec{w}^{(i)} + \lambda \vec{w}_g^{(i)}.$

Iterate until $\mathcal{E} < TOL$.

Reminder: The Optimization Problem

$$\min_{\rho, \vec{w}} \quad \frac{1}{2} \|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2} \|\vec{w}\|_{L_2(\Sigma)}^2$$

subject to:

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \quad \text{in } \Sigma$$

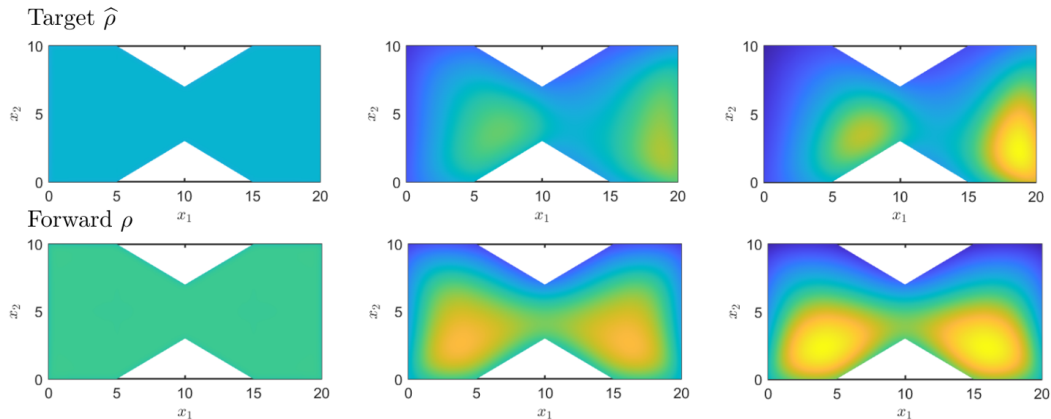
BC and IC:

$$\frac{\partial \rho}{\partial n} - \rho \vec{w} \cdot \vec{n} + \rho \frac{\partial V_{\text{ext}}}{\partial n} + \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \frac{\partial V_2}{\partial n}(|\vec{x} - \vec{x}'|) d\vec{x}' = 0 \quad \text{on } \partial \Sigma$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x})$$

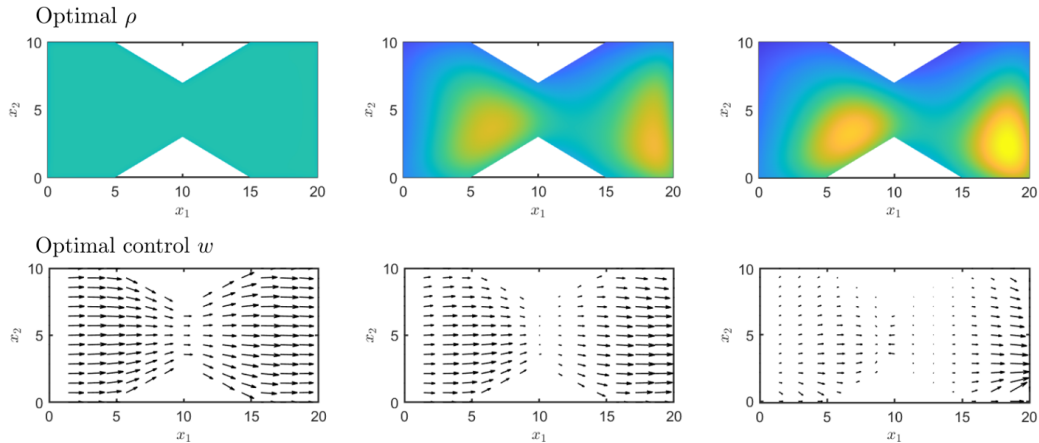
Fixed Point Algorithm Results

Overall Cost: $\mathcal{J} = \frac{1}{2}\|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2}\|\vec{w}\|_{L_2(\Sigma)}^2$, $\mathcal{J}_{\vec{w}=\vec{0}} = 0.0484$.



Fixed Point Algorithm Results

Overall Cost: $\mathcal{J} = \frac{1}{2}\|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2}\|\vec{w}\|_{L_2(\Sigma)}^2$, $\mathcal{J}_{\vec{w}=\vec{0}} = 0.0484$, $\mathcal{J}_{\text{opt}} = 0.0146$.



