

Finite element simulation of ionic electrodiffusion in cellular geometries

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Math bio seminar
University of Pennsylvania, Philadelphia, USA
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simula



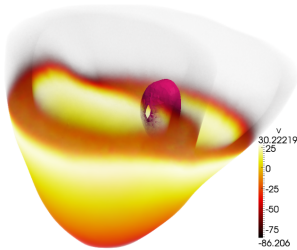
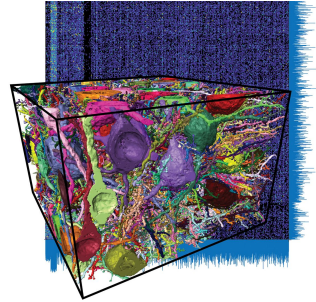
Classical models for excitable tissue assume that the domain can be represented in an homogenized manner

Technology now allows for **numerical resolutions** below **model resolution**.

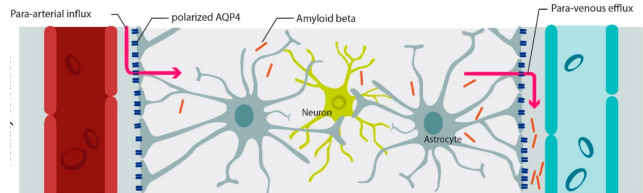
$$\begin{aligned}v_t - \nabla \cdot (M_i \nabla v + M_i \nabla u_e) &= -I_{\text{ion}}, \\ \nabla \cdot (M_i \nabla v + (M_i + M_e) \nabla u_e) &= 0, \\ s_t &= F(v, s).\end{aligned}$$

How to model **spatial variations in membrane properties**, or how **cellular morphology** affect the dynamics?

How to model a **single cell** or a **small collection** of cells?



Physiological heart cell: $h \approx 100\mu\text{m}$
Computational mesh cell: $h \leq 100\mu\text{m}$



The emerging EMI framework use a geometrically explicit representation of the cellular domains

Find the intracellular and extracellular potentials $\phi_i = \phi_i(\mathbf{x}, t)$ and $\phi_e = \phi_e(\mathbf{x}, t)$, and the transmembrane current $I_M = I_M(\mathbf{x}, t)$ s.t.:

$$-\nabla \cdot (\sigma_i \nabla \phi_i) = 0 \quad \text{in } \Omega_i, \quad (1)$$

$$-\nabla \cdot (\sigma_e \nabla \phi_e) = 0 \quad \text{in } \Omega_e, \quad (2)$$

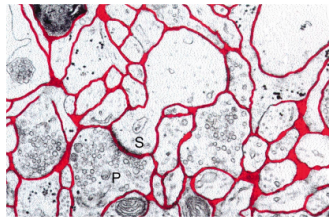
$$\phi_M = \phi_i - \phi_e \quad \text{at } \Gamma, \quad (3)$$

$$\sigma_e \nabla \phi_e \cdot \mathbf{n}_e = -\sigma_i \nabla \phi_i \cdot \mathbf{n}_i = I_M \quad \text{at } \Gamma, \quad (4)$$

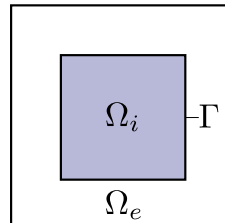
$$\frac{\partial \phi_M}{\partial t} = \frac{1}{C_M} (I_M - I_{\text{ion}}) \quad \text{at } \Gamma. \quad (5)$$

Ion concentrations are assumed to be constant in space and time – often an accurate approximation, but not always . . .

[Krassowska & Neu 1994],
[Ying & Henriquez 2007],
[Tveito et al. 2017]



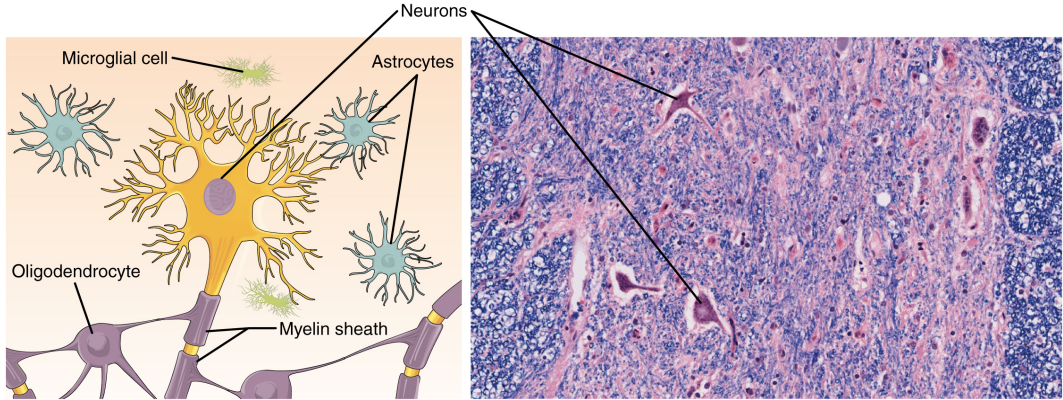
Rat cortex with ECS in red [Nicholson, 1998]



