

# Biofilm Characterization using Large Scale Optimization

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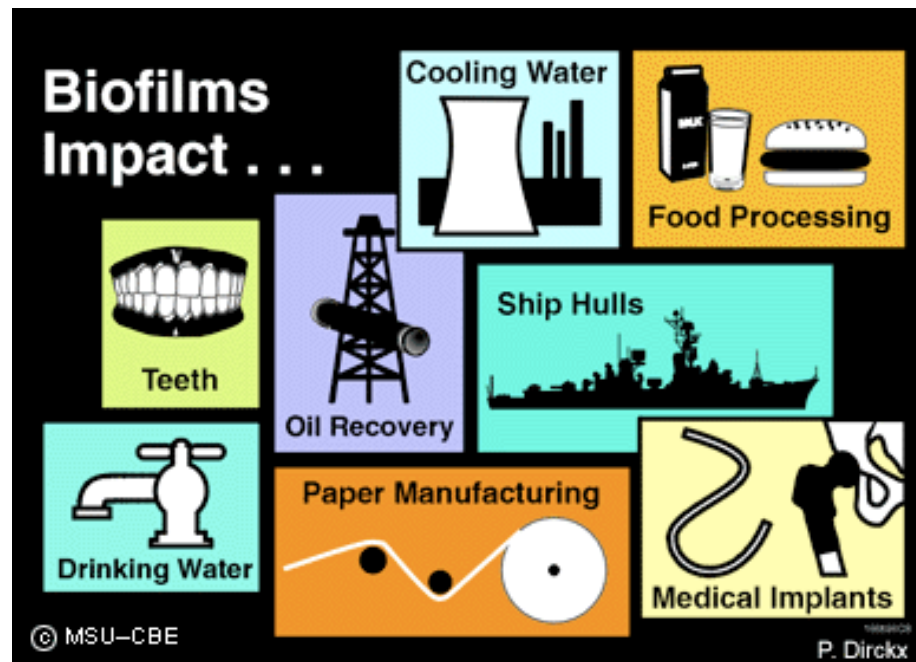
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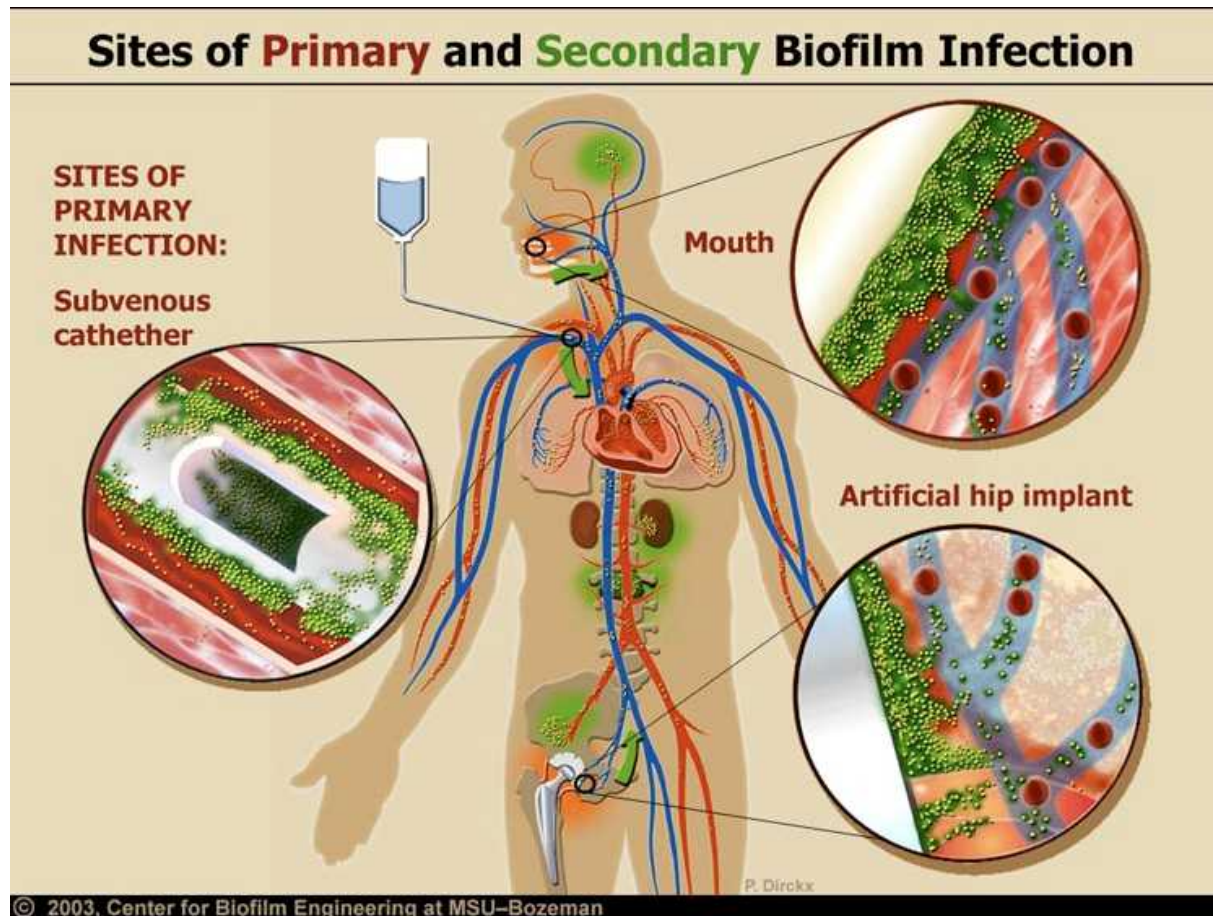
SIAM Optimization Conference  
May, 2008

