



# Ensemble based data assimilation for a multi-compartment porous media model

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- Data assimilation in medicine
- Contrast enhanced dynamic MRI
- Multi-compartment porous media model for blood flow
- Data assimilation
- Case studies
- Conclusion

# Blood flow simulation



- > A. L. Marsden: “Cardiovascular blood flow simulation. From computation to clinic.” SIAM News, 48 (10), 2015.
  - “There is a rising interest in clinical data assimilation and uncertainty quantification in cardiovascular simulations.”

# Blood flow simulation



- > A. L. Marsden: “Cardiovascular blood flow simulation. From computation to clinic.” SIAM News, 48 (10), 2015.
  - “There is a rising interest in clinical data assimilation and uncertainty quantification in cardiovascular simulations.”
- > Boundary value problem
- > Data source: Medical imaging
- > Using variational methods
- > Forward modeling is computationally intensive
- > Adjoint available

# Ensemble based approach



S. Pagani, A. Manzoni and A. Quarteroni: "A reduced basis ensemble Kalman filter for state/parameter identification in large-scale nonlinear dynamical systems". Tech. report 18.2016 Mathematics Institute of Computational Science and Engineering, École polytechnique fédérale de Lausanne

# Data assimilation in oncology - I



- > TE Yankeelov et. al.: “Toward a science of tumor forecasting for clinical oncology,” Cancer Research, 75(6), 2015.
  - “We propose that the quantitative cancer biology community makes a concerted effort to apply lessons from weather forecasting to develop an analogous methodology for predicting and evaluating tumor growth and treatment response.”

# Data assimilation in oncology - II



- > EJ Kostelic et. al.: “Accurate state estimation from uncertain data and models: an application of data assimilation to mathematical models of human brain tumors.” *Biology Direct*, 6:64, 2011.
  - Synthetic study using two models for glioblastoma, MRI data as observations.
  - Local ensemble transform Kalman filter

# Contrast enhanced dynamic MRI



By Jan Ainali - Own work, CC BY 3.0,  
<https://commons.wikimedia.org/w/index.php?curid=3546051>



# Contrast enhanced dynamic MRI



- > Gadolinium Contrast Medium (MRI Contrast agents)

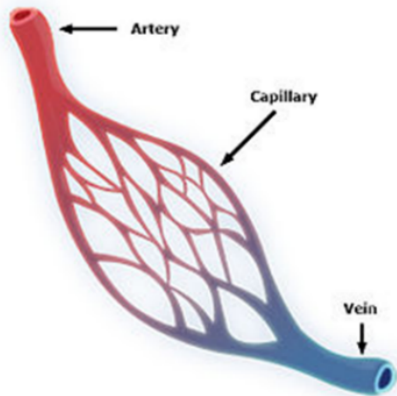


By Jan Ainali - Own work, CC BY 3.0,  
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- > Determine blood perfusion

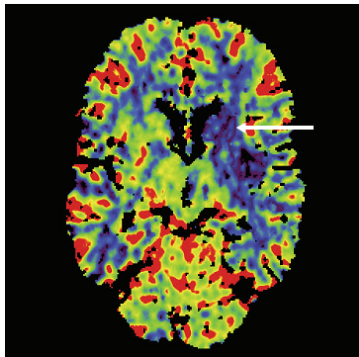


<https://en.wikipedia.org/wiki/Capillary>

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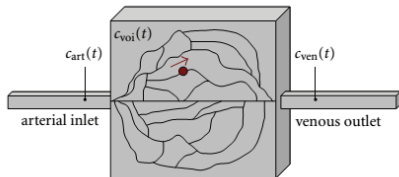


Fieselmann et. al., 2011,  
Int. Journal of Biomedical Computing  
doi:10.1155/2011/467563

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# Contrast enhanced dynamic MRI



- > Gadolinium Contrast Medium (MRI Contrast agents)
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- > Today: Calculated voxel by voxel
- > Here: Model blood flow and use data assimilation