Outline

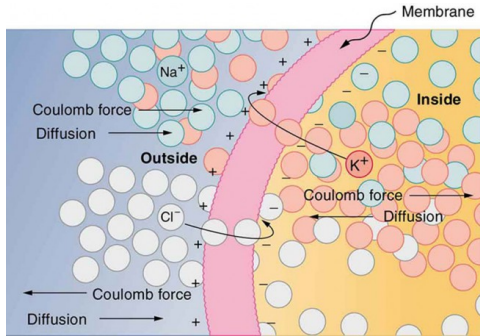
- Motivation and physiological background
- Modelling electrodifusion: main assumptions and core ideas
- The KNP-EMI model: strong form and numerical strategies
 - Multi-dimensional form and a mortar finite element method
 - Single-dimensional form and a DG finite element method
- A study of ephaptic coupling
- Future perspectives

Brain tissue is composed of networks of extracellular spaces and primarily two classes of cells: neurons and glial cells



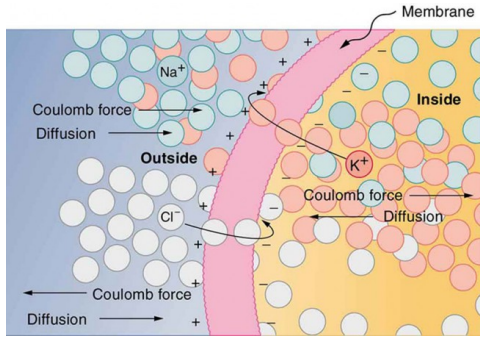
Left panel: Sketch of neurons and glial cells. Right panel: Micrograph of brain tissue. [OpenStax CNX, 2016]

Movement of ions is fundamental in brain signalling and various mechanisms ensure ionic homeostasis

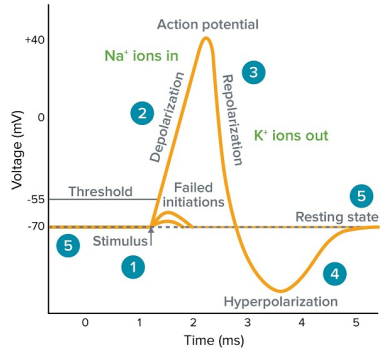


[courses.lumenlearning.com]

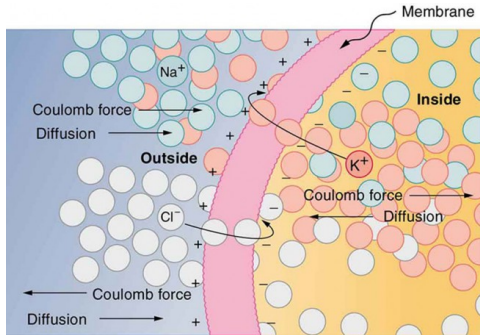
Movement of ions is fundamental in brain signalling and various mechanisms ensure ionic homeostasis



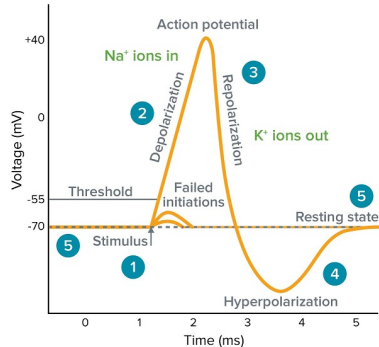
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Movement of ions is fundamental in brain signalling and various mechanisms ensure ionic homeostasis



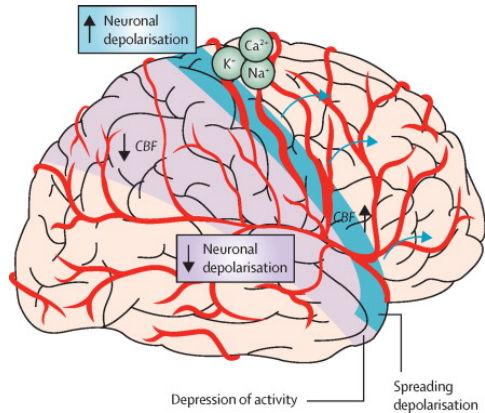
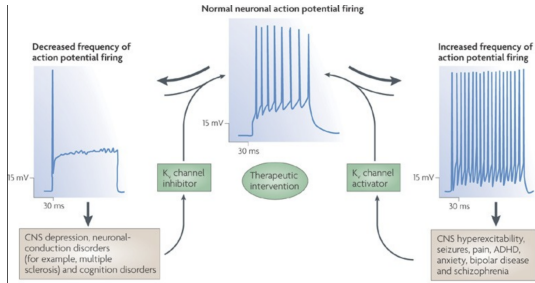
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Homeostatic mechanisms will take the ionic concentrations back towards baseline levels, e.g.:

- Na⁺/K⁺/ATPase pumps (3 Na⁺ out, 2 K⁺ in),
- cotransporters (KCC2, NKCC1),
- glial K⁺ buffering.