Newton-Krylov Algorithm

The (first-order) optimality system

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\partial_t q = -\nabla^2 q - \nabla q \cdot \vec{w} + \nabla q \cdot \nabla V_{\text{ext}} + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\vec{w} = -\frac{1}{\beta} \rho \nabla q$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x}), \quad q(T, \vec{x}) = 0, \quad +\text{BCs}$$

Newton-Krylov Algorithm

$$\partial_t \rho = \nabla^2 \rho + \frac{1}{\beta} \nabla \cdot (\rho \nabla \mathbf{q}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}'$$

$$\begin{aligned} \partial_t \mathbf{q} = & -\nabla^2 \mathbf{q} + \frac{1}{\beta} \nabla \mathbf{q} \cdot \nabla \mathbf{q} + \nabla \mathbf{q} \cdot \nabla V_{\text{ext}} \\ & + \int_{\Omega} \rho(\vec{x}') \left(\nabla \mathbf{q}(\vec{x}) + \nabla \mathbf{q}(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \end{aligned}$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x}), \quad \mathbf{q}(T, \vec{x}) = 0, \quad +\text{BCs}$$

Newton-Krylov Algorithm

$$r_\rho(t) = \int_0^t \left(\nabla^2 \rho + \frac{1}{\beta} \nabla \cdot (\rho^2 \nabla q) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' - \partial_\tau \rho \right) d\tau$$

$$r_q(t) = \int_0^t \left(-\nabla^2 q + \frac{1}{\beta} \rho \nabla q \cdot \nabla q + \nabla q \cdot \nabla V_{\text{ext}} + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' - \partial_\tau q \right) d\tau$$

Newton-Krylov Algorithm

$$r_\rho(t) = \int_0^t \left(\nabla^2 \rho + \frac{1}{\beta} \nabla \cdot (\rho^2 \nabla q) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' - \partial_\tau \rho \right) d\tau$$

$$r_q(t) = \int_0^t \left(-\nabla^2 q + \frac{1}{\beta} \rho \nabla q \cdot \nabla q + \nabla q \cdot \nabla V_{\text{ext}} + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' - \partial_\tau q \right) d\tau$$

Newton-Krylov Algorithm

$$r_\rho(t) = \int_0^t \left(\nabla^2 \rho + \frac{1}{\beta} \nabla \cdot (\rho^2 \nabla q) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \right) d\tau$$

$-\rho(t) + \rho(0)$

$$r_q(t) = \int_0^t \left(-\nabla^2 q + \frac{1}{\beta} \rho \nabla q \cdot \nabla q + \nabla q \cdot \nabla V_{\text{ext}} \right. \\ \left. + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \right) d\tau$$

$-q(t) + q(0)$

Newton-Krylov Algorithm

$$r_\rho(t) = \int_0^t \left(\nabla^2 \rho + \frac{1}{\beta} \nabla \cdot (\rho^2 \nabla q) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \right) d\tau - \rho(t) + \rho(0)$$

$$r_q(t) = \int_0^t \left(-\nabla^2 q + \frac{1}{\beta} \rho \nabla q \cdot \nabla q + \nabla q \cdot \nabla V_{\text{ext}} + \int_{\Omega} \rho(\vec{x}') \left(\nabla q(\vec{x}) + \nabla q(\vec{x}') \right) \cdot \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \right) d\tau - q(t) + q(0)$$

Discretizing in space:

$$\begin{pmatrix} r_\rho(t) \\ r_q(t) \end{pmatrix} = \begin{pmatrix} \int_0^t F(\rho, q, \tau) d\tau \\ \int_0^t G(\rho, q, \tau) d\tau \end{pmatrix} + \begin{pmatrix} -\rho(t) + \rho(0) \\ -q(t) + q(0) \end{pmatrix}$$

Newton-Krylov Algorithm

$$\begin{pmatrix} r_\rho(t) \\ r_q(t) \end{pmatrix} = \begin{pmatrix} \int_0^t F(\rho, q, \tau) d\tau \\ \int_0^t G(\rho, q, \tau) d\tau \end{pmatrix} + \begin{pmatrix} -\rho(t) + \rho(0) \\ -q(t) + q(0) \end{pmatrix}$$

Numerical quadrature:

$$R([\rho, q], t) = \begin{pmatrix} Q(t)F(\rho, q) \\ Q(t)G(\rho, q) \end{pmatrix} + \begin{pmatrix} -\rho(t) + \rho(0) \\ -q(t) + q(0) \end{pmatrix}$$

Define $\mathbf{y} := [\rho, q]$. Full residual vector:

$$\mathbf{R}(\mathbf{y}) = [R(\mathbf{y}, t_0), R(\mathbf{y}, t_1), \dots, R(\mathbf{y}, t_n)] .$$

Newton-Krylov Algorithm

Aim: Approximate $\mathbf{R}(\mathbf{y}) = \mathbf{0}$, with $\mathbf{y} := [\rho, q]$.

