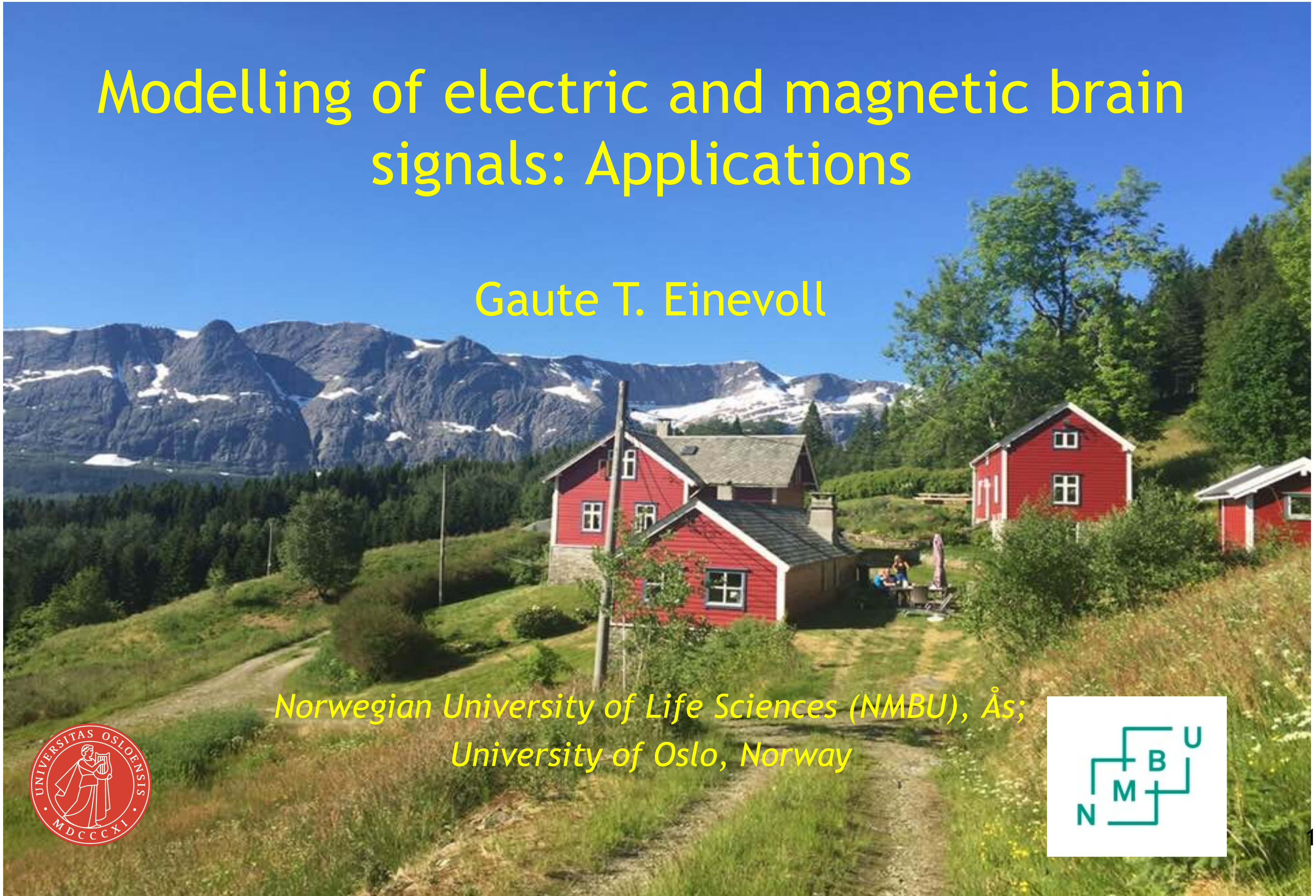
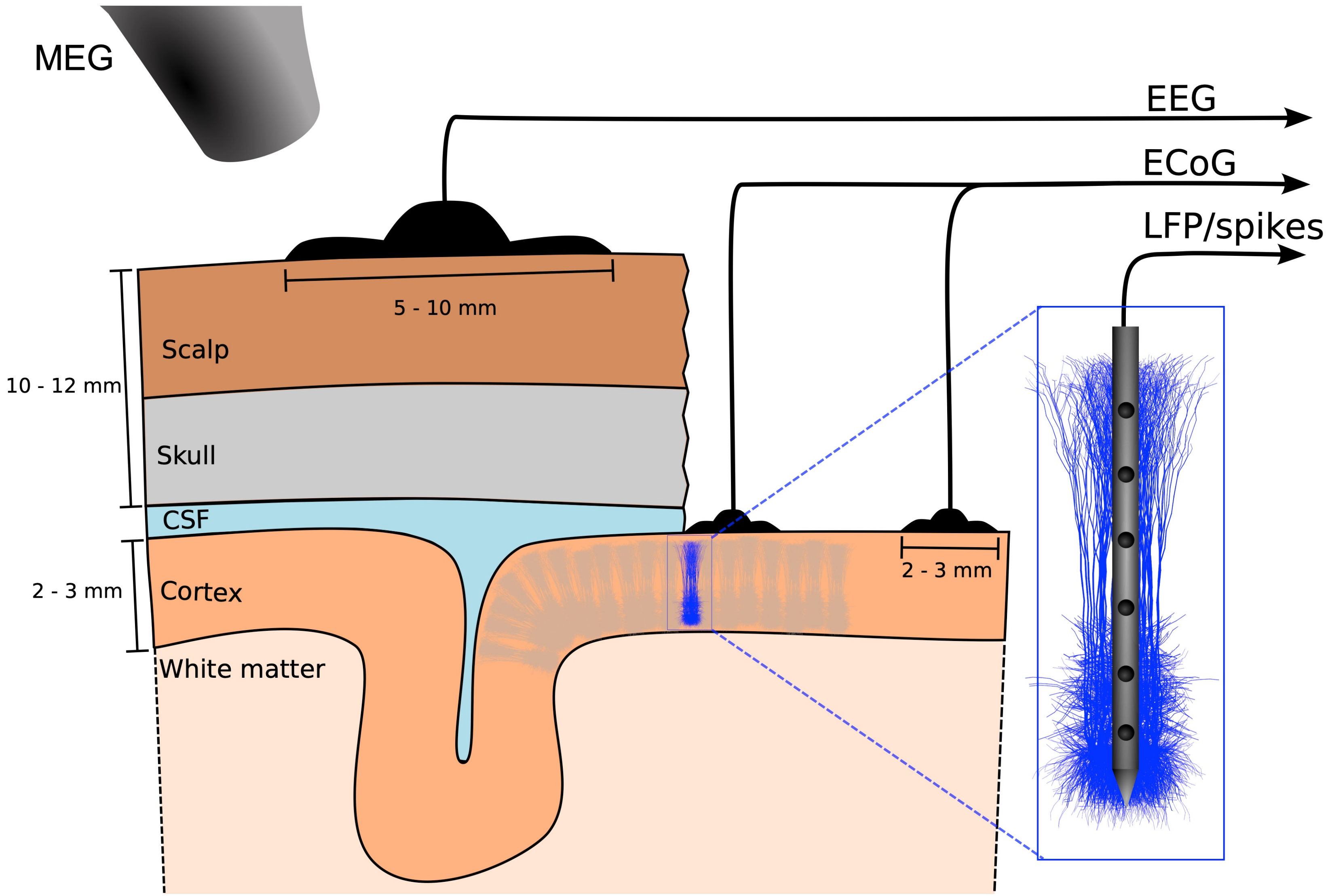
Modelling of electric and magnetic brain signals: Applications



