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Nonlinear Model Order Reduction for Problems with Moving Discontinuities

Christoph Lehrenfeld, Mario Ohlberger, Stephan Rave



Outline

- ▶ Reduced Basis Methods for Nonlinear Evolution Equations:
Trouble with Advection Dominated Problems.

- ▶ The FrozenRB scheme.
(Joint work with Mario Ohlberger.)

- ▶ Nonlinear MOR via Lagrangian Formulation.
(Joint work in progress with Christoph Lehrenfeld.)



Reduced Basis Methods

Parametric Model Order Reduction

Consider time-dependent parametric problems

$$\Phi : \mathcal{P} \rightarrow L^\infty([0, T]; V_h), \quad s : L^\infty([0, T]; V_h) \rightarrow \mathbb{R}^S$$

where

- ▶ $\mathcal{P} \subset \mathbb{R}^P$ parameter domain.
- ▶ V_h “truth” solution state space, $\dim V_h \gg 0$.
- ▶ Φ maps parameters to solutions (*hard* to compute).
- ▶ s maps state vectors to quantities of interest.

Objective

Compute

$$s \circ \Phi : \mathbb{R}^P \rightarrow L^\infty([0, T]; V_h) \rightarrow \mathbb{R}^S$$

for *many* $\mu \in \mathcal{P}$ or *quickly* for unknown single $\mu \in \mathcal{P}$.

Reduced Basis Methods: Three Basic Ideas

Objective

Compute

$$s \circ \Phi : \mathbb{R}^P \rightarrow L^\infty([0, T]; V_h) \rightarrow \mathbb{R}^S$$

When Φ , s sufficiently smooth, quickly computable low-dimensional approximation of $s \circ \Phi$ should exist.

- ▶ **Idea 1:** State space projection:
 - ▶ Define approximation $\Phi_N : \mathcal{P} \rightarrow L^\infty([0, T]; V_N)$, $N := \dim V_N \ll \dim V_h$, via Galerkin projection.
 - ▶ Approximate $s \circ \Phi \approx s \circ \Phi_N$.
- ▶ **Idea 2:** Construct V_N from PODs of solution snapshots $\Phi(\mu_1), \dots, \Phi(\mu_k)$.
- ▶ **Idea 3:** Select μ_1, \dots, μ_k iteratively via greedy search over \mathcal{P} using quickly computable surrogate $\eta(\Phi_N(\mu), \mu) \geq \|\Phi(\mu) - \Phi_N(\mu)\|$ (POD-GREEDY).

RB for Nonlinear Evolution Equations

Full order problem

Find $\Phi(\mu) := u_\mu \in L^\infty([0, T]; V_h)$ such that

$$\partial_t u_\mu(t) + \mathcal{L}_\mu(u_\mu(t)) = 0, \quad u_\mu(0) = u_0,$$

where $\mathcal{L}_\mu : \mathcal{P} \times V_h \rightarrow V_h$ is a parametric (nonlinear) Finite Volume operator.

Reduced order problem

For given $V_N \subset V_h$, find $\Phi_N(\mu) := u_{\mu,N} \in L^\infty([0, T]; V_N)$ such that

$$\partial_t u_{\mu,N}(t) + P_{V_N}(\mathcal{L}_\mu(u_{\mu,N}(t))) = 0, \quad u_{\mu,N}(0) = P_{V_N}(u_0),$$

where $P_{V_N} : V_h \rightarrow V_N$ is orthogonal proj. onto V_N .

Empirical Operator Interpolation (a.k.a. DEIM, EIM)

Problem: Still expensive to evaluate

$$P_{V_N} \circ \mathcal{L}_\mu : V_N \longrightarrow V_h \longrightarrow V_N.$$

Solution:

- ▶ Use locality of finite volume operators:

to evaluate M DOFs of $\mathcal{L}_\mu(u)$ we need $M' \leq C \cdot M$ DOFs of u .

