

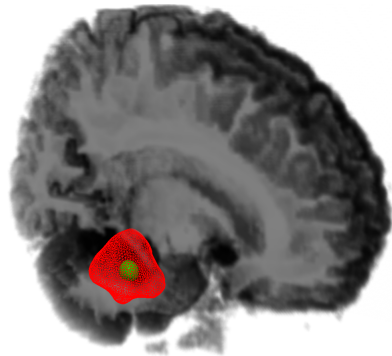
On Preconditioning Newton Method for PDE Constrained Optimization Problems

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Outline

1 Introduction

2 Forward Model

3 Inverse Problem

4 Hessian

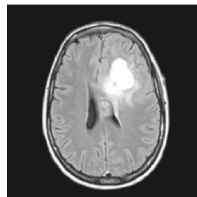
Gliomas:

- Account for **80%** of all malignant brain tumors.
- More than **60,000** new cases each year in US.

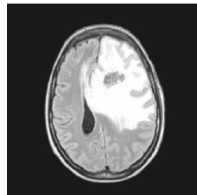
Goals of biophysical tumor growth model:

- Determining the extent of tumor infiltration
- Pre- and post-operative planning

This requires a patient specific method to approximate a **tumor growth model** parameters.



Initial FLAIR Scan



Time2 FLAIR Scan

Image from (P. Mosayebi et. al.)

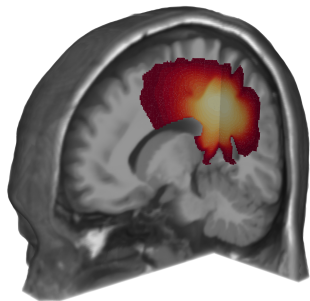
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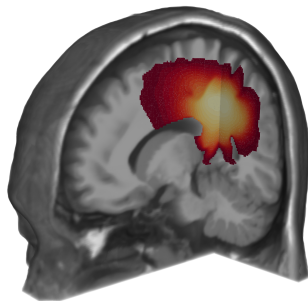
4 Hessian



Phenomenological model:

$$\frac{\partial c}{\partial t} - \nabla \cdot (\mathbf{k}(x) \nabla c) - \rho c(1 - c) = 0 \text{ in } U = \Omega \times (0, T],$$

$$\frac{\partial c}{\partial n} = 0 \text{ on } \Gamma \times (0, 1),$$



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$$\frac{\partial c}{\partial t} - \nabla \cdot (k(x) \nabla c) - \rho c(1 - c) = 0 \text{ in } U = \Omega \times (0, T],$$

$$\frac{\partial c}{\partial t} - Dc - r(c) = 0 \text{ in } U = \Omega \times (0, T],$$

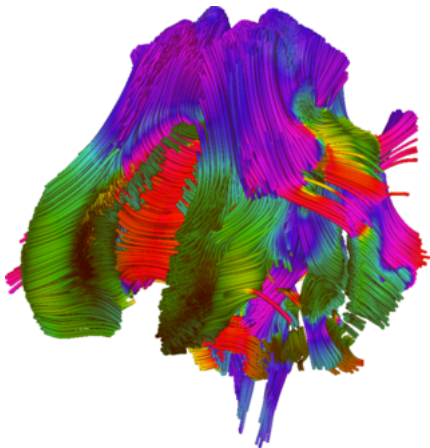
$$\frac{\partial c}{\partial n} = 0 \text{ on } \Gamma \times (0, 1),$$

$$Dc = \nabla \cdot (k(\mathbf{x}) \nabla c),$$

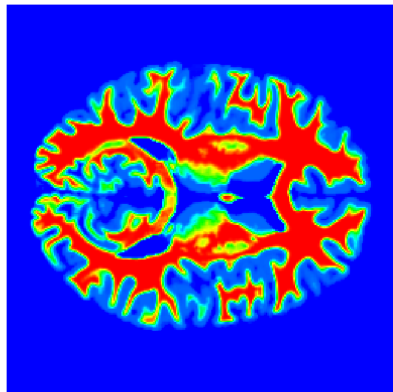
$$k(\mathbf{x}) = k_0(\mathbf{x})I + k_f T(\mathbf{x})$$

- k_0 : Inhomogeneous diffusion part
- $T(\mathbf{x})$: Anisotropic diffusion part
- k_f : Anisotropic diffusion coefficient

Forward Model - Diffusion



Principle direction extracted from DTI
(raw data provided by LONI lab of USC).