# Motivation: Definition and Impact

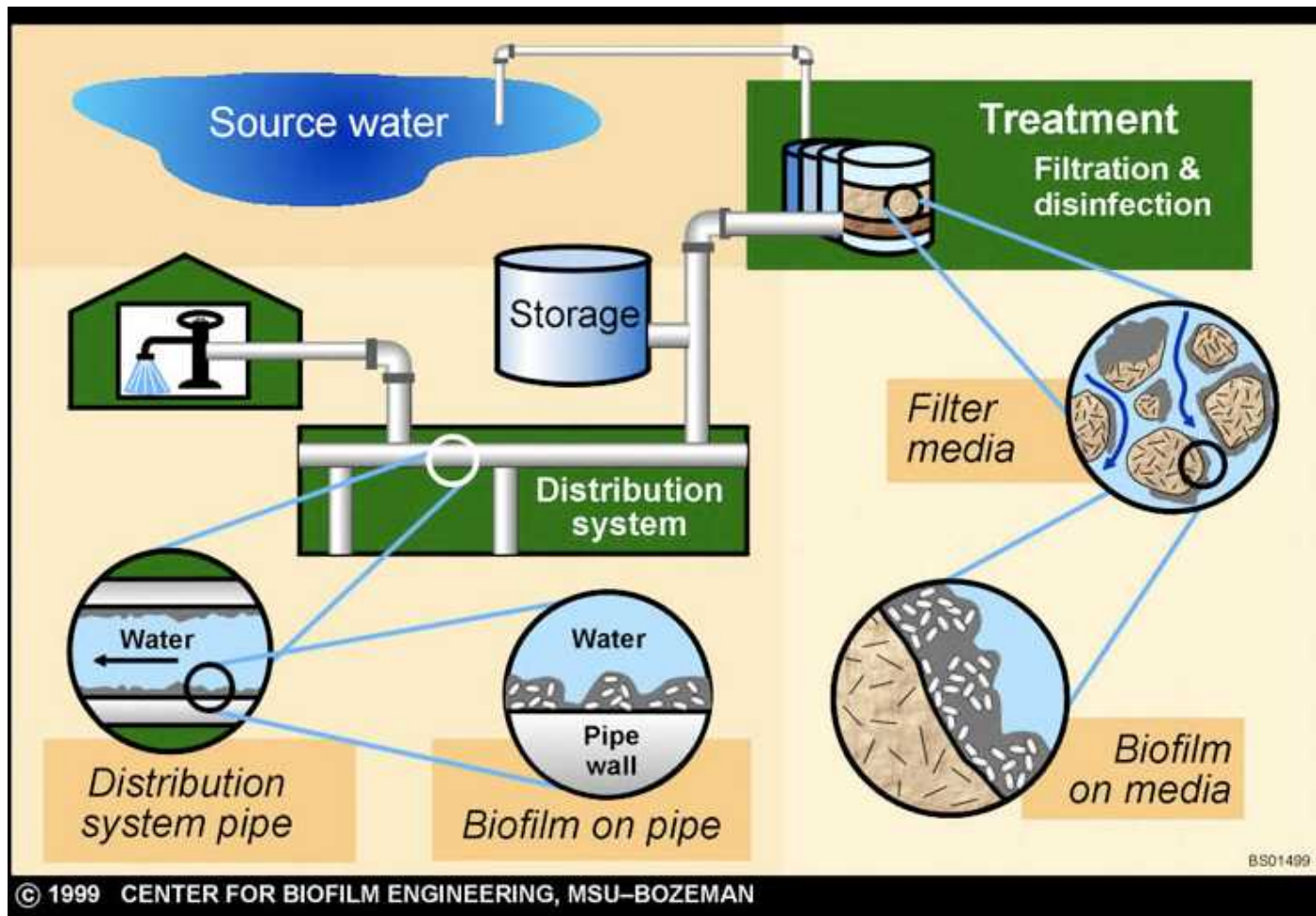
A biofilm is a complex aggregation of microorganisms marked by the excretion of a protective and adhesive matrix.



# Motivation: Human Physiology



# Motivation: Water Distribution & Security





## Goals of the project:

- Develop simulation capabilities to predict the dynamics of biofilms
- Calibrate model with experimental observations
- Develop efficient and flexible extension capabilities
- Characterize uncertainties



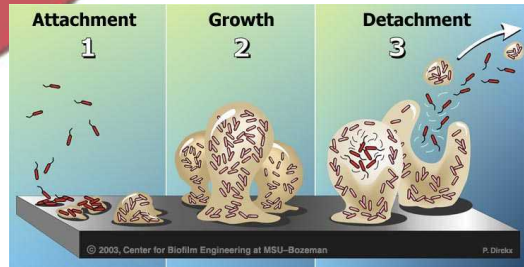
# Outline

- Motivation
- Physics
- Inversion
- Implementation
- Numerical examples/results

Goal of the presentation: 1) motivate **PDE Constrained Optimization** through biofilm problem, 2) demonstrate convenient PDECO framework



- Bacteria Adhesion
- EPS Production
- Bacteria duplication
- Transport of interface
- Detachment



# Biofilm Physics

## Multi-species Model for growth: (Alpkvist and Klapper 06)

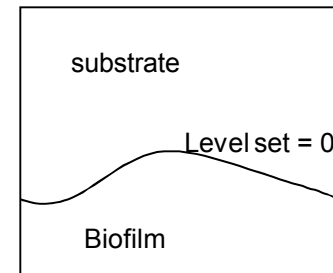
QuickTime™ and a  
TIFF (Uncompressed) decompressor  
are needed to see this picture.