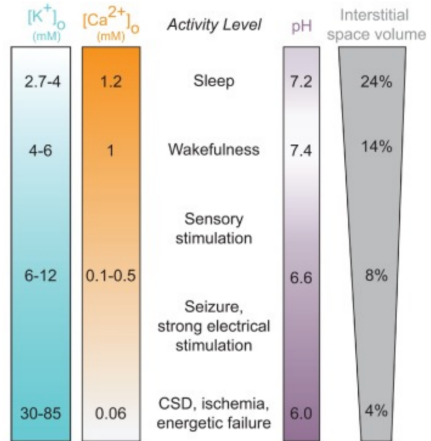
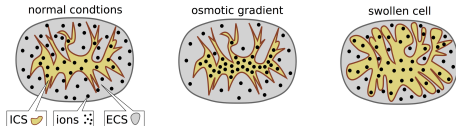
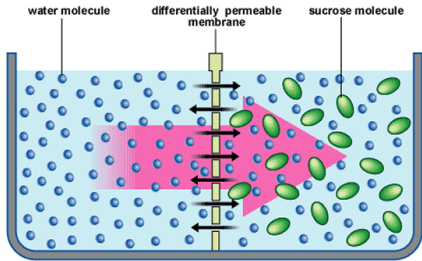
Ion concentration changes are a trademark of several pathological conditions, such as epilepsy or spreading depression



- Homeostatic mechanisms are not able to "keep up"
- Shifts in the ECS ion concentrations

The extracellular ion composition changes with local neuronal activity and across brain states

Ionic shift may set up **osmotic gradients** causing **cellular swelling**.

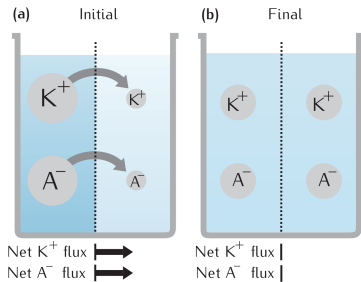


[Rasmussen, 2021]

Modeling electrodiffusion: main assumptions and core ideas

Electrodiffusion is governed by the Nernst–Planck equation, stating that ions move due to diffusion or drift in the electrical field

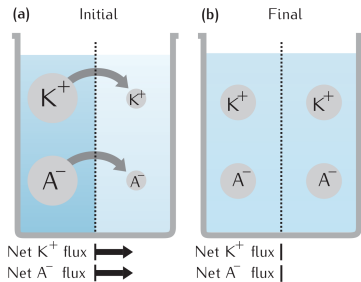
Diffusion



$$\mathbf{J}^k = - \underbrace{D^k \nabla [k]}_{\text{diffusion}}$$

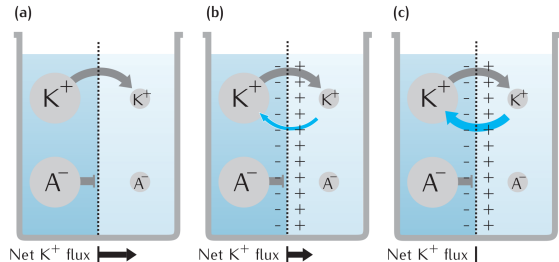
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Diffusion



$$\mathbf{J}^k = \underbrace{-D^k \nabla [k]}_{\text{diffusion}}$$

Electrodiffusion



$$\mathbf{J}_r^k = \underbrace{-D^k \nabla [k]}_{\text{diffusion}} - \underbrace{D^k \frac{z_k F}{RT} [k] \nabla \phi_r}_{\text{electrical drift}}$$

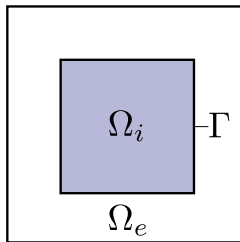
Ions are conserved within each region and move due to diffusion or drift in the electrical field (Nernst–Planck)

Let $c_r^k = c_r^k(x, t)$ denote the concentration of (ion) species k in compartment r . Conservation of ions in the bulk of each compartment yields:

$$\frac{\partial c_r^k}{\partial t} + \nabla \cdot \mathbf{J}_r^k = 0,$$

where the ion flux density is given by:

$$\mathbf{J}_r^k = \underbrace{-D_r^k \nabla c_r^k}_{\text{diffusion}} - \underbrace{D_r^k \frac{z_k F}{RT} c_r^k \nabla \phi_r}_{\text{electrical drift}}.$$



Tissue domain $\Omega = \Omega_i \cup \Omega_e \subset \mathbb{R}^d$, with (ion) species $k \in K$ (e.g. Na^+ , K^+ , Cl^-).

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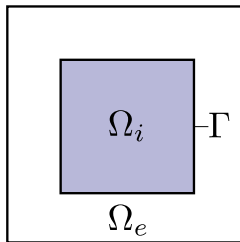
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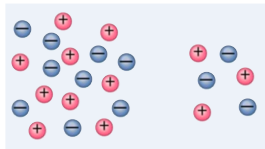
$2|K| + 2$ unknowns, but only $2|K|$ equations:

- Poisson–Nernst–Planck (PNP)
- Kirchhoff–Nernst–Planck (KNP)

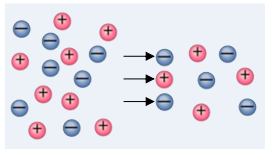


Tissue domain $\Omega = \Omega_i \cup \Omega_e \subset \mathbb{R}^d$, with (ion) species $k \in K$ (e.g. Na^+ , K^+ , Cl^-).

A charge imbalance in the ECS will typically vanish within nanoseconds

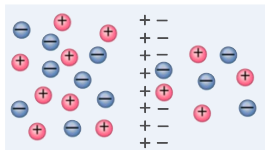


$t = 0$



$t < 10 \text{ ns}$

$D_{\text{Cl}^-} > D_{\text{Na}^+}$: Diffusion
give net (-) charge
transport from left to right.