- ▶ Approximate

$$\mathcal{L}_\mu \approx \mathcal{I}_M[\mathcal{L}_\mu] := I_M \circ \mathcal{L}_{M,\mu} \circ R_{M'},$$

where

$R_{M'}: V_h \rightarrow \mathbb{R}^{M'}$	restriction to M' DOFs needed for evaluation
$\mathcal{L}_{M,\mu}: \mathbb{R}^{M'} \rightarrow \mathbb{R}^M$	\mathcal{L}_μ restricted to M interpolation DOFs
$I_M: \mathbb{R}^M \rightarrow V_h$	linear combination with interpolation basis

- ▶ Use greedy algorithm to determine DOFs and interpolation basis from operator evaluations on appropriate solution trajectories.

Full Reduction

Reduced order problem (with EI)

Find $\Phi_N(\mu) := u_{\mu,N} \in L^\infty([0, T]; V_N)$ such that

$$\partial_t u_{\mu,N}(t) + \{(P_{V_N} \circ I_M) \circ \mathcal{L}_{M,\mu} \circ R_{M'}\}(u_{\mu,N}(t)) = 0, \quad u_{\mu,N}(0) = P_{V_N}(u_0).$$

Offline/Online decomposition

- ▶ Precompute the linear operators $P_{V_N} \circ I_M$ and $R_{M'}$ w.r.t. basis of V_N .
- ▶ Effort to evaluate $(P_{V_N} \circ I_M) \circ \mathcal{L}_{M,\mu} \circ R_{M'}$ w.r.t. this basis:

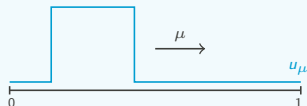
$$\mathcal{O}(MN) + \mathcal{O}(M) + \mathcal{O}(MN).$$

Trouble with Advection Dominated Problems

Typically slow decay of Kolmogorov N -widths d_N of the solution manifold, but RB will only work well for rapid decay!

$$d_N := \inf_{\substack{V_N \subseteq V_h \\ \dim V_N \leq N}} \sup_{\substack{u \in \Phi(\mathcal{P}) \\ t \in [0, T]}} \|u(t) - P_{V_N}(u(t))\|.$$

Basic example



$$\begin{aligned} \partial_t u(t, x) + \mu \cdot \partial_x u_\mu(t, x) &= 0 \\ u_\mu(0, x) &= u_0(x), \quad u_\mu(0, t) = u_\mu(1, t) \\ \mu, x, t &\in [0, 1] \end{aligned}$$

Here: $d_N \sim N^{-1/2}$ w.r.t. $L^2([0, 1])$.



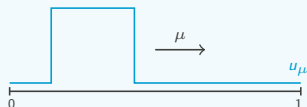
The FrozenRB scheme

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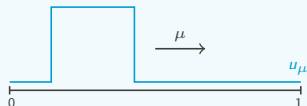
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However: We can describe solution easily as

$$u_\mu(t, x) = u_0(x - \mu \cdot t \bmod 1).$$



Nonlinear Approximation

- ▶ Write $u_\mu(t, x)$ as

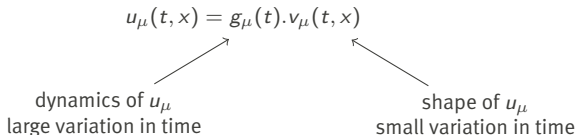
$$u_\mu(t, x) = u_0(x - \mu \cdot t \bmod 1) =: ((\mu \cdot t) \cdot u_0)(x)$$

Nonlinear Approximation

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$$u_\mu(t, x) = u_0(x - \mu \cdot t \bmod 1) =: ((\mu \cdot t) \cdot u_0)(x)$$

- ▶ **General idea:** Write $u_\mu(t, x)$ as

$$u_\mu(t, x) = g_\mu(t) \cdot v_\mu(t, x)$$


dynamics of u_μ
large variation in time

shape of u_μ
small variation in time

where \mathcal{V} function space, $v_\mu(t) \in \mathcal{V}$ and $g_\mu(t)$ is element of Lie group G acting on \mathcal{V} .