## Simplified model:

QuickTime™ and a  
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Computational domain:

$C = 1.0$



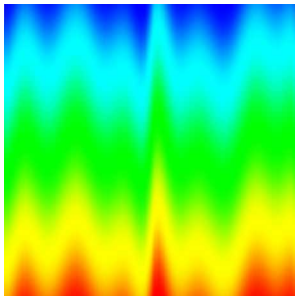
# Forward Simulation Results

(Realizations shown at final timestep)

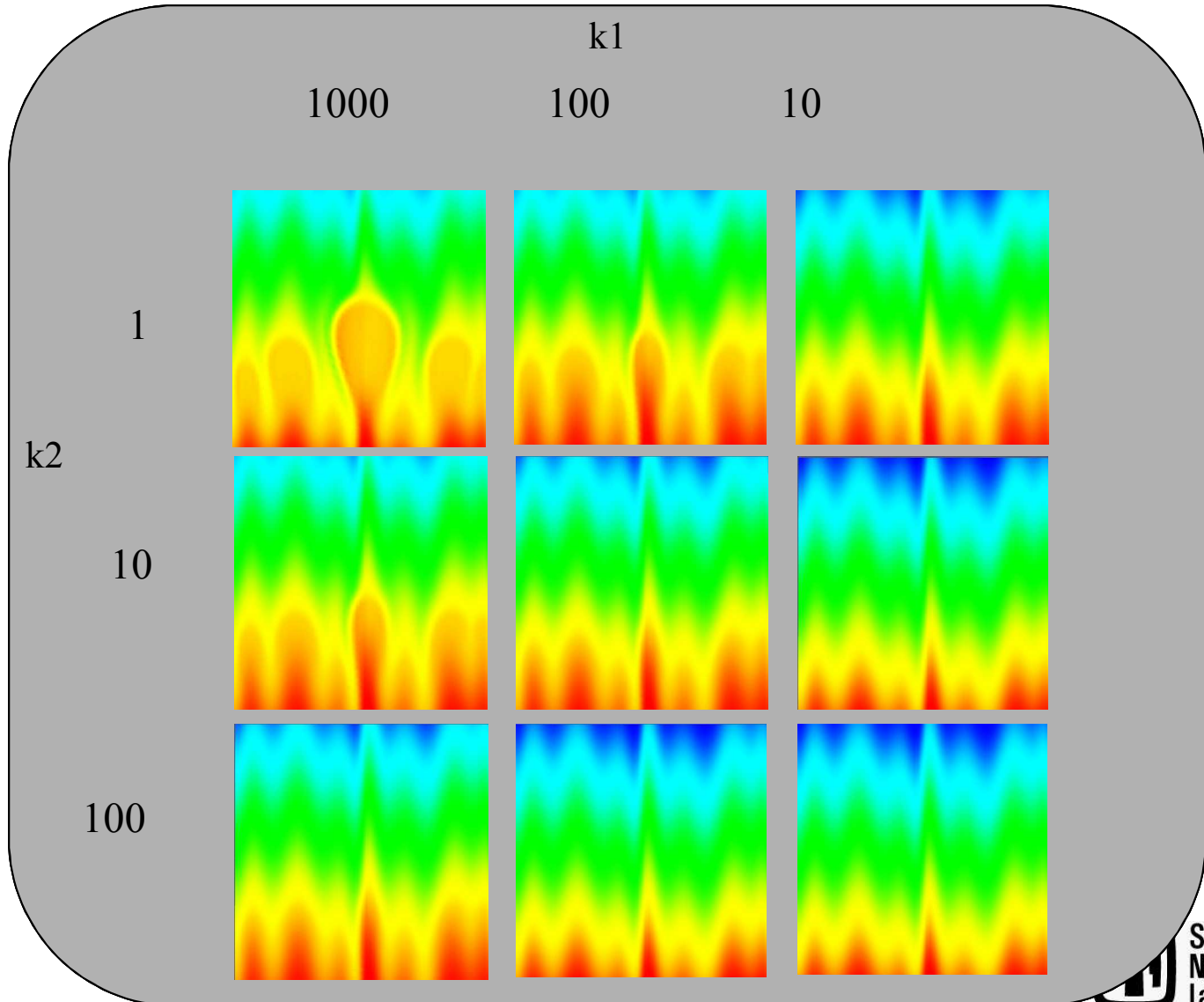
QuickTime™ and a  
TIFF (Uncompressed) decompressor  
are needed to see this picture.

## Simulation Details:

- $\Delta t = 0.005$
- grid  $64 \times 64$
- $D = 1.0$
- Newton-GMRES
- ILU preconditioner
- CPU time = 70s



Initial Condition





# Forward Simulation Results

(Realizations shown at final timestep)

QuickTime™ and a  
TIFF (Uncompressed) decompressor  
are needed to see this picture.

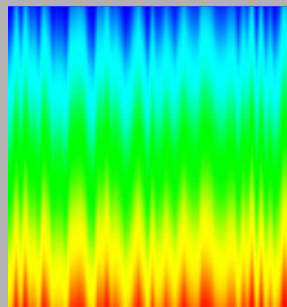
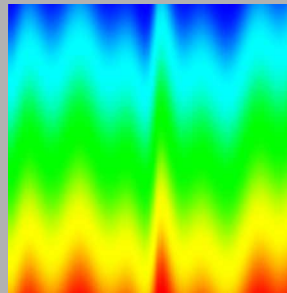
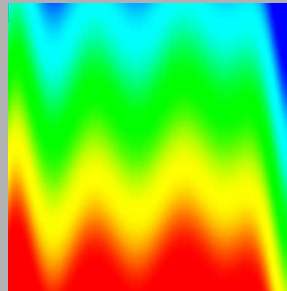
## Simulation Details:

- timesteps = 30
- deltaT = 0.005
- grid 64x64
- D = 1.0
- Newton-GMRES
- ILU preconditioner
- CPU time = 70s