# Flow of blood and contrast indicator

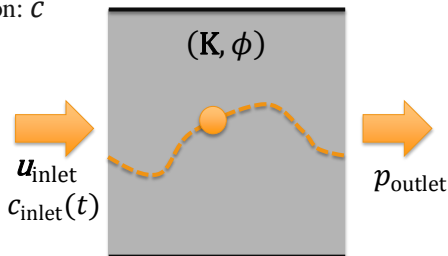


Incompressible porous media:  $\mathbf{u} = -\mu^{-1}\mathbf{K} \cdot \nabla p$  ,  $\nabla \cdot \mathbf{u} = 0$

Passive tracer:  $\phi \frac{\partial c}{\partial t} - \nabla \cdot (c\mathbf{u}) = 0$

- Contrast indicator concentration:  $c$
- Filtration velocity:  $\mathbf{u}$
- Pressure:  $p$

- 
- Blood viscosity:  $\mu$
  - Flow conductivity:  $\mu^{-1}\mathbf{K}$
  - Porosity:  $\phi$

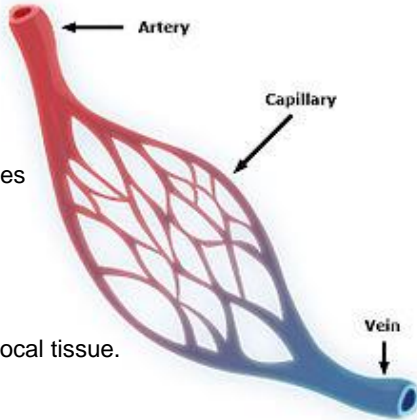


## Two-compartment model (“dual por. / dual perm.”)



The amount of contrast indicator observed within a «voxel» comprises

- Arterial transit.
- Venular transit.
- Capillary perfusion feeding the local tissue.



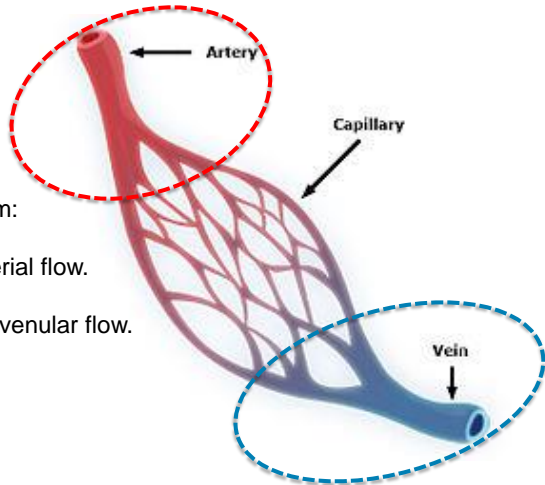
(<https://en.wikipedia.org/wiki/Capillary>)

## Two-compartment model (“dual por. / dual perm.”)



Decompose the flow problem:

- One global model for arterial flow.
- Another global model for venular flow.
- ...