- ▶ $v_\mu(t, x)$ should be easier to approximate than $u_\mu(t, x)$!

Method of Freezing [Bejn, Thümmeler, 2004], [Rowley et. al., 2000, 2003]

- ▶ Consider Lie group G acting on \mathcal{V} and evolution equation of the form:

$$\partial_t u_\mu(t) + \mathcal{L}_\mu(u_\mu(t)) = 0, \quad u_\mu(0) = u_0, \quad u_\mu(t) \in \mathcal{V}$$

- ▶ Substituting the *ansatz* $u_\mu(t) = g_\mu(t) \cdot v_\mu(t)$ leads to:

$$\begin{aligned} \partial_t v_\mu(t) + g_\mu(t)^{-1} \cdot \mathcal{L}_\mu(g_\mu(t) \cdot v_\mu(t)) + \mathfrak{g}_\mu(t) \cdot v_\mu(t) &= 0 \\ \mathfrak{g}_\mu(t) &= g_\mu(t)^{-1} \partial_t g_\mu(t). \end{aligned}$$

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- ▶ Have $\dim(G)$ additional degrees of freedom.
→ Add additional algebraic constraint (phase condition):

$$\Phi(v_\mu(t), \mathfrak{g}_\mu(t)) = 0.$$

- ▶ Further assume invariance of \mathcal{L}_μ under action of G :

$$h^{-1} \cdot \mathcal{L}_\mu(h \cdot w) = \mathcal{L}_\mu(w) \quad \forall h \in G, w \in \mathcal{V}.$$

Method of Freezing [Beyn, Thümmeler, 2004], [Rowley et. al., 2000, 2003]

Definition (Method of Freezing)

With initial conditions $v_\mu(0) = u(0)$, $g_\mu(0) = e$, solve:

$$\partial_t v_\mu(t) + \mathcal{L}_\mu(v_\mu(t)) + g_\mu(t) \cdot v_\mu(t) = 0$$

$$\Phi(v_\mu(t), g_\mu(t)) = 0$$

frozen PDAE

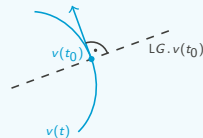
$$g_\mu(t) = g(t)_\mu^{-1} \partial_t g_\mu(t)$$

reconstruction equation

Orthogonality phase condition

$$\Phi(v, g) = 0 \iff \partial_t v(t) \perp \text{LG} \cdot v(t)$$

$$\iff (\mathcal{L}(v) + g \cdot v, h \cdot v) = 0 \quad \forall h \in \text{LG}$$



Example: 2D-Shifts

Consider $G = \mathbb{R}^2$, $LG = \mathbb{R}^2$ acting via

$$\begin{aligned}g \cdot u(x) &:= u(x - g), \quad x \in \mathbb{R}^2 \\g \cdot u &= -g \cdot \nabla u\end{aligned}$$

The Method of Freezing for 2D-shifts

Solve

$$\begin{aligned}\partial_t v_\mu(t) + \mathcal{L}_\mu(v_\mu(t)) - g_\mu(t) \cdot \nabla v_\mu(t) &= 0 \\[(\partial_{x_i} v_\mu, \partial_{x_j} v_\mu)]_{i,j} \cdot [g_\mu]_j &= [(\mathcal{L}_\mu(v_\mu), \partial_{x_i} v_\mu)]_i\end{aligned}$$

and

$$\partial_t g_\mu(t) = g_\mu(t)$$

with initial conditions $v_\mu(0) = u(0)$, $g_\mu(0) = (0, 0)^T$.