Inhomogeneous part of the diffusion

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PDE-constrained optimization:

$$\min_{\mathbf{p}} \mathcal{J} := \frac{1}{2} \|O_0 \mathbf{c}_0 - \mathbf{d}_0\|_{L^2(\Omega)}^2 + \frac{1}{2} \|O_1 \mathbf{c}_1 - \mathbf{d}_1\|_{L^2(\Omega)}^2 + \frac{\beta_p}{2} \|\mathbf{p}\|_{\mathcal{R}^{N_k}}^2,$$

subject to:

$$\frac{\partial \mathbf{c}}{\partial t} - D\mathbf{c} - r(\mathbf{c}) = 0 \text{ in } U$$

$$\mathbf{c}_0 - \Phi \mathbf{p} = 0.$$

By requiring stationarity of the Lagrangian with respect to the adjoint, state, and inversion variable, we obtain the so called KKT optimality conditions:

$$\frac{\partial \mathcal{L}}{\partial c} = 0 \Rightarrow \text{adjoint equation}$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} = 0 \Rightarrow \text{state equation}$$

$$\frac{\partial \mathcal{L}}{\partial p} = 0 \Rightarrow \text{inversion equation}$$

Find c, α, p such that:

$$\left\{ \begin{array}{l} -\frac{\partial \alpha}{\partial t} - D\alpha - \frac{\partial r(c)}{\partial c} \alpha = 0 \\ \alpha_1 + O_1^T (O_1 c_1 - d_1) = 0 \\ \frac{\partial c}{\partial t} - Dc - r(c) = 0 \\ c_0 - \Phi p = 0 \\ \beta p + O_0^T (O_0 p - d_0) - \Phi^T \alpha_0 = 0 \end{array} \right.$$

$$H\tilde{p} = -\partial_p \mathcal{L}|_{p^0}.$$

where H is the reduced Hessian and $H\tilde{p}$ is computed by:

1. Given p^0 , compute c^0 and α^0 from the state and adjoint equations.
2. Solve for \tilde{c} and $\tilde{\alpha}$:

$$\frac{\partial \tilde{c}}{\partial t} - \nabla \cdot (\mathbf{k} \nabla \tilde{c}) - \rho(1 - 2c^0)\tilde{c} = 0$$

$$\tilde{c}(0) - \Phi \tilde{p} = 0$$

$$-\frac{\partial \tilde{\alpha}}{\partial t} - \nabla \cdot (\mathbf{k} \nabla \alpha) - \rho(1 - 2c^0)\tilde{\alpha} + 2\rho \tilde{c} \alpha^0 = 0$$

$$\tilde{\alpha}(T) + O^T O \tilde{c}(T) = 0$$

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$$\tilde{\alpha}(T) + O^T O \tilde{c}(T) = 0$$

- 1 Solve $\frac{\partial c}{\partial t} = Dc$ over time $\Delta t/2$ with c^n as initial condition, to obtain c^\dagger .
- 2 Solve $\frac{\partial c}{\partial t} = R(c)$ over time Δt with c^\dagger as initial condition, to obtain $c^{\dagger\dagger}$.
- 3 Solve $\frac{\partial c}{\partial t} = Dc$ over time $\Delta t/2$ with $c^{\dagger\dagger}$ as initial condition, to obtain c^{n+1} .