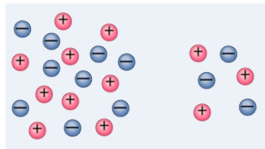


$t > 10 \text{ ns}$

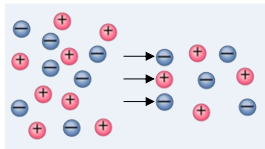
Quasi steady state: the
potential ϕ_e prevents
further charge separation.

ϕ_e

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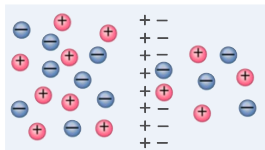


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Quasi steady state: the
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further charge separation.

Poisson–Nernst–Planck (PNP):

$$\nabla^2 \phi_r = \frac{-\rho_r}{\epsilon_r}, \quad \rho_r = F \sum_k z_k [k]_r.$$

Kirchhoff–Nernst–Planck (KNP):

$$\frac{\partial \rho_r}{\partial t} = 0, \quad \rho_r = F \sum_k z_k [k]_r.$$

The electroneutrality condition (KNP) is a good approximation on spatiotemporal scales larger than $\sim$ nanoseconds / nanometers

Poisson–Nernst–Planck (PNP)

Explicit modelling of charge relaxation processes - requires fine resolution

[Lopreore et al., 2008]

[Pods et al., 2013]

[Holcman and Yuste, 2015]

[Cartailler et al., 2017, 2017]

[Sacco et al., 2017]

Kirchhoff–Nernst–Planck (KNP)

Electroneutrality assumption - good approximation on larger scales ($>$ nano)

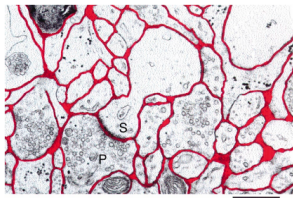
[Mori, 2009]

[Ellingsrud et al., 2020]

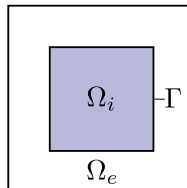
The KNP-EMI model

A computational framework for ionic electrodiffusion in brain tissue with explicit representation of the cells (KNP-EMI)

Consider a (tissue) domain $\Omega = \Omega_i \cup \Omega_e \subset \mathbb{R}^d$, where Ω_i (with boundary Γ) and Ω_e represent respectively intracellular and extracellular regions, with (ion) species $k \in K$ (e.g. Na^+ , K^+ , Cl^-).



Rat cortex with ECS in red [Nicholson, 1998]



A computational framework for ionic electrodiffusion in brain tissue with explicit representation of the cells (KNP-EMI)

For each ion species $k \in K$, find the *ion concentrations*

$c_r^k : \Omega_r \times (0, T] \rightarrow \mathbb{R}$ (mol/m³) and the *electrical potentials*

$\phi_r : \Omega_r \times (0, T] \rightarrow \mathbb{R}$ (V) such that:

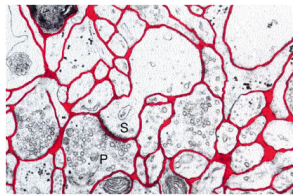
$$\frac{\partial c_r^k}{\partial t} + \nabla \cdot \mathbf{J}_r^k = 0 \quad \text{in } \Omega_r, \quad (6)$$

$$-F \sum_k z^k \nabla \cdot \mathbf{J}_r^k = 0 \quad \text{in } \Omega_r, \quad (7)$$

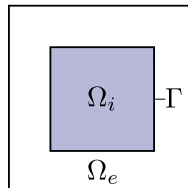
for $r = \{i, e\}$, where the *ion flux densities* are given by:

$$\mathbf{J}_r^k = -D_r^k \nabla c_r^k - z^k \psi^k c_r^k \nabla \phi_r, \quad \text{in } \Omega_r. \quad (8)$$

The system remains to be closed by appropriate initial conditions, boundary conditions, and *importantly interface conditions*.



Rat cortex with ECS in red [Nicholson, 1998]



A computational framework for ionic electrodiffusion in brain tissue with explicit representation of the cells (KNP-EMI)

At the interface Γ , apply the following coupling conditions, and find the *total ionic current density* $I_M : \Gamma \times (0, T] \rightarrow \mathbb{R}$ (cm/m²s) such that:

$$\phi_i - \phi_e = \phi_M, \quad \text{on } \Gamma, \quad (9)$$

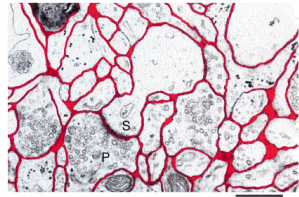
$$\frac{\partial \phi_M}{\partial t} = \frac{1}{C_M} (I_M - \sum_{k \in K} I_{\text{ion}}^k), \quad \text{on } \Gamma, \quad (10)$$

$$I_M \equiv F \sum_k z^k J_i^k \cdot n_i = -F \sum_k z^k J_e^k \cdot n_e, \quad \text{on } \Gamma, \quad (11)$$

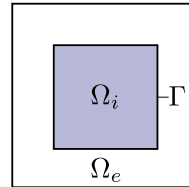
$$J_i^k \cdot n_i = \frac{I_{\text{ion}}^k + \alpha_i^k I_{\text{cap}}}{Fz^k}, \quad \text{on } \Gamma, \quad (12)$$

$$-J_e^k \cdot n_e = \frac{I_{\text{ion}}^k + \alpha_e^k I_{\text{cap}}}{Fz^k}, \quad \text{on } \Gamma. \quad (13)$$

The **transmembrane ion fluxes** $I_{\text{ion}}^k = I_{\text{ion}}^k(\phi_M, [k], s)$ are subject to modelling, and may depend on **gating variables governed by ODEs**.