Test Problem

2D Burgers-type problem

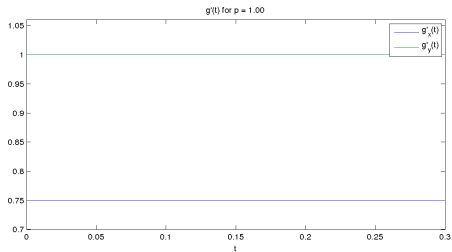
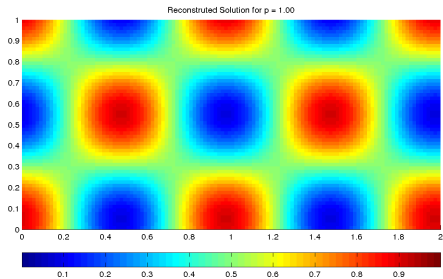
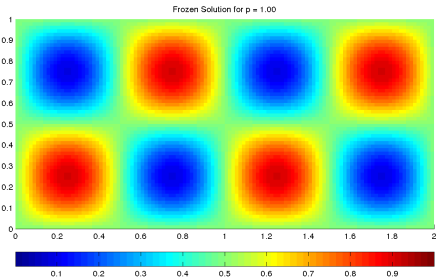
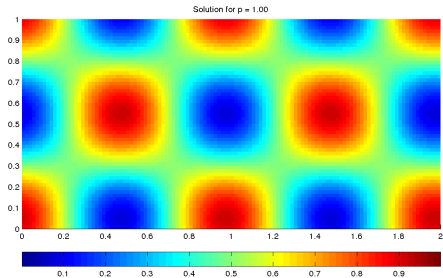
Solve on $\Omega = [0, 2] \times [0, 1]$:

$$\begin{aligned}\partial_t u + \nabla \cdot (\vec{v} \cdot u^\mu) &= 0 \\ u(0, x_1, x_2) &= 1/2(1 + \sin(2\pi x_1) \sin(2\pi x_2))\end{aligned}$$

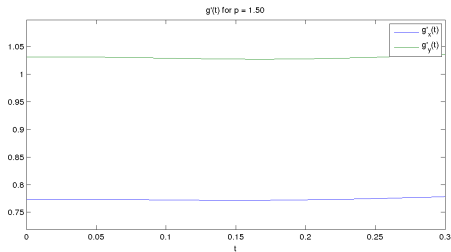
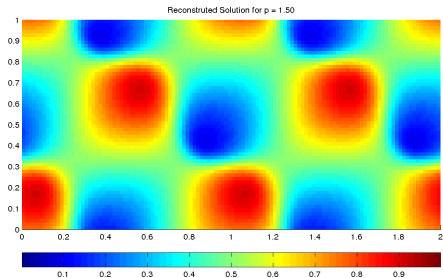
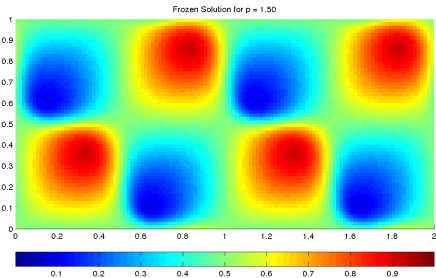
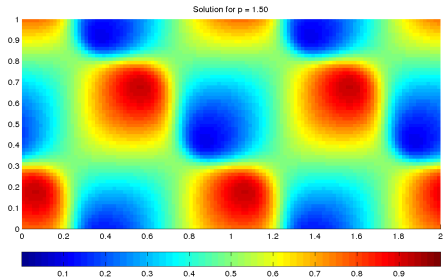
for $t \in [0, 0.3]$, $\vec{v} \in \mathbb{R}$ with periodic boundary conditions and $\mu \in \mathcal{P} = [1, 2]$.

- ▶ Finite volume (Lax-Friedrichs) space discretization on 240 x 120 grid.
- ▶ Explicit Euler time-stepping (200 time steps).
- ▶ Same problem as in [Drohmann, Haasdonk, Ohlberger, 2012].
- ▶ (The following videos are actually computed on a 120 x 60 grid.)