This scheme can more compactly be written as:

$$c^{n+1} = S_D^{\frac{\Delta t}{2}} S_R^{\Delta t} S_D^{\frac{\Delta t}{2}} c^n,$$

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Extensive work on Hessian preconditioners on stationary problems but much less work on solvers for nonlinear parabolic systems

General ideas:

- Low rank approximation,
- Domain-decomposition,
- Analytic preconditioners,
- Multilevel preconditioners,

Our approach fits in the last two categories with some elements on multilevel.

Hessian Preconditioner

1. Given p^0 , compute c^0 and α^0 from the state and adjoint equations.
2. Solve for \tilde{c} and $\tilde{\alpha}$:

$$\frac{\partial \tilde{c}}{\partial t} - \nabla \cdot (\mathbf{k} \nabla \tilde{c}) - \rho(1 - 2c^0)\tilde{c} = 0$$

$$\tilde{c}(0) - \Phi \tilde{p} = 0$$

$$-\frac{\partial \tilde{\alpha}}{\partial t} - \nabla \cdot (\mathbf{k} \nabla \alpha) - \rho(1 - 2c^0)\tilde{\alpha} + 2\rho \tilde{c} \alpha^0 = 0$$

$$\tilde{\alpha}(T) + O^T O \tilde{c}(T) = 0$$

3. $H\tilde{p} = \beta\tilde{p} - \Phi^T \tilde{\alpha}(0)$.

★ Approximate J^{-1} by including the nonlinear reaction term, and using average diffusion coefficient ($\bar{\mathbf{k}}$)

Hessian Preconditioner

1. Given p^0 , compute c^0 and α^0 from the state and adjoint equations.
2. Solve for \tilde{c} and $\tilde{\alpha}$:

$$\frac{\partial \tilde{c}}{\partial t} - \nabla \cdot (\bar{\mathbf{k}} \nabla \tilde{c}) - \rho(1 - 2c^0)\tilde{c} = 0$$

$$\tilde{c}(0) - \Phi \tilde{p} = 0$$

$$-\frac{\partial \tilde{\alpha}}{\partial t} - \nabla \cdot (\bar{\mathbf{k}} \nabla \alpha) - \rho(1 - 2c^0)\tilde{\alpha} + 2\rho \tilde{c} \alpha^0 = 0$$

$$\tilde{\alpha}(T) + O^T O \tilde{c}(T) = 0$$

3. $P_H \tilde{p} = \beta \tilde{p} - \Phi^T \tilde{\alpha}(0)$.

- AP_0 : Use \bar{k} for the diffusion term and ignore the rest
 - Computational cost **independent** of the number of time steps.
- AP_1 : Use \bar{k} for the diffusion term and numerically solve the rest
 - Computational cost scales linearly with the number of time steps.

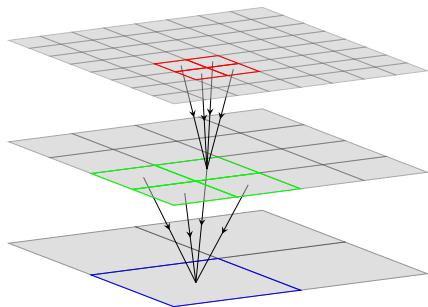
OR

Compute the true H^{-1} , on a coarser grid $\rightarrow MLP_i$

$$\tilde{H} = \tilde{J}^{-T} O^T O \tilde{J}^{-1} + \beta I.$$

Use an iterative solver to compute the matvec of \tilde{H}^{-1}

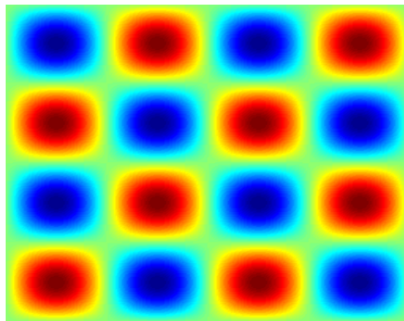
- Higher computational cost compared to APs.



- (1) Start with some p^0 .
- (2) $P_H^{-1} H \tilde{p} = -P_H^{-1} \frac{\partial J}{\partial p}$.
- (3) Set $p^0 = p^0 + \gamma \tilde{p}$ (with line search).
- (4) If tolerance is reached break, otherwise go back to 2.