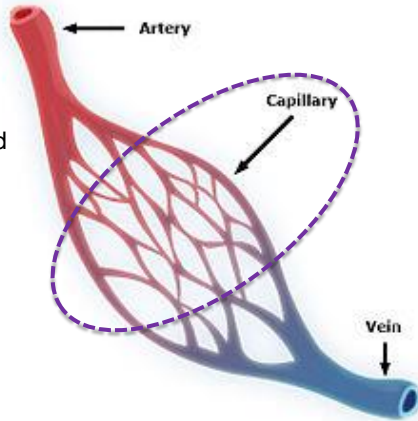


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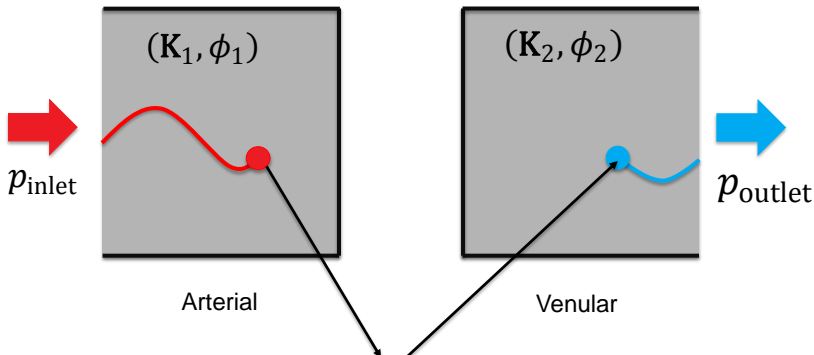


Capillary perfusion is represented by local transfer functions:

- Sinks for the arterial flow.
- Sources for venular flow.



## Two-compartment model (“dual por. / dual perm.”)



Transfer between arterial and venular system, relates explicitly to perfusion as «feeding blood flow to the tissue».

$$\nabla \cdot \mathbf{u}_1 = -Q = -\mu^{-1} K_X \sigma (p_2 - p_1)$$

$$\nabla \cdot \mathbf{u}_2 = Q$$

# Ensemble Kalman filter (Evensen (1994))

$$x_n = F(x_{n-1}) + \epsilon_n$$

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Ensemble Kalman filter solution:

$$X_n = [x_{n,1} \dots x_{n,N}]$$

$$x_{n,i} = F(x_{n-1,i}) + \epsilon_{n,i}$$

$$y_{n,i} = Gx_{n,i} + \eta_{n,i}$$

$$\bar{x}_n = \frac{1}{N} \sum_{i=1}^N x_{n,i}$$

$$\bar{C}_n = \frac{1}{N-1} \sum_{i=1}^N (x_{n,i} - \bar{x}_n)(x_{n,i} - \bar{x}_n)^T$$

$$K_n = \bar{C}_n G^T (G \bar{C}_n G^T + C_D)^{-1}$$

$$\hat{x}_{n,i} = x_{n,i} + K_n(y_{o,n} - y_{n,i})$$

ensemble of size  $N$

(linear observations)

Estimated Kalman gain

$$i = 1, \dots, N$$

# Parameter estimation using EnKF

$$\begin{bmatrix} x_n \\ p_n \\ y_n \end{bmatrix} = \begin{bmatrix} F(x_{n-1}) \\ p_{n-1} \\ G(x_n) \end{bmatrix}$$

$p_n$ : unknown parameter vector  
(porosity, tissue permeability)

$x_n$ : pressure, saturations

$y_n = G(x_n)$ : non-linear measurements

Lorentzen et. al. 2001 (parameter estimation)

Nævdal et. al. 2002 ( + non-linear measurements)

# Implementation for presented cases

Here: Half-iterative EnKF (or modification)

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Case 1:

- > Adaptive Gaussian mixture filter
  - Stordal et. al., Computational Geosciences, Vol. 15, 2011
- > 500 model realizations

# Implementation for presented cases

Here: Half-iterative EnKF (or modification)

Case 1:

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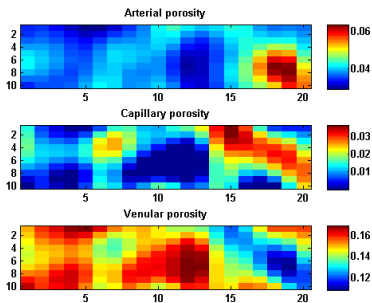
Case 2:

- > EnKF with extreme localization
- > Only updating grid block where contrast is measured



# Case study 1

- > 10 cm × 10 cm
- > Upper, lower and right side have zero-flow boundary conditions
- > Pressure at boundary:  
Arterial: 13300 Pa  
Venular: 133 Pa
- > Arterial inlet: Pulse lasting 4 seconds,  $c_a = 1$
- > Contrast agent concentration:  $m_{mri}(\vec{x}) = \phi_a \cdot c_a + \phi_{av} \cdot c_{av} + \phi_v \cdot c_v$