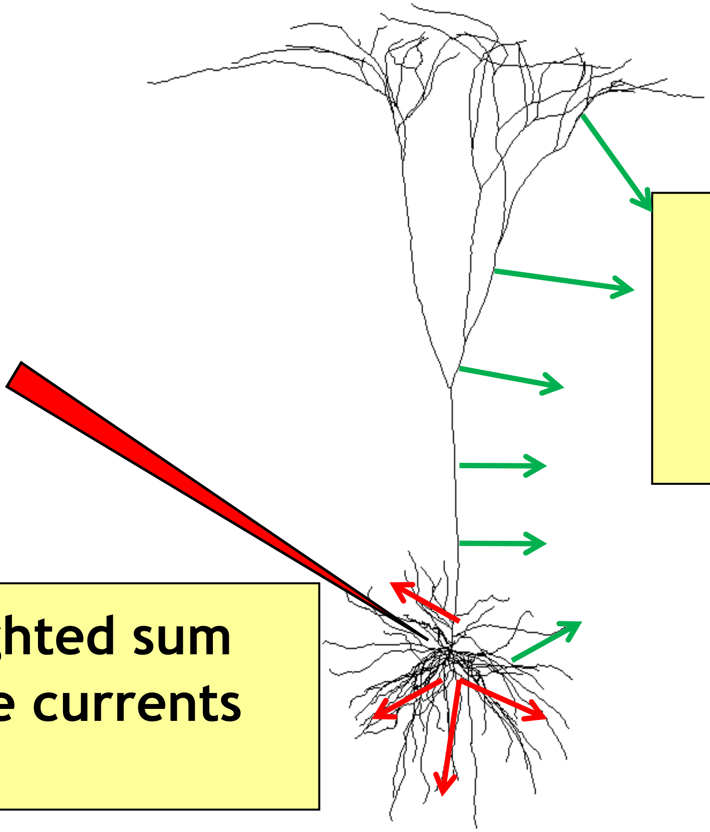
Gaute T. Einevoll

Norwegian University of Life Sciences (NMBU), Ås;
University of Oslo, Norway

Systems level measurements of neural activity



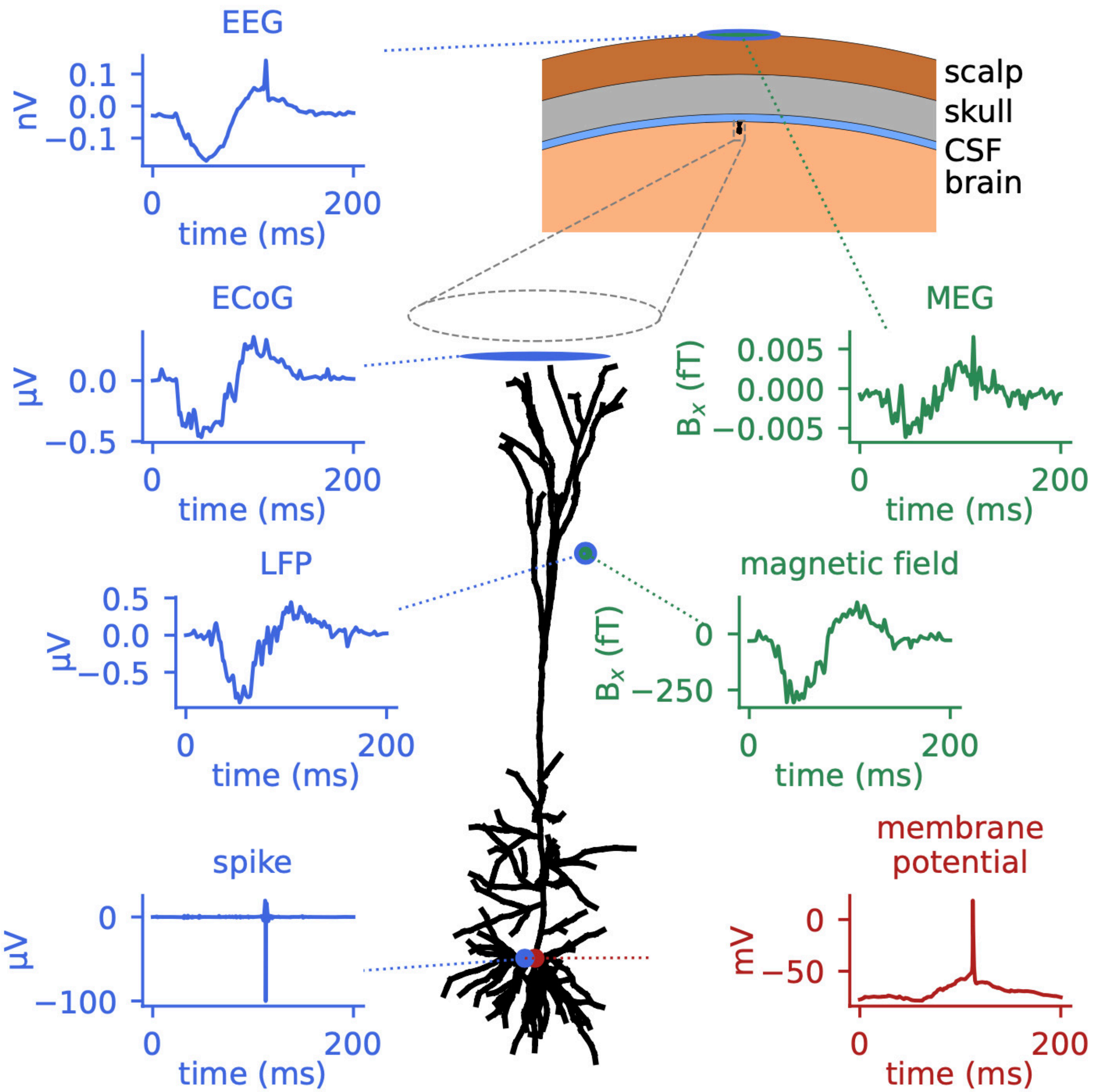
Mechanistic modeling of electric and magnetic brain signals