Preconditioner Performance: Test Case 1

$$\frac{\partial c}{\partial t} - \nabla \cdot (k(x) \nabla c) - \rho c(1 - c) = 0$$




$k = 1 + \sin(2x)$ and ρ constant

Preconditioner Performance: Test Case 1

The number of Hessian matvecs to solve the optimality conditions for one iteration ($\text{tol}=1\text{E-}3$, $N = 128^2$). *AP*: Analytical Preconditioner, MLP_i Coarse Grid Preconditioner (level i coarsening).

ρ	No Prec	P_0	P_1	MLP_1	MLP_2	MLP_3
0	6	3+0.00	3+0.07	3+1.50	3+0.29	4+0.07
0.1	6	3+0.00	3+0.07	3+1.50	3+0.29	4+0.07
1	8	5+0.01	4+0.11	3+1.82	4+0.51	6+0.11
5	13	15+0.02	6+0.40	5+9.00	6+2.28	10+0.71

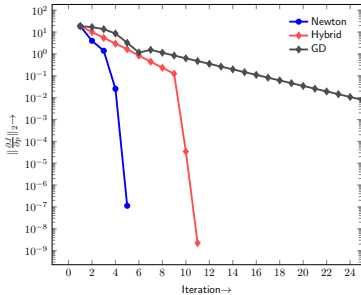
 Since the preconditioners perform very well, we can use them at the early stages of the Newton solves

→ **hybrid inexact Newton Method**

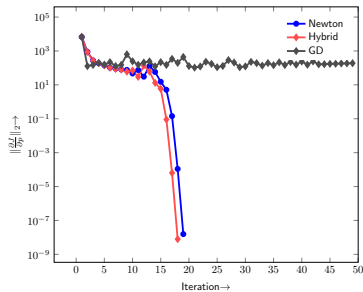
Preconditioner Performance: Test Case 1

The total of Hessian matvecs to required to reduce the L2 norm of the gradient below $1E-3$.

Method	$\rho = 0$	$\rho = 0.1$	$\rho = 1.0$	$\rho = 5.0$
UnPrec. Newton	12	12	22	85
Prec. Newton	8.90	8.90	15.00	44.43
Hybrid Newton	2.34	2.35	5.69	32.59



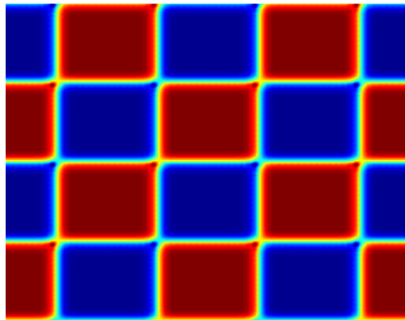
(a) $\rho = 0$.



(b) $\rho = 5.0$

Preconditioner Performance: Test Case 2

$$\frac{\partial c}{\partial t} - \nabla \cdot (\mathbf{k}(\mathbf{x}) \nabla c) - \rho c(1 - c) = 0$$



Checkerboard diffusion coefficient, and $\rho = 1$ constant

Preconditioner Performance: Test Case 2

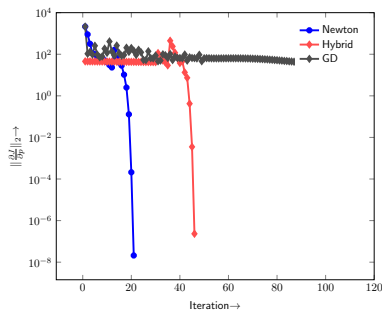
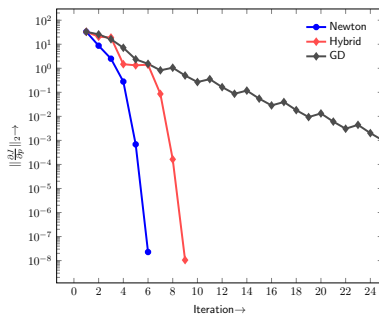
The number of Hessian matvecs to solve the optimality conditions for one iteration ($\text{tol}=1\text{E-}3$, $N = 128^2$). *AP*: Analytical Preconditioner, MLP_i Coarse Grid Preconditioner (level i coarsening).