## Porosity values

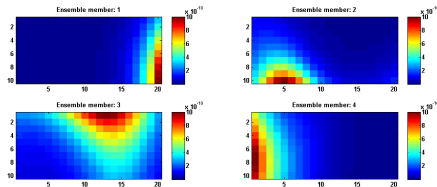
- > Measurement every 0.6sec
- > Measurement noise:  $10^{-4}$

# Estimating perfusion

- > Darcy law:  $\vec{u}_i = -\mu^{-1} K_i(\vec{x}) \nabla p_i$
- > Estimate  $K_i(\vec{x})$
- >  $K_a(\vec{x}) = K_v(\vec{x})$
- > Conductivity factor  $K_{av}(\vec{x}) \sigma_{av}(\vec{x}) \sim 10 K_a(\vec{x})$

# Estimating perfusion

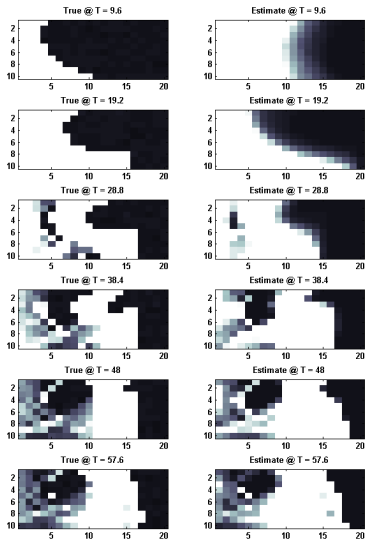
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$K_a$

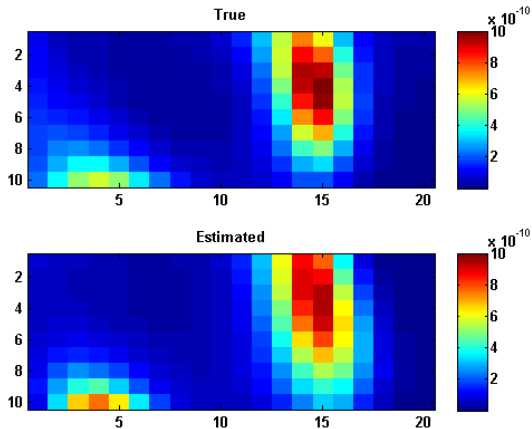
Four initial ensemble members  
The units are [ $m^2$ ].

# Observed and simulated MRI data



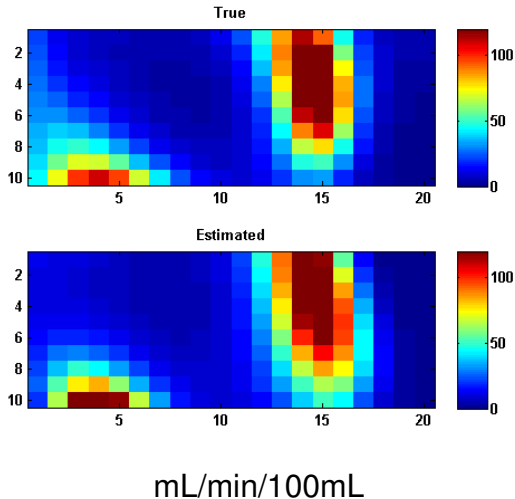
- > Black: Low concentration
- > White: High concentration
- > Range:  $[0, 10^{-2}]$ .

# Estimated $K_a$ field



Units [ $m^2$ ].