- Update \mathbf{y} using a Newton step

$$\mathbf{y}^{(i+1)} = \mathbf{y}^{(i)} + \left[D\mathbf{R} \left(\mathbf{y}^{(i)} \right) \right]^{-1} \mathbf{R} \left(\mathbf{y}^{(i)} \right).$$

- Approximate $D\mathbf{R} \left(\mathbf{y}^{(i)} \right)$.
- Approximate

$$D\mathbf{R} \left(\mathbf{y}^{(i)} \right) \mathbf{x} = \mathbf{R} \left(\mathbf{y}^{(i)} \right),$$

using GMRES and the preconditioner in Güttel and Pearson¹.

¹S. Güttel and J. W. Pearson. “A spectral-in-time Newton–Krylov method for nonlinear PDE-constrained optimization”. In: *IMA Journal of Numerical Analysis* (2021).

The Optimization Problem

$$\min_{\rho, \vec{w}} \quad \frac{1}{2} \|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2} \|\vec{w}\|_{L_2(\Sigma)}^2$$

subject to:

$$\partial_t \rho = \nabla^2 \rho - \nabla \cdot (\rho \vec{w}) + \nabla \cdot (\rho \nabla V_{\text{ext}}) + \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \quad \text{in } \Sigma$$

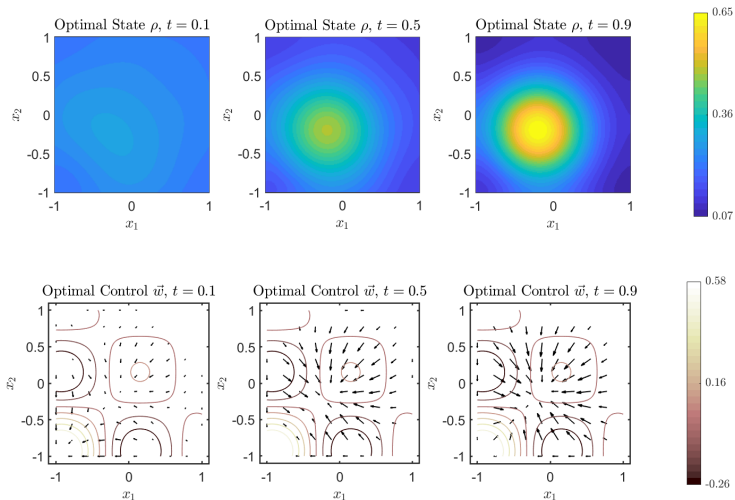
BC and IC:

$$\frac{\partial \rho}{\partial n} - \rho \vec{w} \cdot \vec{n} + \rho \frac{\partial V_{\text{ext}}}{\partial n} + \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \frac{\partial V_2}{\partial n}(|\vec{x} - \vec{x}'|) d\vec{x}' = 0 \quad \text{on } \partial \Sigma$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x})$$

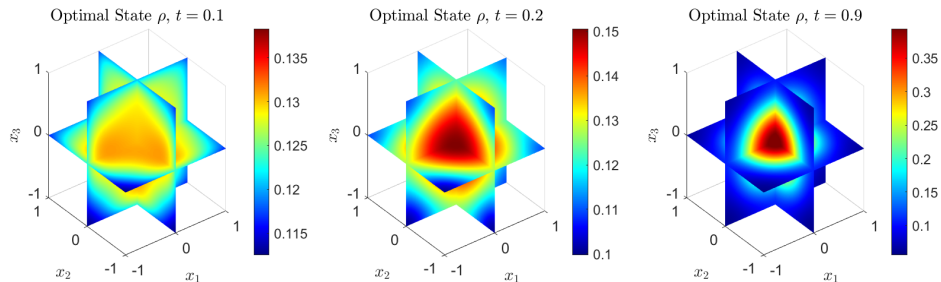
Newton Krylov Result 2D

Overall Cost: $\mathcal{J} = \frac{1}{2}\|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2}\|\vec{w}\|_{L_2(\Sigma)}^2$, $\mathcal{J}_{\vec{w}=\vec{0}} = 0.0209$, $\mathcal{J}_{opt} = 0.0026$.