T	No Prec	P_0	P_1	MLP_1	MLP_2	MLP_3
0.2	6	3+0.01	3+0.22	2+1.31	3+0.37	3+0.08
0.5	7	4+0.01	4+0.14	3+2.19	3+0.39	4+0.12
1	9	6+0.00	5+0.12	3+2.84	4+0.61	6+0.18
2	15	12+0.01	8+0.15	5+7.77	6+1.46	10+0.39
4	22	23+0.00	16+0.20	10+23.84	9+3.79	14+0.05

Preconditioner Performance: Test Case 2

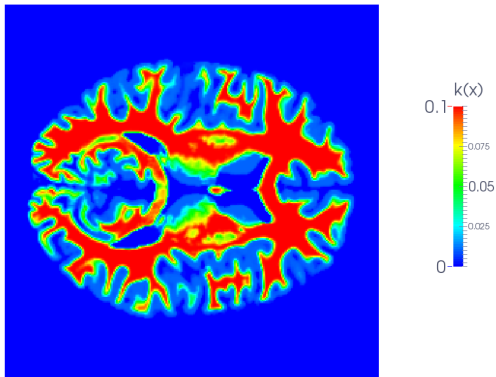
The total of Hessian matvecs to required to reduce the L2 norm of the gradient below $1E-3$.

Method	$T = 0.2$	$T = 0.5$	$T = 1.0$	$T = 2.0$	$T = 4.0$
UnPrec. Newton	12	12	27	43	96
Prec. Newton	8.37	8.37	16.63	27.06	54.41
Hybrid Newton	2.63	5.90	11.81	22.13	54.60



Preconditioner Performance: Test Case 3

$$\frac{\partial c}{\partial t} - \nabla \cdot (\mathbf{k}(x) \nabla c) - \rho c(1 - c) = 0$$



Diffusion coefficient for test case 4.

Preconditioner Performance: Test Case 3

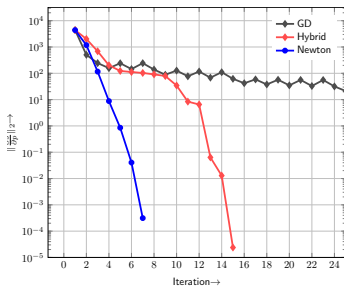
The number of Hessian matvecs to solve the optimality conditions for one iteration (tol=1E-3, $N = 64^3$). *AP*: Analytical Preconditioner, MLP_i Coarse Grid Preconditioner (level i coarsening).

ρ	No Prec	AP_0	AP_1	MLP_1	MLP_2
1.0	7	3.00	3+0.05	3+0.25	3+0.02
2.0	8	5+0.01	3+0.06	5+0.63	6+0.10
4.0	9	10+0.02	3+0.06	12+0.06	12+0.24

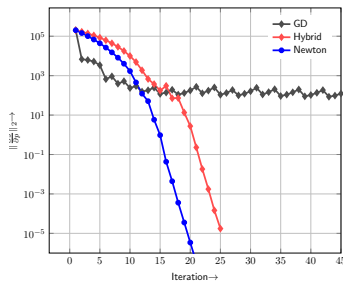
Preconditioner Performance: Test Case 3

Total number of Hessian matvecs necessary to reach convergence (i.e. $\|\frac{\partial J}{\partial p}\|_2 < 1E-3$)

Method	$\rho = 1.0$	$\rho = 2.0$	$\rho = 4.0$
UnPrec. Inexact Newton	69	74	137
Prec. Inexact Newton	34.34	38.42	47.66
Hybrid Inexact Newton	28.06	28.01	42.6



(a) $\rho = 1.0$



(b) $\rho = 4.0$

Thank You

- Andreas Mang
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- Nick Alger