Rat cortex with ECS in red [Nicholson, 1998]

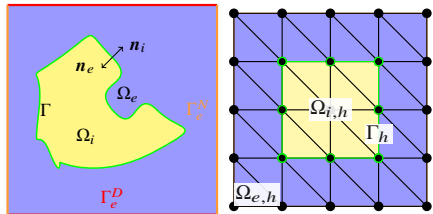


The strongly coupled and non-linear KNP-EMI equations set a rich scene for numerical exploration and can be solved in a multitude of ways

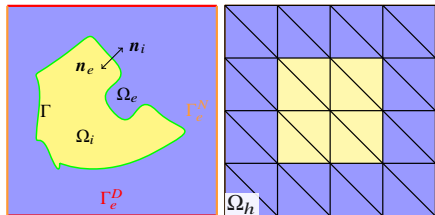
Numerical strategy:

- Split PDEs from ODEs (two-step first order)
- Finite difference ODE and PDE time discretizations (explicit handling of non-linear terms)
- Two different finite element based spatial discretization schemes:

Multi-dimensional form with mortar elements



Single-dimensional form with DG elements



[Illustrations taken from Tveito et al. 2021. Modeling Excitable Tissue: The EMI Framework, chapter 5, Springer Nature]

We discretize the PDEs in space using a multi-dimensional formulation and mortar finite element spaces

Continuous form

The **jumps across the interface** Γ hinders us from defining global, differentiable concentrations and potentials in $H^1(\Omega)$. We **instead** seek for each r :

$$c_r^k \in H^1(\Omega_r), \quad \phi_r \in H^1(\Omega_r), \quad l_M \in H^1(\Gamma).$$

At each time step, find $c_i^k, \phi_i : \Omega_i \rightarrow \mathbb{R}, c_e^k, \phi_e : \Omega_e \rightarrow \mathbb{R}$ and $l_M : \Gamma \rightarrow \mathbb{R}$ such that:

$$\begin{bmatrix} \partial_t - \Delta & \pm \Delta & \pm \epsilon \\ \pm \Delta & -\Delta & -I \\ & I & -I & I \\ & & -I & -\Delta & \pm \Delta \\ & & \pm \epsilon & \pm \Delta & \partial_t - \Delta \end{bmatrix} \begin{bmatrix} c_i^k \\ \phi_i \\ l_M \\ \phi_e \\ c_e^k \end{bmatrix} = f$$

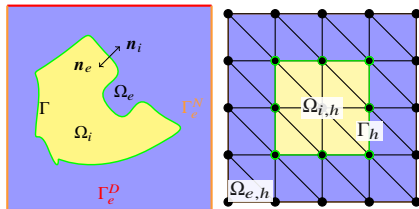
Different variational problems posed over **non-overlapping domains**.

Spatial discretization

We discretize in space using a **mortar finite element** method:

$$c_{r,h}^k \in V_{r,h}, \quad \phi_{r,h} \in T_{r,h}, \quad l_{M,h} \in S_h,$$

where $V_{r,h}, T_{r,h}, S_h$ are constructed using continuous piecewise linear polynomials.



$[\Omega_{e,h}$ and $\Omega_{i,h}$ have identical facets on Γ , and the facets define the finite element cells of Γ_h .]

Implementing the system requires finite element software with mixed dimensional functionality

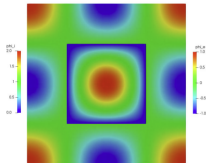
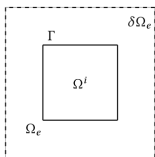
For a problem with a **smooth manufactured solution** we observe expected convergence rates.

$$c_i^{\text{Na}} = 0.7 + 0.3 \sin(2\pi x) \sin(2\pi y)(1 + e^{-t}),$$

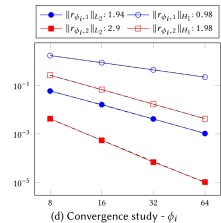
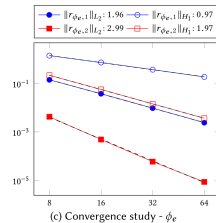
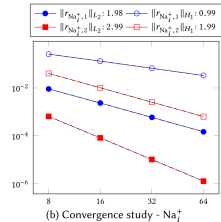
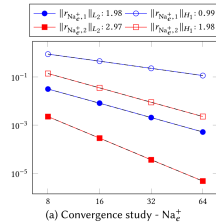
$$c_e^{\text{Na}} = 1.0 + 0.6 \sin(2\pi x) \sin(2\pi y)(1 + e^{-t}),$$

$$\phi_e = \cos(2\pi x)\cos(2\pi y); \phi_i = \phi_e(1 + e^{-t}),$$

...