LFP, ECoG, EEG,MEG:
Weighted sum over transmembrane currents all over neuron

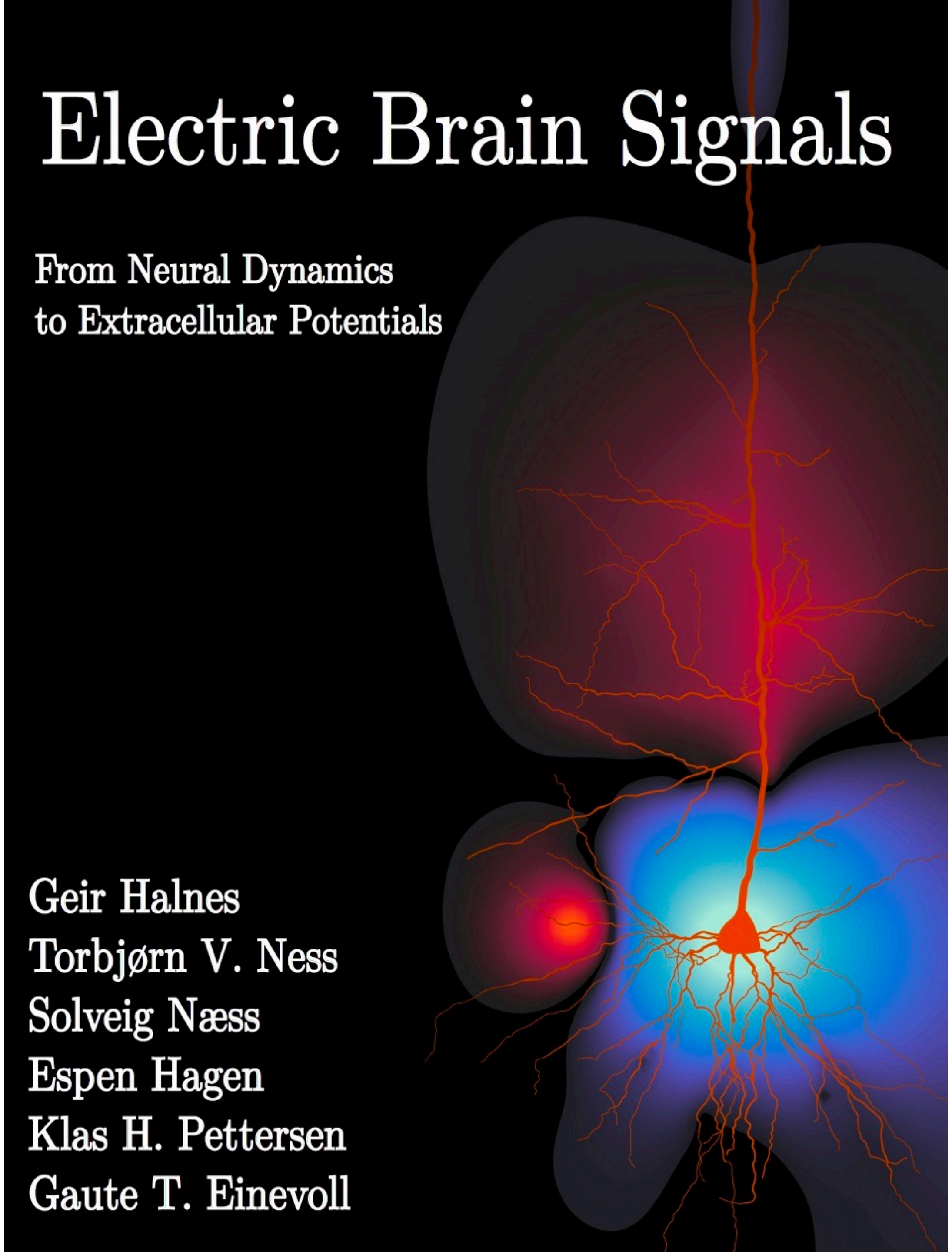
Spike, MUA: Weighted sum over transmembrane currents in soma region