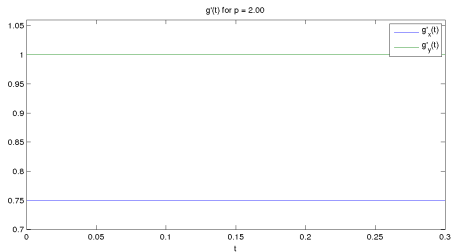
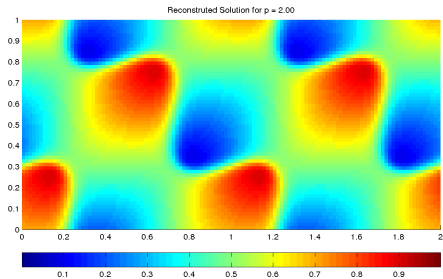
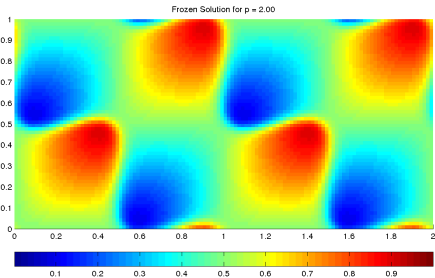
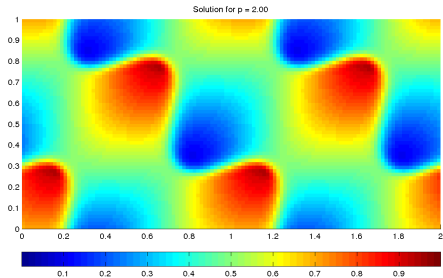
Frozen vs. Non-frozen Solution ($\mu = 1, \vec{v} = (0.75, 1)^T$)



Frozen vs. Non-frozen Solution ($\mu = 1.5, \vec{v} = (0.75, 1)^T$)

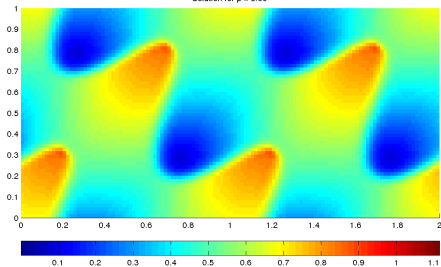


Frozen vs. Non-frozen Solution ($\mu = 2, \vec{\nu} = (0.75, 1)^T$)

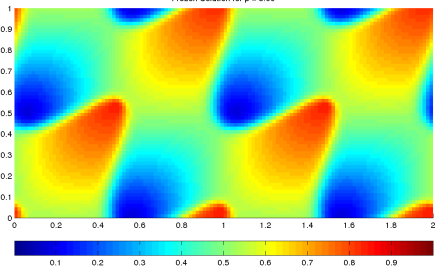


Frozen vs. Non-frozen Solution ($\mu = 3, \vec{\nu} = (0.75, 1)^T$)

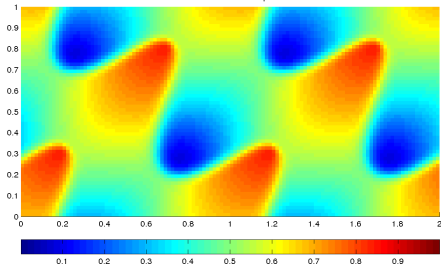
Solution for $p = 3.00$



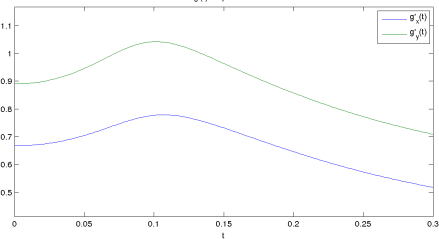
Frozen Solution for $p = 3.00$



Reconstructed Solution for $p = 3.00$



$g(t)$ for $p = 3.00$





Combining RB with the Method of Freezing

Combining RB with the Method of Freezing

FrozenRB-Scheme for 2D-shifts [Ohlberger, R, 2013]