[Daversin-Catty, et al. 2021. Abstractions and automated algorithms for mixed domain finite element methods. TOMS]



Alternatively, we can consider a single-dimensional formulation for the PDEs, discretized with DG elements

Single-dimensional form

- We eliminate the unknown $I_M : \Gamma \rightarrow \mathbb{R}$.
- We seek global concentrations and potentials:

$$c^k \in H^1(\cup_r \Omega_r), \quad \phi \in H^1(\cup_r \Omega_r),$$

belonging to the broken H^1 space $H^1(\cup_r \Omega_r) := \{u \in L^2(\Omega_r) : u|_{\Omega_r} \in H^1(\Omega_r), r \in \{i, e\}\}$.

Splitting scheme

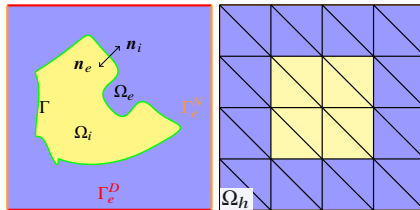
- Split the equations for the concentrations and the potential and obtain two smaller, and more standard, sub-problems.

DG finite element discretization

Look for approximations in broken polynomial spaces for $k \geq 1$:

$$V_h^k(\mathcal{E}_h) = \{v \in L^2(\Omega) : v|_E \in P^k(E), \forall E \in \mathcal{E}_h\},$$

where $P^k(E)$ is the space of polynomials with total degree less than or equal to k .



[Illustration taken from Tveito et al. 2021. Modeling Excitable Tissue: The EMI Framework, chapter 5, Springer Nature]

We apply a splitting scheme to obtain two smaller, and importantly more standard, sub-problems

Consider $n \in [1, \dots, N]$ with t_n and assume that c_{n-1}^k at time step t_{n-1} are known.

Step I: Find $\phi_n \in H(\Omega)$ s.t.:

$$-F \sum_{k \in K} z^k \nabla \cdot \mathbf{J}^k(\phi_n, c_{n-1}^k) = 0, \quad (14)$$

$$\mathbf{J}^k(\phi_n, c_{n-1}^k) = -D^k \nabla c_{n-1}^k - z^k \psi^k c_{n-1}^k \nabla \phi_n. \quad (15)$$

Step II: Given ϕ_n (solution from Step I), find c_n^k for $k \in K$ such that:

$$\frac{\partial c_n^k}{\partial t} + \nabla \cdot \mathbf{J}^k(\phi_n, c_n^k) = 0, \quad (16)$$

$$\mathbf{J}^k(\phi_n, c_n^k) = -D^k \nabla c_n^k - z^k \psi^k c_n^k \nabla \phi_n. \quad (17)$$

We apply a splitting scheme to obtain two smaller, and importantly more standard, sub-problems

Consider $n \in [1, \dots, N]$ with t_n and assume that c_{n-1}^k at time step t_{n-1} are known.

Step I: Find $\phi_n \in H(\Omega)$ s.t.:

$$-F \sum_{k \in K} z^k \nabla \cdot \mathbf{J}^k(\phi_n, c_{n-1}^k) = 0, \quad (14)$$

$$\mathbf{J}^k(\phi_n, c_{n-1}^k) = -D^k \nabla c_{n-1}^k - z^k \psi^k c_{n-1}^k \nabla \phi_n. \quad (15)$$

Insert (15) into (14) and we obtain:

$$\nabla \cdot (\kappa \nabla \phi_n) = f, \quad \kappa = F \sum_{k \in K} z^{k^2} \psi^k c_{n-1}^k. \quad (18)$$

Step II: Given ϕ_n (solution from Step I), find c_n^k for $k \in K$ such that:

$$\frac{\partial c_n^k}{\partial t} + \nabla \cdot \mathbf{J}^k(\phi_n, c_n^k) = 0, \quad (16)$$

$$\mathbf{J}^k(\phi_n, c_n^k) = -D^k \nabla c_n^k - z^k \psi^k c_n^k \nabla \phi_n. \quad (17)$$

Insert (17) into (16) and we obtain:

$$\frac{\partial c_n^k}{\partial t} - \nabla \cdot (D^k \nabla c_n^k) - \nabla \cdot (z^k \psi^k c_n^k \nabla \phi_n) = 0. \quad (19)$$

We apply a splitting scheme to obtain two smaller, and importantly more standard, sub-problems

Consider $n \in [1, \dots, N]$ with t_n and assume that c_{n-1}^k at time step t_{n-1} are known.

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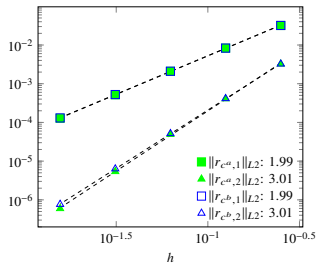
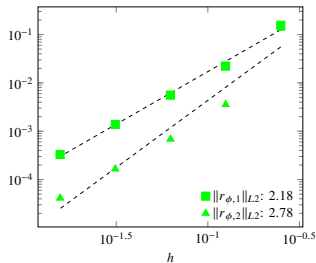
$$\frac{\partial c_n^k}{\partial t} - \nabla \cdot (D^k \nabla c_n^k) - \nabla \cdot (z^k \psi^k c_n^k \nabla \phi_n) = 0. \quad (19)$$

- + Reduces system to two smaller, more standard problems
- Introduces constraint on time step Δt

The weak formulation is discretized using a DG finite element method

- Symmetric interior penalty (SIPG) for the EMI sub-problem (18)
- SIPG on diffusion term; upwinding on advection term for the diffusion advection sub-problem (19).