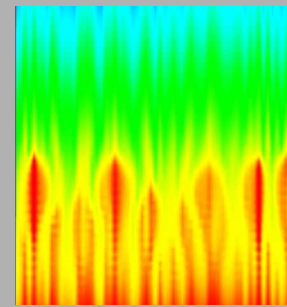
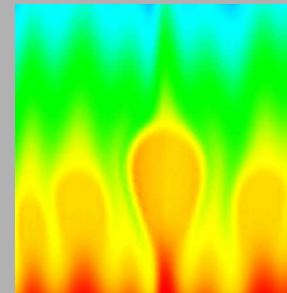
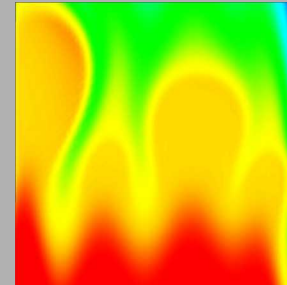
## Constant:

- K1 = 1000.0
- K2 = 1.0

TS=0



TS=30



# Biofilm Optimization Formulation

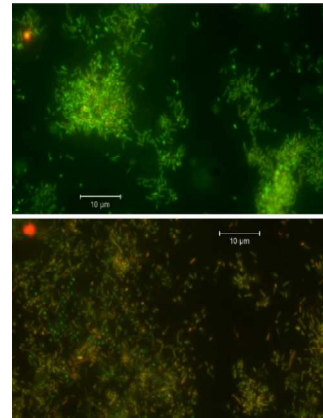
*The PDE constrained optimization problem*

$$\min_{\rho, \rho_0} \mathcal{F}(\rho, \rho_u) = \frac{1}{2} \sum_{i=0}^N \int_0^T \int_{\Omega} (\rho - \rho^*)^2 \delta(x - x_i) \, \mathbf{dx} \, \mathbf{dt} + \frac{\beta}{2} \int_{\Omega} \rho_0^2 \, \mathbf{dx}$$

subject to:

$$\begin{aligned} \frac{\partial \rho}{\partial t} + \frac{D}{\rho_b} \nabla c \cdot \nabla \rho &= 0 && \text{in } \Omega \times [0, T] \\ \rho &= \rho_0 && \text{in } \Omega \times \{t = 0\}. \\ D \Delta c &= \frac{k_1 c \rho}{k_2 + c} && \text{in } \Omega \\ c &= c_D && \text{in } \Gamma_D \end{aligned}$$

Match confocal microscope images



# Biofilm Optimality Conditions

*The forward coupled problem*

$$\begin{aligned}
 D\Delta c &= \frac{k_1 c \rho}{k_2 + c} && \text{in } \Omega \\
 c &= c_D && \text{in } \Gamma_D \\
 \frac{\partial \rho}{\partial t} + \frac{D}{\rho_b} \nabla c \cdot \nabla \rho &= 0 && \text{in } \Omega \times [0, T] \\
 \rho &= \rho_0 && \text{in } \Omega \times \{t = 0\}.
 \end{aligned}$$

*The adjoint problem*

$$\begin{aligned}
 D\Delta \lambda_1 - \frac{k_1 k_2 \rho}{(k_2 + c)^2} \lambda_1 - \frac{D}{\rho_b} \lambda_2 \Delta \rho &= 0 && \text{in } \Omega \\
 -D \nabla \lambda_1 \cdot n + \lambda_2 \frac{D}{\rho_b} \nabla \rho \cdot n &= 0 && \text{on } \Gamma_N \\
 \lambda_1 &= 0 && \text{on } \Gamma_D \\
 -\frac{\partial \lambda_2}{\partial t} - \frac{D}{\rho_b} \lambda_2 \Delta c - \frac{k_1 c \lambda_1}{k_2 + c} &= -\Sigma(\rho - \rho^*) \delta_j && \text{in } \Omega \times [0, T] \\
 \lambda_2 &= 0 && \text{in } \Omega \times \{t = 0\}
 \end{aligned}$$

*The initial concentration equation*

$$\beta \rho_0 - \lambda_2|_{t=0} = 0 \quad \text{in } \Omega.$$



## Implementation Goals

Need **efficient** capability to implement **embedded** algorithms (i.e. PDECO)

**Possible solutions:** compile time transformation (**tricky** on complex codes), friendly interfaces, i.e. Comsol (**slow, inflexible**), armies of programmers (**expensive, error-prone, unmaintainable**)

**Our approach:** 1) State in **mathematical form** the general problem of “writing” an efficient intrusive code 2) Write (**by hand**) a code to solve that meta-problem, 3) Write papers while the computer does the dirty work

**Added benefits:** The key to intrusion turns out to **simplify automation** as well a mathematical definition of the simulation development process aids in establishing **code correctness**

# Implementation Mathematics

- Test/Unkown/Auxiliary variables
- Functional spaces
- Frechet differentiation
- Discrete spaces

## Examples:

### Steady Navier-Stokes flow

$$F[\mathbf{v}, \mathbf{u}, q, p] = \int_{\Omega} [\nu \nabla \mathbf{v} : \nabla \mathbf{u} + p \nabla \cdot \mathbf{v} + \mathbf{v} \cdot (\mathbf{u} \cdot \nabla) \mathbf{u} + q \nabla \cdot \mathbf{u}]$$

### Lagrangian for Poisson source inversion w/ Tikhonov

$$F[v, \mu, \beta, u, \lambda, \alpha] = \int_{\Omega} [(u - u^*) v + \nabla \lambda \cdot \nabla v] dx + \\ + \int_{\Omega} [\nabla \mu \cdot \nabla u + \mu \alpha] dx + \\ + \int_{\Omega} [\nabla \alpha \cdot \nabla \beta + \lambda \beta] dx$$