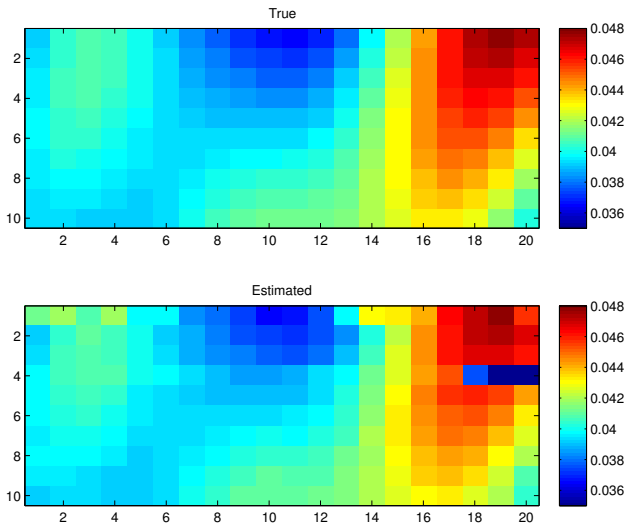
# Estimated perfusion



## Case 2: Porosity of compartments

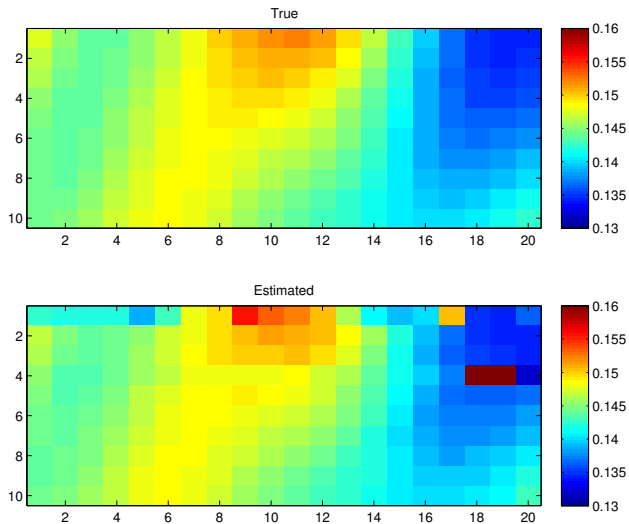
- > Goal: Estimate  $\phi_a(\vec{x})$ ,  $\phi_v(\vec{x})$  and  $\phi_{av}(\vec{x})$
- > Constant hydraulic conductivity:
  - $K_{av} = 2 \cdot 10^{-9} \text{m}^{-2}$
  - $K_a = K_v = 2 \cdot 10^{-10} \text{m}^{-2}$
- > Initial ensemble:
  - geostatistical distribution of the fields
  - $\phi_v + \phi_a + \phi_{av} = 0.2$
- > EnKF, ensemble size 200
- > Localization: Only update porosities based on observations in its own grid block

# True and estimated $\phi_a$

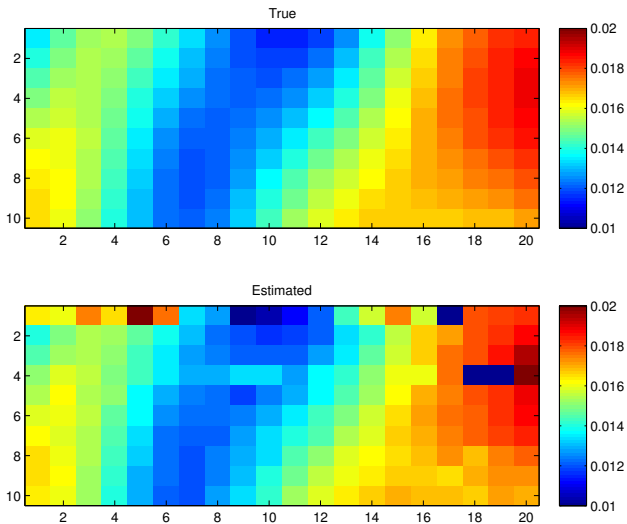




# True and estimated $\phi_v$



# True and estimated $\phi_{av}$



# Conclusion



- > Paper available at  
[eccomas2016.org/proceedings/pdf/9975.pdf](http://eccomas2016.org/proceedings/pdf/9975.pdf)

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- > Further plans: Extend to 3-D, and apply on real data set

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## Thank you!