Newton Krylov Result 3D

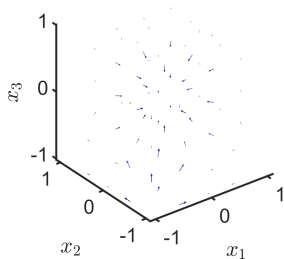
Overall Cost: $\mathcal{J} = \frac{1}{2}\|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2}\|\vec{w}\|_{L_2(\Sigma)}^2$, $\mathcal{J}_{\vec{w}=\vec{0}} = 0.0477$, $\mathcal{J}_{opt} = 0.0059$.



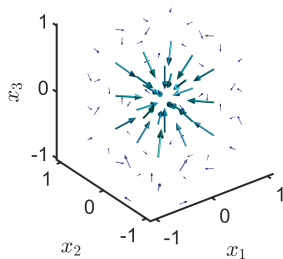
Newton Krylov Result 3D

Overall Cost: $\mathcal{J} = \frac{1}{2}\|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2}\|\vec{w}\|_{L_2(\Sigma)}^2$, $\mathcal{J}_{\vec{w}=\vec{0}} = 0.0477$, $\mathcal{J}_{opt} = 0.0059$.

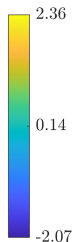
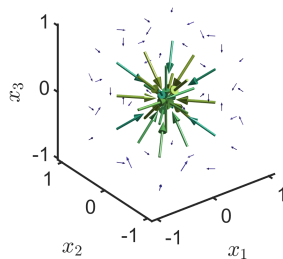
Optimal Control \vec{w} , $t = 0.1$



Optimal Control \vec{w} , $t = 0.5$

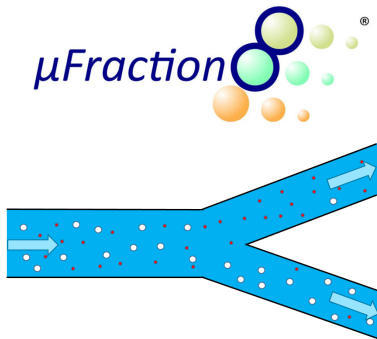


Optimal Control \vec{w} , $t = 0.9$



Next steps

Industrial partners of the PhD



Summary

Up to now:

- ▶ Developed a numerical framework for solving PDE-constrained optimization problems.

Current:

- ▶ More complex domains.
- ▶ Extended models.
- ▶ Different boundary conditions.

Up next:

- ▶ Application of the Newton-Krylov Algorithm to more complex domains.
- ▶ Application of the method to other extended models.
- ▶ Application of the numerical framework to industrial processes.



Aduamoah, M. et al. “PDE-constrained optimization models and pseudospectral methods for multiscale particle dynamics”. In: *Preprint* (2020).



Güttel, S. and J. W. Pearson. “A spectral-in-time Newton–Krylov method for nonlinear PDE-constrained optimization”. In: *IMA Journal of Numerical Analysis* (2021).



Nold, A. et al. “Pseudospectral methods for density functional theory in bounded and unbounded domains”. In: *Journal of Computational Physics* 334 (2017), pp. 639–664. URL:
[https://datashare.is.ed.ac.uk/handle/10283/2647\(2DChebClass\)](https://datashare.is.ed.ac.uk/handle/10283/2647(2DChebClass)).