Approach unifies diverse set of problems:

### A linearized forward problem: find Newton step $\delta \mathbf{u}$ at $\mathbf{u}_0$

$$\left. \frac{\partial \hat{F}}{\partial v_i} \right|_{\mathbf{u}_0} + \left. \frac{\partial^2 \hat{F}}{\partial v_i \partial u_j} \right|_{\mathbf{u}_0} \delta u_j = 0$$

### A quadratic eigensystem: find $\sigma, \mathbf{u}$

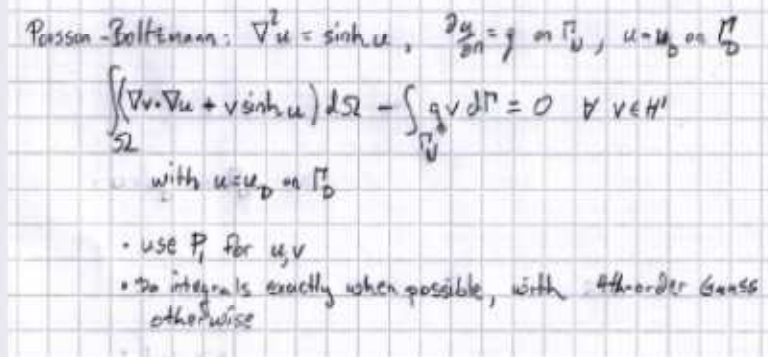
$$\left. \frac{\partial^2 \hat{F}}{\partial v_i \partial u_j} \right|_0 u_j + \left. \frac{\partial^3 \hat{F}}{\partial v_i \partial u_j \partial \sigma} \right|_0 \sigma u_j + \frac{1}{2} \left. \frac{\partial^4 \hat{F}}{\partial v_i \partial u_j \partial \sigma^2} \right|_0 u_j \sigma^2 = 0$$

### A sensitivity problem: find $\partial \mathbf{u} / \partial \sigma$ at $\mathbf{u}_0$

$$\left. \frac{\partial^2 \hat{F}}{\partial v_i \partial \sigma} \right|_{\mathbf{u}_0} + \left. \frac{\partial^2 \hat{F}}{\partial v_i \partial u_j} \right|_{\mathbf{u}_0} \frac{\partial u_j}{\partial \sigma} = 0$$

# Implementation Syntax

Sundance is a toolkit that is based on these principles



Poisson-Boltzmann:  $\nabla^2 u = \sinh u$ ,  $\frac{\partial u}{\partial n} = f$  on  $\Gamma_D$ ,  $u = u_D$  on  $\Gamma_D$

$$\int_{\Omega} (\nabla v \cdot \nabla u + v \sinh u) d\Omega - \int_{\Gamma_D} g v d\Gamma = 0 \quad \forall v \in H^1$$

with  $u = u_D$  on  $\Gamma_D$

- use  $P_1$  for  $u, v$
- do integrals exactly when possible, with 4th-order Gauss otherwise

Poisson-Boltzmann equation in a notebook

```
u = UnknownFunction(Lagrange(1))
v = TestFunction(Lagrange(1))

quad = GaussianQuadrature(4)

weak = Integral(omega, (grad*u)*(grad*v)+v*sinh(u), quad)
```

Poisson-Boltzmann equation in Sundance



# Implementation Syntax for Optimization: Approach 1

The forward coupled problem

$$\begin{aligned} D\Delta c &= \frac{k_1 c \rho}{k_2 + c} && \text{in } \Omega \\ c &= c_D && \text{in } \Gamma_D \\ \frac{\partial \rho}{\partial t} + \frac{D}{\rho_b} \nabla c \cdot \nabla \rho &= 0 && \text{in } \Omega \times [0, T] \\ \rho &= \rho_0 && \text{in } \Omega \times \{t = 0\}. \end{aligned}$$

The adjoint problem

$$\begin{aligned} D\Delta \lambda_1 - \frac{k_1 k_2 \rho}{(k_2 + c)^2} \lambda_1 - \frac{D}{\rho_b} \lambda_2 \Delta \rho &= 0 && \text{in } \Omega \\ -D \nabla \lambda_1 \cdot n + \lambda_2 \frac{D}{\rho_b} \nabla \rho \cdot n &= 0 && \text{on } \Gamma_N \\ \lambda_1 &= 0 && \text{on } \Gamma_D \\ -\frac{\partial \lambda_2}{\partial t} - \frac{D}{\rho_b} \lambda_2 \Delta c - \frac{k_1 c \lambda_1}{k_2 + c} &= -\Sigma(\rho - \rho^*) \delta_j && \text{in } \Omega \times [0, T] \\ \lambda_2 &= 0 && \text{in } \Omega \times \{t = 0\} \end{aligned}$$

The initial concentration equation

$$\beta \rho_0 - \lambda_2|_{t=0} = 0 \quad \text{in } \Omega.$$

```
Expr state = Integral(interior, (u - u0)*uHat* 1.0/deltaT + v*(grad*u)*uHat
+ D*(grad*uHat)*(grad*u), q2);
Expr stateBC = EssentialBC(left, u*uHat, q2);
stateProb = rcp(new LinearProblem(mesh_, state, stateBC, mu, u, vecType));
```

forward

```
CellFilter sensors = sensorFilter() ;
Expr adjoint = Integral(interior, (lambda - lambda0)*v/deltaT
+ D*(grad*u)*(grad*lambda)
+ v*(grad*u)*lambda, q2)
+ Integral(sensors, v*(u - uTarget), q2) ;
Expr adjointBC = EssentialBC(left, lambda*v, q2)
+ EssentialBC(bottom, lambda*v, q2) ;
adjointProb = rcp(new LinearProblem(mesh_, adjoint, adjointBC,
v, lambda, vecType));
```

adjoint

```
Expr sens = Integral(interior_, -Reg_ * u0_*beta + lambda0_*beta + beta*u, q2);
Expr sensBC;
Expr sensProb = new LinearProblem(mesh, sens, sensBC, beta, u, vecType);
```

sensitivity



## Implementation Syntax for Optimization: Approach 2

QuickTime™ and a  
TIFF (Uncompressed) decompressor  
are needed to see this picture.

```
Expr lag = Integral(interior, 0.5*pow(u - target, 2.0) *directData + R*alpha*alpha
+ (u - uOld)*lambda + deltaT*D*(grad*lambda)*(grad*u)
+ lambda*v*(grad * u), q2);
```