For a problem with a [smooth manufactured solution](#) we observe expected convergence rates.



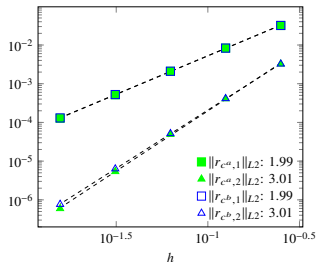
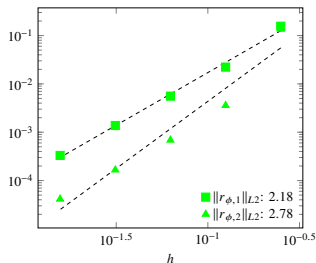
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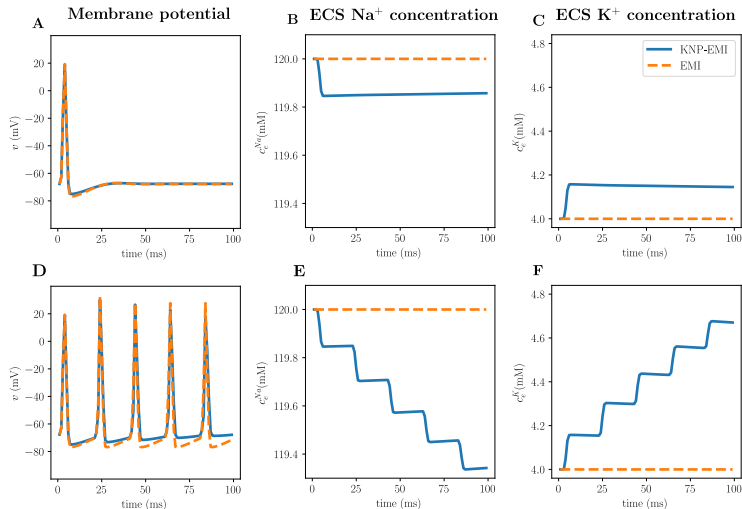
Ongoing work ...

- Peclet number in physiological scenarios?
- Robust preconditioners for the sub-problems?
- Stability and restriction on Δt in splitting scheme?



Comparing KNP-EMI and EMI

During hyperactivity, the KNP-EMI and EMI models differ due to shifts in the ion concentration gradients



Normal activity (A, B, C):

- 1 Hz
- KNP-EMI and EMI give comparable results

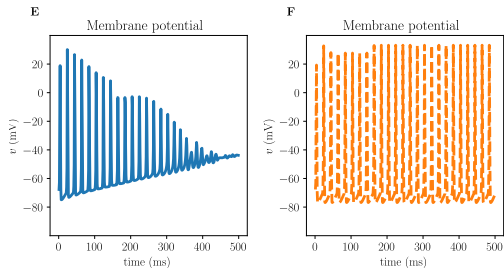
Hyperactivity (D, E, F):

- 50 Hz
- Membrane potential predicted by KNP-EMI slightly (and persistently) depolarizes for each AP

During hyperactivity, the KNP-EMI and EMI models differ due to shifts in the ion concentration gradients

Normal activity (not shown):

- 1 Hz
- KNP-EMI and EMI give comparable results



Hyperactivity (E, F):

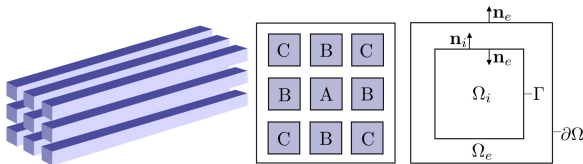
- 50 Hz
- Membrane potential predicted by KNP-EMI slightly (and persistently) depolarizes for each AP

A study of ephaptic coupling

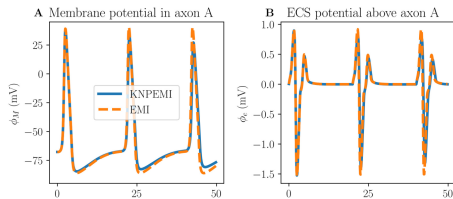
Comparing KNP-EMI and EMI: Do diffusive currents affect ephaptic coupling through the ECS in unmyelinated axon bundles?

In an **idealized axon bundle** with cell gaps of $0.1\mu\text{m}$, action potentials are induced (via a synaptic current) every 20 seconds in either:

- Axon A (1 active neighbour), or
- Axons B and C (8 active neighbour).