Modeled brain signals from single neuron firing action potential following synaptic inputs



From “Electric Brain Signals” (2024)




Cambridge University Press (2024)

Applications of forward-modeling of brain signals

Spikes

- What determines the shape and size of spikes? (Pettersen & Einevoll, 2008)
- What does spikes look like in micro-electrode arrays MEAs? (Ness et al, 2015)
- Multiunit activity in bat inferior culliculus (Luo et al, 2018)
- Spikes from axonal terminations in mouse cortex (Thunemann et al, bioRxiv, 2022)

LFPs

- How “local” are local field potentials? (Linden et al, 2010; 2011; Leski et al, 2013)
- How does active dendritic conductances affect LFPs? (Ness et al, 2016; 2017)
- What is the “unitary” LFP from a thalamocortical spike? (Hagen et al, 2017)
- Network LFPs using kernel trick (Hagen et al, 2022)
- Simplified formula for LFP modeling (Mazzoni et, 2015)

EEG/ECoG/MEG

- What is the link between EEG, LFP, ECoG and MEG? (Næss et al, 2021)
- Simplified formula for EEG modeling (Martinez-Canada et al, 2021)

Data analysis

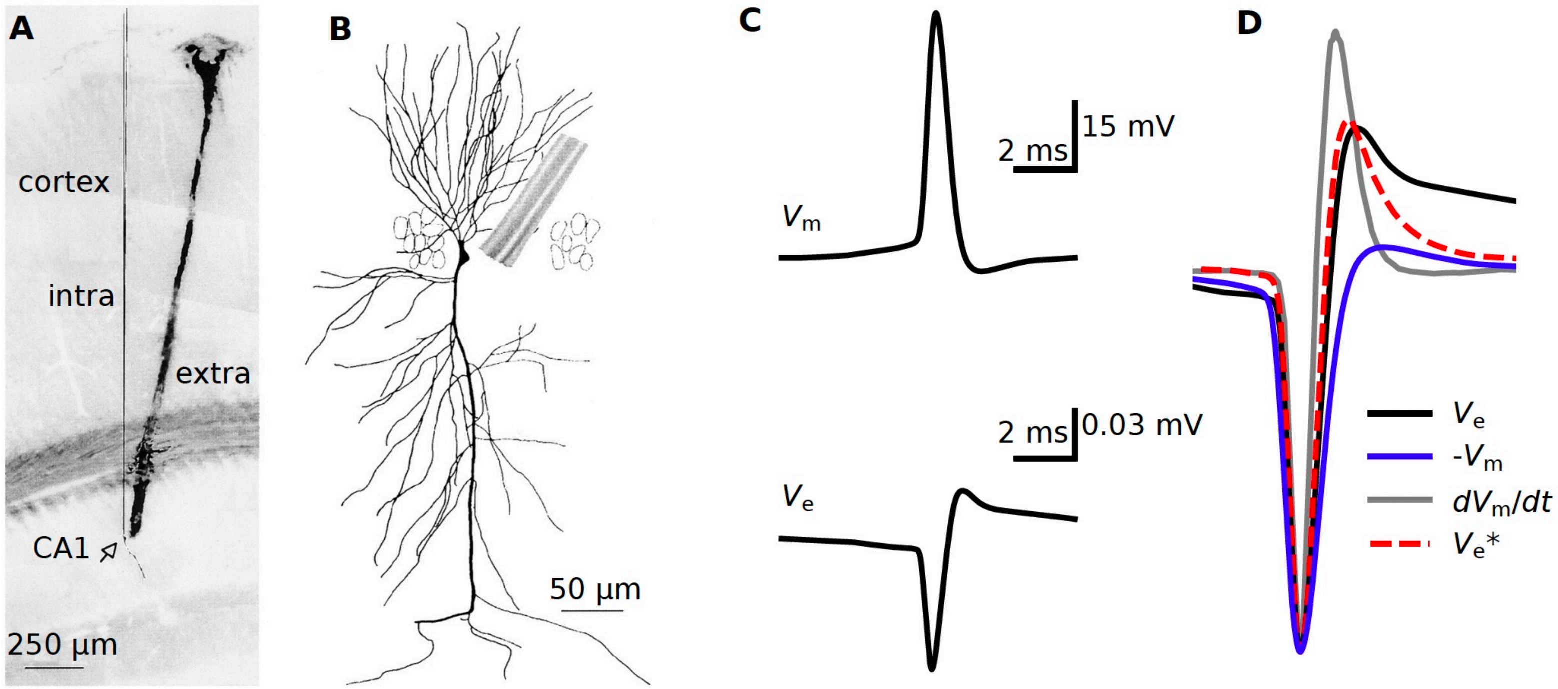
- Development and validation of iCSD method in vivo (Pettersen et al. 2006; 2008; Leski et al. 2011)
- Development and validation of iCSD method in MEAs (Ness et al. 2015)
- Benchmarking data for spike sorters (Hagen et al, 2015; Buccino & Einevoll, 2020)
- Spike-based classification and localization of neurons (Buccino et al, 2018)
- Laminar Population Analysis (LPA) for joint analysis of spikes and LFPs (Einevoll et al, 2007; Glabska et al., 2016)
- Multilinear Population Analysis (MLPA) of LFP data (Geddes et al, 2020)