Lagrangian definition

```
Expr lagBC = EssentialBC(left, lambda*u, q2);
```

Boundary conditions

```
Functional L(mesh, lag, lagBC, vecType);
LinearProblem stateProb = L.linearVariationalProb(lambda, lambda0,
u, alpha, alpha0);
```

Define functional

Variational statement

```
LinearSolver<double> solver
= LinearSolverBuilder::createSolver(solverParams);
```

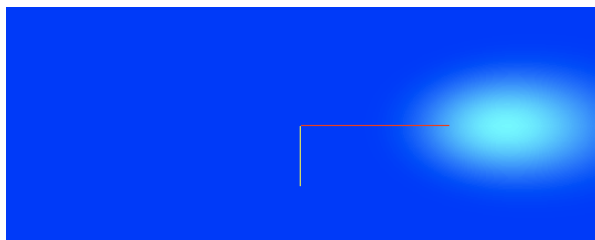
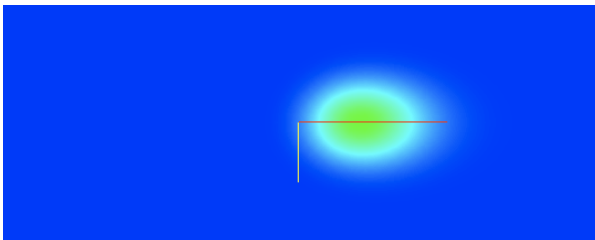
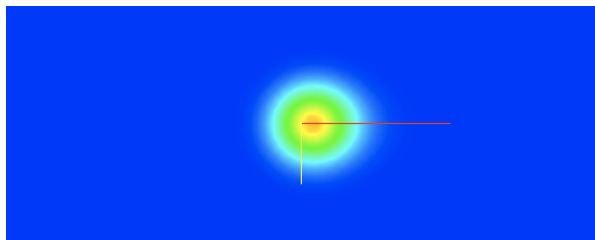
Solver definition

```
for (int i=0; i<Nts; i++)
{
    uSoln = stateProb.solve(solver);
    CopyOldSol(uSoln, uOld);
}
```

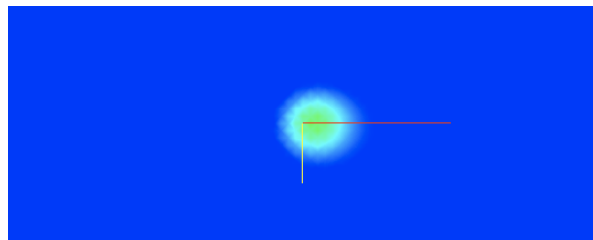
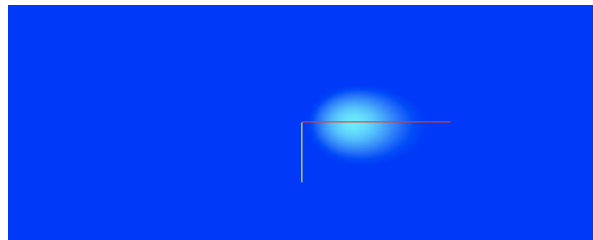
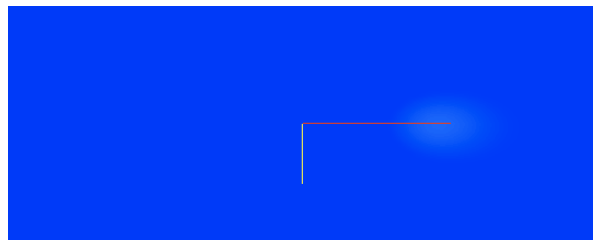
Time-stepping loop

## Example: Convection Diffusion Forward and Adjoint

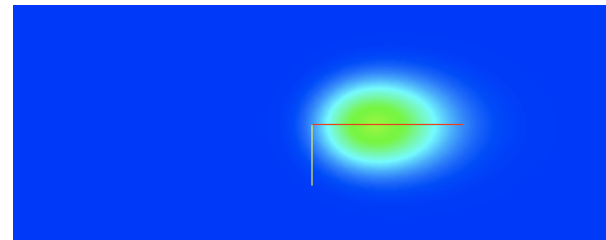
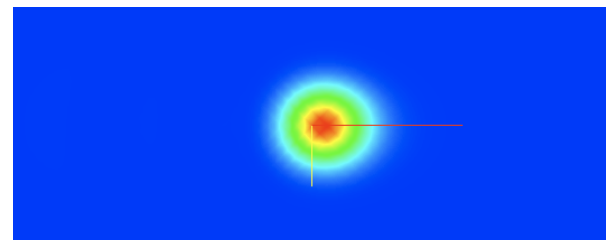
Target :



Adjoint :



Inversion:



# Biofilm Inversion Formulation and implementation

## Approach 1

The PDE constrained optimization problem

$$\min_{\rho, \rho_0} \mathcal{F}(\rho, \rho_0) = \frac{1}{2} \sum_{i=0}^N \int_0^T \int_{\Omega} (\rho - \rho^*)^2 \delta(x - x_i) \, dx \, dt + \frac{\beta}{2} \int_{\Omega} \rho_0^2 \, dx$$

subject to:

$$\begin{aligned} \frac{\partial \rho}{\partial t} + \frac{D}{\rho_b} \nabla c \cdot \nabla \rho &= 0 & \text{in } \Omega \times [0, T] \\ \rho &= \rho_0 & \text{in } \Omega \times \{t=0\}. \\ D \Delta c &= \frac{k_1 c \rho}{k_2 + c} & \text{in } \Omega \\ c &= c_D & \text{in } \Gamma_D \end{aligned}$$

**Additional complications:**

- SUPG
- Crank-Nicholson

```
Expr state = Integral(interior_, (rho - rho0_)*rhoHat/deltaT
+0.5*(D_/rhoB_)*((grad*rho)*(grad*c))*rhoHat
+0.5*(D_/rhoB_)*((grad*rho0_)*(grad*c0_))*rhoHat
+(rho - rho0_)/deltaT
*stau*(D_/rhoB_)*((grad*st2)*(grad*rhoHat))
+0.5*(D_/rhoB_)*((grad*rho)*(grad*c))*rhoHat
*stau*(D_/rhoB_)*((grad*st2)*(grad*rhoHat))
+0.5*(D_/rhoB_)*((grad*rho0_)*(grad*c0_))*rhoHat
*stau*(D_/rhoB_)*((grad*st2)*(grad*rhoHat))
-D_*(grad*c)*(grad*cHat)
-Hrho*k1_*c/(k2+c) * c, q2);
```

```
Expr adjoint1 = Integral(interior_, (lrho - lrho1_)*lrhoHat/deltaT *deltaT
+0.5*(D_/rhoB_)*((grad*lrhoHat)*(grad*c0_))*lrho*deltaT
-0.5*k1_*dHlrho*c0_/(k2+c0_)*lc*lrhoHat
+0.5*(D_/rhoB_)*((grad*lrhoHat)*(grad*c1_))*lrho1_*deltaT
-0.5*k1_*dHlrho1*c1_/(k2+c1_)*lc*lrhoHat
+(lrho - lrho1_)/deltaT
*atau*(D_/rhoB_)*((grad*at2)*(grad*lrhoHat))
+0.5*(D_/rhoB_)*((grad*lrho)*(grad*c0_))*lrho
*atau*(D_/rhoB_)*((grad*at2)*(grad*lrhoHat))
-0.5*k1_*dHlrho*c0_/(k2+c0_)*lc
*atau*(D_/rhoB_)*((grad*at2)*(grad*lrhoHat))
+0.5*(D_/rhoB_)*((grad*lrho1_)*(grad*c1_))
*atau*(D_/rhoB_)*((grad*at2)*(grad*lrhoHat))
-0.5*k1_*dHlrho1*c1_/(k2+c1_)*lc
*atau*(D_/rhoB_)*((grad*at2)*(grad*lrhoHat))
-D_*(grad*lc)*(grad*lcHat)
-Hlrho*k1_*k2_/((k2+c0_)*(k2+c0_))*lc*lcHat
+(D_/rhoB_)*lrho*((grad*lcHat)*(grad*rho0_))*del q2) ;
Expr adjoint2 = adjoint1
+ Integral(interior_, 0.5*lrhoHat*(rho1_ - rhoTarget1_)*boolExpr_*deltaT, q2)
+ Integral(interior_, 0.5*lrhoHat*(rho0_ - rhoTarget0_)*boolExpr_*deltaT, q2) ;
```

# Biofilm Inversion Formulation and implementation: Approach 2

The PDE constrained optimization problem

$$\min_{\rho, \rho_0} \mathcal{F}(\rho, \rho_0) = \frac{1}{2} \sum_{i=0}^N \int_0^T \int_{\Omega} (\rho - \rho^*)^2 \delta(x - x_i) \, dx \, dt + \frac{\beta}{2} \int_{\Omega} \rho_0^2 \, dx$$

subject to:

$$\begin{aligned} \frac{\partial \rho}{\partial t} + \frac{D}{\rho_b} \nabla c \cdot \nabla \rho &= 0 && \text{in } \Omega \times [0, T] \\ \rho &= \rho_0 && \text{in } \Omega \times \{t = 0\}. \\ D \Delta c &= \frac{k_1 c \rho}{k_2 + c} && \text{in } \Omega \\ c &= c_D && \text{in } \Gamma_D \end{aligned}$$

## Additional complications:

- SUPG
- Crank-Nicholson

```
Expr state = Integral(interior_, (rho - rho0_)*rhoHat/deltaT
+0.5*(D_/rhoB_)*((grad*rho)*(grad*c))*rhoHat
+0.5*(D_/rhoB_)*((grad*rho0_)*(grad*c0_))*rhoHat
+(rho - rho0_)/deltaT
*stau*(D_/rhoB_)*((grad*st2)*(grad*rhoHat))
+0.5*(D_/rhoB_)*((grad*rho)*(grad*c))*rhoHat
*stau*(D_/rhoB_)*((grad*st2)*(grad*rhoHat))
+0.5*(D_/rhoB_)*((grad*rho0_)*(grad*c0_))*rhoHat
*stau*(D_/rhoB_)*((grad*st2)*(grad*rhoHat))
-D_*(grad*c)*(grad*cHat)
-Hrho*k1_*c/(k2+c) * c, q2);
```

```
Expr lag = Integral(interior, 0.5*pow(u - target, 2.0)*direcDelta + R*alpha*alpha, q2)
+ Supg_CN_Integral;

Expr lagBC = EssentialBC(top, lambda*u=1.0, q2);

Functional L(mesh, lag, lagBC, vecType);

NonlinearOperator<double> stateProb = F.nonlinearVariationalProb(lambda, lambda0,
                                                                    rho, rho0,
                                                                    alpha, alpha0);

NOXSolver solver(noxParams, stateProb);
solver.solve();
```