[Ellingsrud et al., 2020]



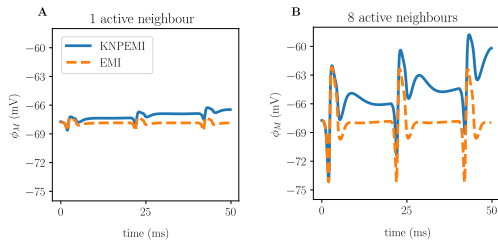
Diffusive currents contribute to ECS potential shifts in the KNP-EMI framework:

$$\text{EMI} \quad \nabla \cdot (\sigma_e \nabla \phi_e) = 0, \text{ in } \Omega_e,$$

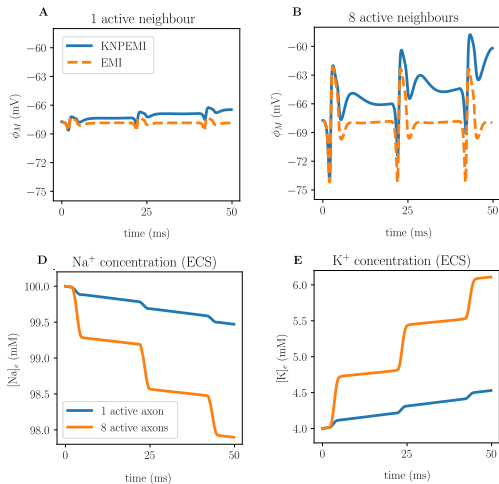
$$\text{KNP-EMI} \quad \nabla \cdot (\sigma_e \nabla \phi_e + \nabla b_e) = 0, \text{ in } \Omega_e,$$

where $b_e = F \sum_k z^k D_e^k [k]_e$.

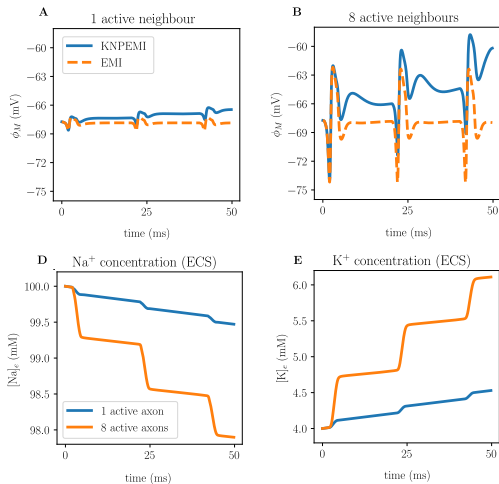
Diffusive currents do not strengthen the *electrical* ephaptic coupling (via the extracellular potential), however we see *diffusive* ephaptic coupling



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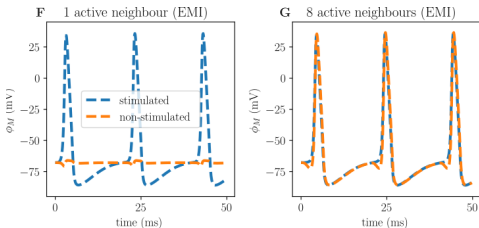


Ephaptic coupling is **inversely proportional** to the **extracellular conductivity**:

$$\sigma_i = \frac{F}{\psi} \sum_k D_i^k[k]_i (z^k)^2 = 2.01 \quad \sigma_i = 1.0, \text{ (S/m)}$$

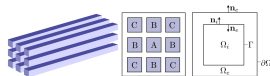
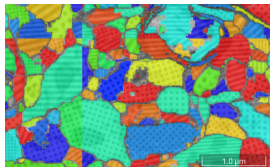
$$\sigma_e = \frac{F}{\psi} \sum_k D_e^k[k]_e (z^k)^2 = 1.31 \quad \sigma_e = 0.1, \text{ (S/m)}$$

[Bokil et al., 2001]



Future perspectives

Exciting times: Extreme modelling of excitable tissue



Ambition

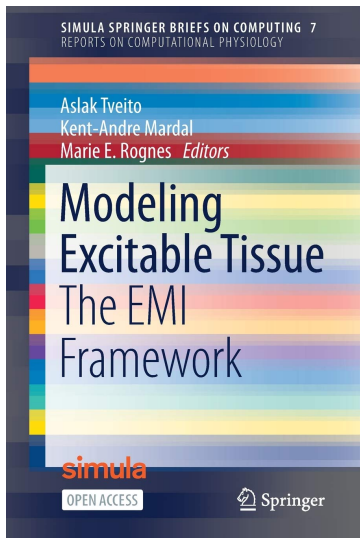
To establish mathematical and technological foundations for modelling and simulation of **electrical, chemical and mechanical interplay between brain cells at unprecedented detail**, allowing for pioneering in-silico studies of brain signalling, volume balance and clearance.

Topics and expected outcomes

- Well-posed general mathematical and numerical framework allowing for geometrically-explicit representations of moving excitable cells;
- New computational geometries and models, highly scalable algorithms, and solution software for high-resolution high-realism simulations of excitable cell ensembles – all distributed as open source;
- New physiological insight into inter-neuronal and astrocyte membrane mechanisms and their role in brain homeostasis and learning.

Funding

Research Council of Norway, FRIPRO (12 MNOK, 2021–2025)



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Collaborators: Cécile Daversin-Catty, Gaute Einevoll, Geir Halnes, Miroslav Kutcha, Rami Masri, Marie Rognes, Andreas Solbrå.

KNP-EMI paper: <https://doi.org/10.3389/fninf.2020.00011>

Modeling Excitable Tissue - The EMI Framework:

<https://doi.org/10.1007/978-3-030-61157-6>

Abstractions and automated algorithms for mixed domain finite element methods: <https://doi.org/10.1145/3471138>

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