Network model parameter estimation

- Parameter estimation for Brunel network from LFPs with deep networks (Skaar et al, 2020)
- Parameter estimation for Brunel network from LFPs with Gaussian processes (Skaar et al, bioRxiv, 2022)
- Network parameters from spikes and LFPs for mouse V1 (Rimehaug et al, bioRxiv, 2022)

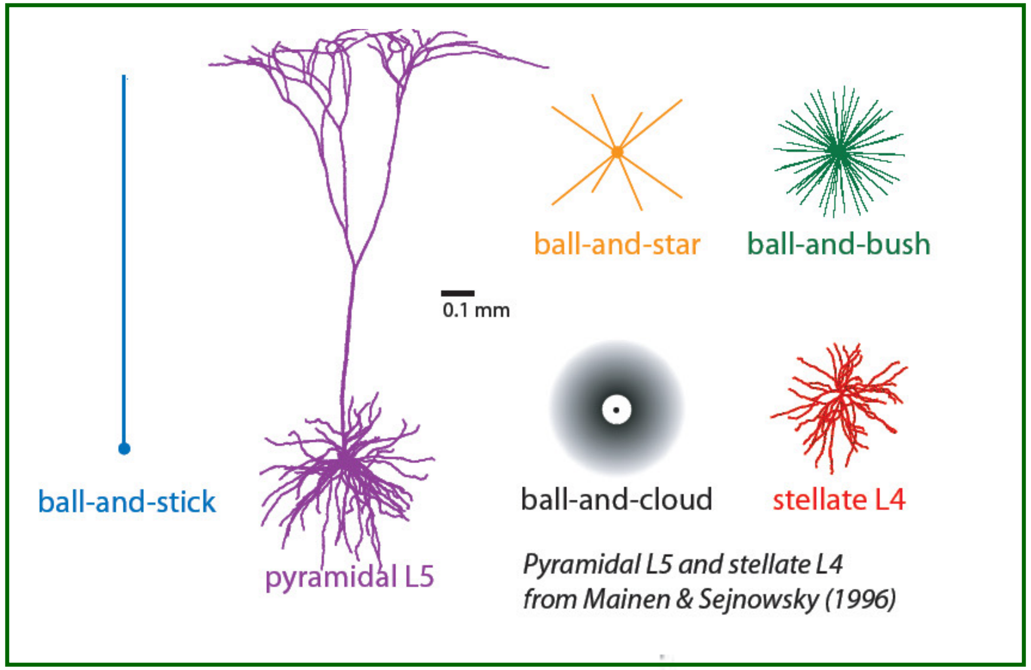
Extracellular spikes

Experimental data from Henze et al (2000)



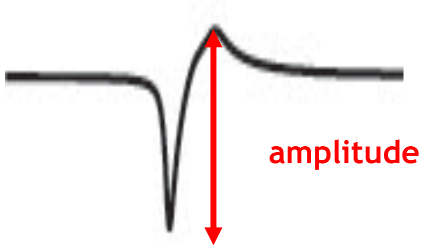
From “Electric Brain Signals” (2024)

How do the extracellular spikes depend on neuronal morphology?