2D Results Table

		$\beta = 10^{-5}$	$\beta = 10^{-3}$	$\beta = 10^{-1}$	$\beta = 10^1$	$\beta = 10^3$
$\kappa = 0$	\mathcal{J}_{uc}	$2,67 \cdot 10^{-2}$	$2,67 \cdot 10^{-2}$	$2,67 \cdot 10^{-2}$	$2,67 \cdot 10^{-2}$	$2,67 \cdot 10^{-2}$
	\mathcal{J}_c	$8,23 \cdot 10^{-5}$	$3,87 \cdot 10^{-3}$	$2,50 \cdot 10^{-2}$	$2,67 \cdot 10^{-2}$	$2,67 \cdot 10^{-2}$
$\kappa = 1$	\mathcal{J}_{uc}	$3,29 \cdot 10^{-2}$	$3,29 \cdot 10^{-2}$	$3,29 \cdot 10^{-2}$	$3,29 \cdot 10^{-2}$	$3,29 \cdot 10^{-2}$
	\mathcal{J}_c	$1,16 \cdot 10^{-4}$	$5,44 \cdot 10^{-3}$	$3,13 \cdot 10^{-2}$	$3,29 \cdot 10^{-2}$	$3,29 \cdot 10^{-2}$
$\kappa = -1$	\mathcal{J}_{uc}	$2,09 \cdot 10^{-2}$	$2,09 \cdot 10^{-2}$	$2,09 \cdot 10^{-2}$	$2,09 \cdot 10^{-2}$	$2,09 \cdot 10^{-2}$
	\mathcal{J}_c	$5,71 \cdot 10^{-5}$	$2,63 \cdot 10^{-3}$	$1,92 \cdot 10^{-2}$	$2,09 \cdot 10^{-2}$	$2,09 \cdot 10^{-2}$

Table: Flow Control No-Flux Problem: Cost when $\vec{w} = \vec{0}$ and optimal control cost for a range of κ, β .

Optimization for DDFT

A more general DDFT model

$$\min_{\rho, \vec{w}} \quad \frac{1}{2} \|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2} \|\vec{w}\|_{L_2(\Sigma)}^2$$

subject to:

$$\partial_t \rho = \nabla \cdot \left(\rho \nabla \frac{\delta \mathcal{F}[\rho]}{\delta \rho} - \rho \vec{w} \right) := -\nabla \cdot \vec{j} \quad \text{in } \Sigma$$

$$\mathcal{F}[\rho] = \mathcal{F}_{id}[\rho] + \mathcal{F}_{ext}[\rho] + \mathcal{F}_{int}[\rho] + \int_{\Omega} \rho \left(-1 - \ln(1 - a\rho) + \frac{1}{1 - a\rho} \right) d\vec{x}$$

BC and IC:

$$\vec{j} \cdot \vec{n} = 0 \quad \text{on } \partial\Sigma$$

$$\rho(0, \vec{x}) = \rho_0(\vec{x})$$

Deriving optimality conditions

Deriving (first-order) optimality conditions

Define the Lagrangian $\mathcal{L}(\rho, \vec{w}, q)$:

$$\begin{aligned}\mathcal{L}(\rho, \vec{w}, q) = & \frac{1}{2} \|\rho - \hat{\rho}\|_{L_2(\Sigma)}^2 + \frac{\beta}{2} \|\vec{w}\|_{L_2(\Sigma)}^2 \\ & + \int_{\Sigma} q \left(\partial_t \rho - \nabla^2 \rho + \nabla \cdot (\rho \vec{w}) - \nabla \cdot \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \nabla V_2(|\vec{x} - \vec{x}'|) d\vec{x}' \right) d\vec{x} dt \\ & + \int_{\partial \Sigma} q \left(\frac{\partial \rho}{\partial n} - \rho \vec{w} \cdot \vec{n} + \int_{\Omega} \rho(\vec{x}) \rho(\vec{x}') \frac{\partial V_2}{\partial n}(|\vec{x} - \vec{x}'|) d\vec{x}' \right) d\vec{x} dt\end{aligned}$$

1. Take derivatives of $\mathcal{L}(\rho, \vec{w}, q)$ with respect to ρ , \vec{w} and q .
2. Set derivatives to zero to find stationary points.

Figure References



ufraction8 Logo. Digital Image.
www.ufraction8. *ufraction8.com*



WEST Logo. Digital Image.
WEST Brewery *www.westbeer.com*

Some References

M. Aduamoah et al. “PDE-constrained optimization models and pseudospectral methods for multiscale particle dynamics”. In: *Preprint* (2020) and A. Nold et al. “Pseudospectral methods for density functional theory in bounded and unbounded domains”. In: *Journal of Computational Physics* 334 (2017), pp. 639–664. URL: [https://datashare.is.ed.ac.uk/handle/10283/2647\(2DChebClass\)](https://datashare.is.ed.ac.uk/handle/10283/2647(2DChebClass))