Solve

$$\begin{aligned} \partial_t v_{\mu(t),N} + P_{V_N} \circ \mathcal{I}_M[\mathcal{L}_\mu](v_{\mu,N}(t)) - g_{\mu(t),N} \cdot (P_{V_N} \circ \nabla)(v_{\mu,N}(t)) &= 0 \\ [(\partial_{x_i} v_{\mu,N}, \partial_{x_j} v_{\mu,N})]_{i,j} \cdot [g_{\mu,N}]_j &= [(\mathcal{I}_M[\mathcal{L}_\mu](v_\mu), \partial_{x_i} v_{\mu,N})]_i \end{aligned}$$

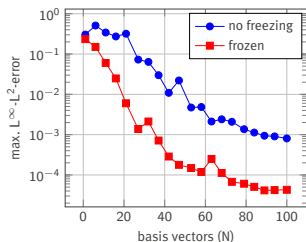
and

$$\partial_t g_\mu(t) = g_\mu(t)$$

with initial conditions $v_\mu(0) = u(0)$, $g_\mu(0) = (0, 0)^T$.

- ▶ EI-GREEDY, POD-GREEDY algorithms for basis generation.
- ▶ Full offline/online decomposition.
- ▶ No additional evaluations of nonlinearity (small overhead).

Results for the Burgers Problem ($\vec{v} = (1, 1)^T$)

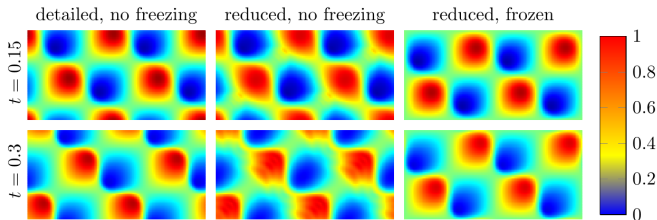


Left:

- ▶ $1.9 \cdot N$ interpolation points.
- ▶ Test set: 100 random μ .

Bottom:

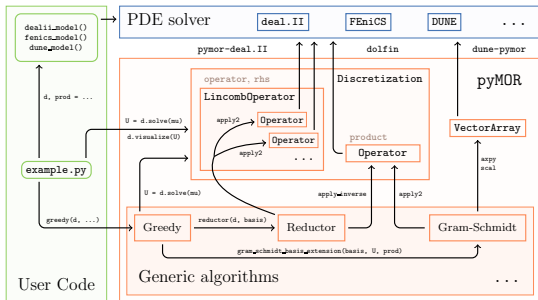
- ▶ $\dim V_N = 20$, 38 interpolation points.
- ▶ $\mu = 1.5$.





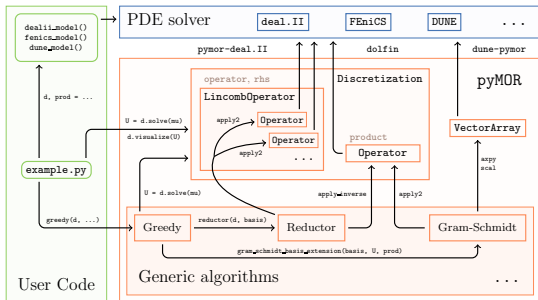
Advertisement Break

pyMOR – Model Reduction with Python



- ▶ Quick prototyping with Python.
- ▶ Seamless integration with high-performance PDE solvers.
- ▶ Out of box MPI support for reduction algs. and PDE solvers.
- ▶ BSD-licensed, fork us on Github!