The PDE constrained optimization problem

$$\min_{\rho, \rho_o} \mathcal{F}(\rho, \rho_u) = \frac{1}{2} \sum_{i=0}^N \int_0^T \int_{\Omega} (\rho - \rho^*)^2 \delta(x - x_i) dx dt + \frac{\beta}{2} \int_{\Omega} \rho_0^2 dx$$

subject to:

$$\frac{\partial \rho}{\partial t} + \frac{D}{\rho_b} \nabla c \cdot \nabla \rho = 0$$

in  $\Omega \times [0, T]$

$$\rho = \rho_0$$

in  $\Omega \times \{t = 0\}$ .

$$D \Delta c = \frac{k_1 c \rho}{k_2 + c}$$

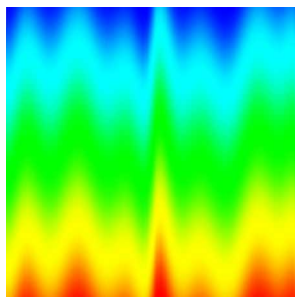
in  $\Omega$

$$c = c_D$$

in  $\Gamma_D$

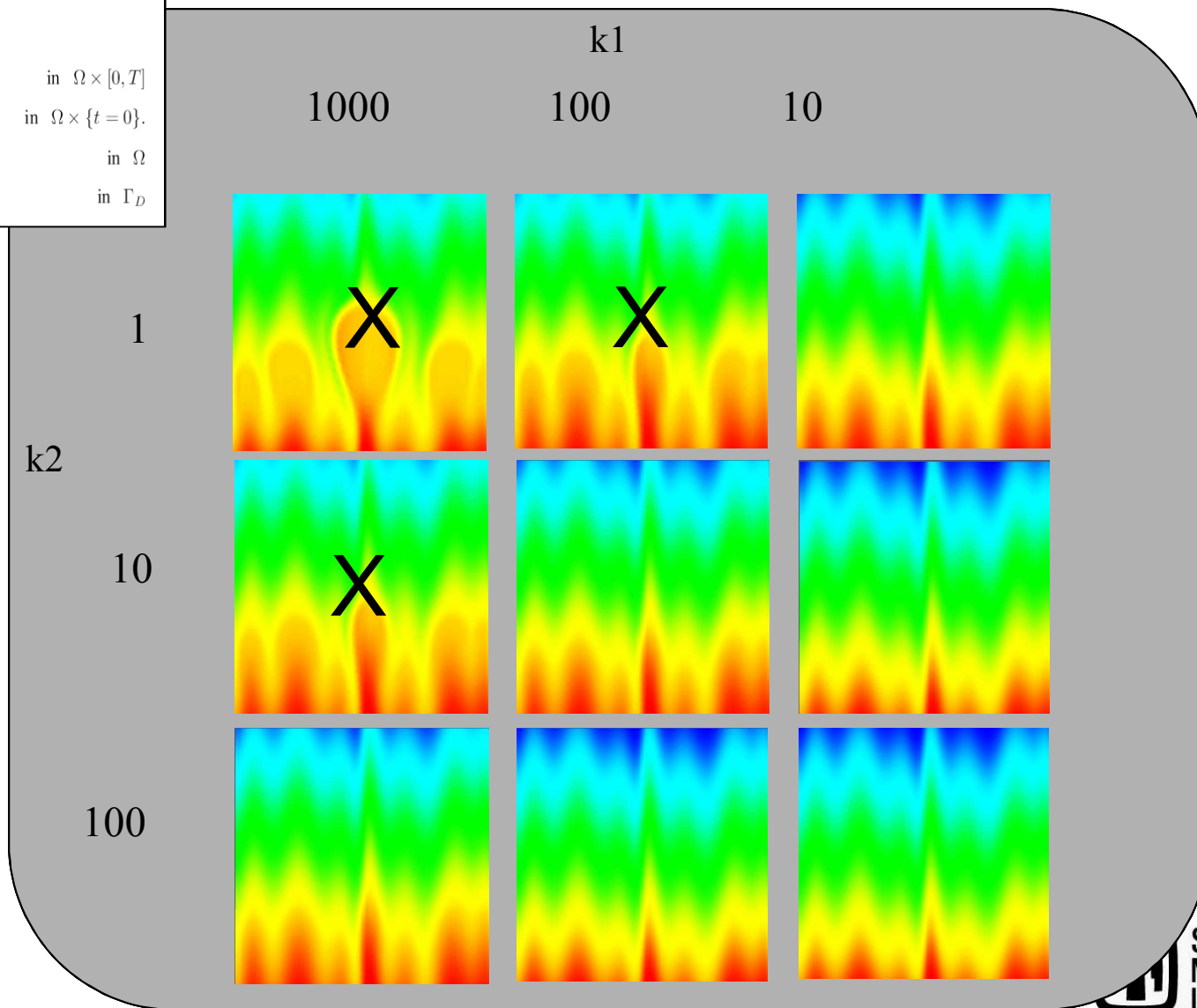
#### Inversion Details:

- deltaT = 0.005
- grid 64x64
- R=0.0001
- QN-BFGS



Initial Condition

## Preliminary Inversion Results (Realizations shown at final timestep)







## Summary

- Work on biofilm is motivated by range of industrial applications
- Extensive physics defines biofilms dynamics: deposition, transport and detachment
- Inversion of IC or material parameters requires extensive formulation
- Efficient PDECO toolkit isolates users from implementation cost and errors
- Reconstruction of level set function needs to be investigated