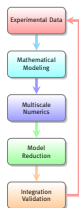
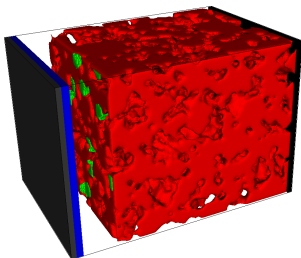
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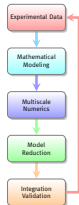
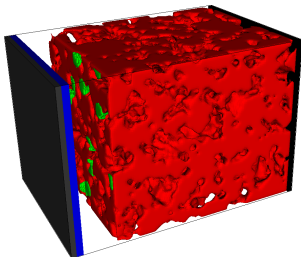
pyMOR – RB Approximation of Li-Ion Battery Models



MULTIBAT: Gain understanding of degradation processes in rechargeable Li-Ion Batteries through mathematical modeling and simulation.

- ▶ Focus: Li-Plating.
- ▶ Li-plating initiated at interface between active particles and electrolyte.
- ▶ Need large microscale models which resolve active particle geometry.

pyMOR – RB Approximation of Li-Ion Battery Models



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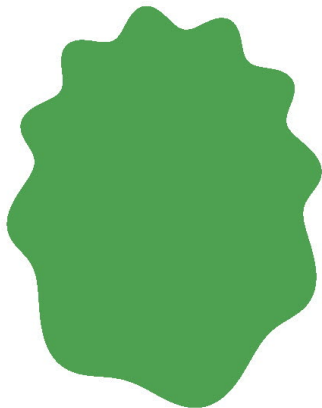
- ▶ Focus: Li-Plating.
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- ▶ Need large microscale models which resolve active particle geometry.
- ▶ **New project coming!**





Nonlinear MOR via Lagrangian Formulation

A Free Boundary Problem



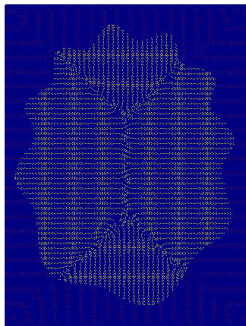
Osmotic cell swelling model

$$\begin{aligned} \partial_t u - \alpha \Delta u &= 0 && \text{in } \Omega(t) \\ \mathcal{V}_n u + \alpha \partial_n u &= 0 && \text{on } \partial\Omega(t) \\ -\beta \kappa + \gamma(u - u_0) &= \mathcal{V}_n && \text{on } \partial\Omega(t) \end{aligned}$$

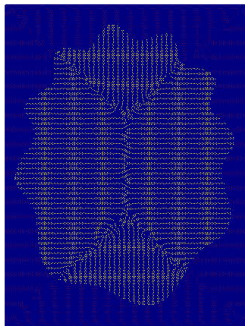
- ▶ u : concentration field
- ▶ u_0 : concentration in outside
- ▶ \mathcal{V}_n : normal velocity of $\partial\Omega(t)$
- ▶ κ : curvature of $\partial\Omega(t)$

Eulerian Approximation in $L^2(\mathbb{R}^2)$

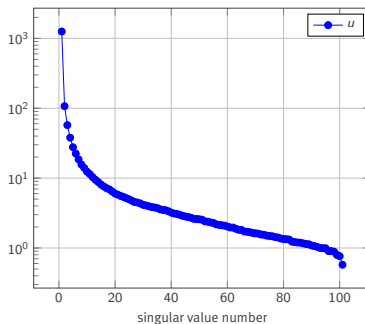
- ▶ Could consider $u(t) \in L^2(\Omega(t)) \hookrightarrow L^2(\mathbb{R}^2)$ to define joint approximation space.



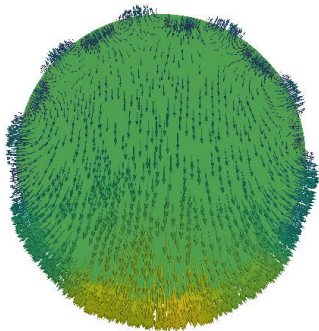
Eulerian Approximation in $L^2(\mathbb{R}^2)$



- ▶ Could consider $u(t) \in L^2(\Omega(t)) \hookrightarrow L^2(\mathbb{R}^2)$ to define joint approximation space.
- ▶ However, moving domain boundary leads to slow singular value decay of solution trajectory:



Lagrangian Formulation



- ▶ Fix reference domain $\widehat{\Omega}$ and introduce deformation field $\Psi(t)$ s.t. $\Psi(t)(\widehat{\Omega}) = \Omega(t)$.

- ▶ Time-discrete concentration equation on $\widehat{\Omega}$,

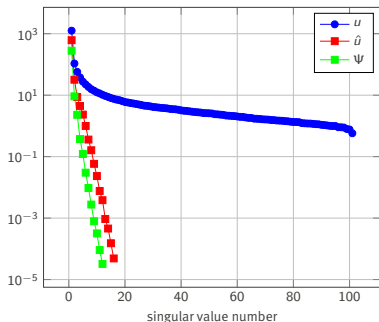
$$\int_{\widehat{\Omega}} J_{n+1} \hat{u}_{n+1} \hat{v} \, dx + \Delta t \int_{\widehat{\Omega}} J_{n+1} \partial_t \Psi_{n+1} \cdot (\partial_x \Psi_{n+1}^{-T} \cdot \nabla_{\hat{x}} \hat{v}) \hat{u}_{n+1} \, dx \\ + \Delta t \int_{\widehat{\Omega}} \alpha J_{n+1} (\partial_x \Psi_{n+1}^{-T} \nabla_{\hat{x}} u) \cdot (\partial_x \Psi_{n+1}^{-T} \nabla_{\hat{x}} \hat{v}) \, dx = \int_{\widehat{\Omega}} J_n \hat{u}_n \hat{v} \, dx,$$

where $J_n := |\det(\partial_x \Psi_n)|$.

- ▶ Compute updated Ψ_{n+1} on $\partial\widehat{\Omega}$, and extend to $\widehat{\Omega}$ via harmonic extension.

- ▶ After space discretization this corresponds to moving-mesh approach (\rightarrow ALE), where $\Psi(t)(v)$ is the trajectory of the vertex v .

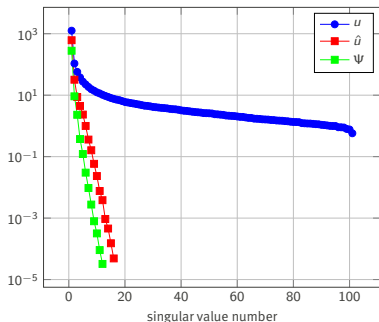
Nonlinear MOR via Lagrangian Formulation



Lagrangian ROM construction:

- ▶ Both trajectories $\hat{u}(t)$, $\Psi(t)$ are smooth and exhibit fast singular value decay.
- ▶ Compute low-rank approximation spaces $V_{\hat{u}}$, V_{Ψ} via POD.
- ▶ Note: V_{Ψ} acts nonlinearly on $V_{\hat{u}}$.
- ▶ Use EIM to approximate nonlinearities in coefficient functions.

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Preliminary MOR results:

- ▶ $\mu \in \mathbb{R}^3$ (2D initial conditions + diffusivity)
- ▶ FOM: 3988 / 5592 DOFs
- ▶ ROM: 38 / 24 DOFs
- ▶ 40 / 42 / 21 / 20 / 2 / 33 El points
- ▶ max rel. space-time error: $3 \cdot 10^{-3}$
- ▶ Speedup: 64



Thank you for your attention!

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Ohlberger, R, *Reduced Basis Methods: Success, Limitations and Future Challenges*, Proceedings of ALGORITHMY 2016.

pyMOR – Generic Algorithms and Interfaces for Model Order Reduction
SIAM J. Sci. Comput., 38(5), 2016.
<http://www.pymor.org/>

My homepage (with FrozenRB code)
<http://stephanrave.de/>