Pyramidal L5 and stellate L4 from Mainen & Sejnowsky (1996)

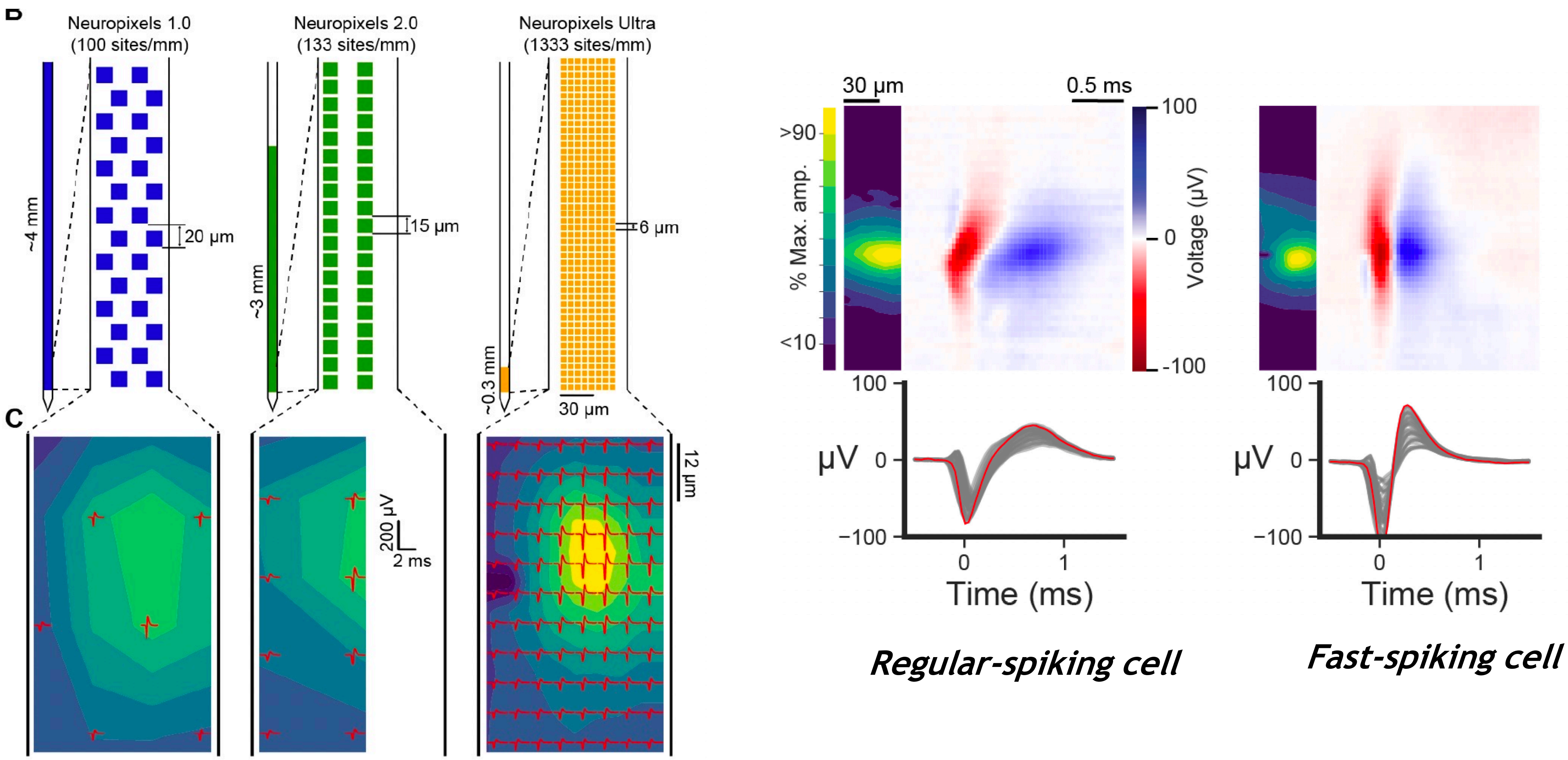
- **Amplitude** is (i) roughly proportional to ***sum of cross-sectional areas*** of dendrites connected to soma, (ii) independent of *membrane resistance* R_m, …



- **Spike width** increases with distance from soma, i.e., high-frequency dampening also with simple ohmic extracellular medium

Pettersen & Einevoll, Biophysical Journal 2008

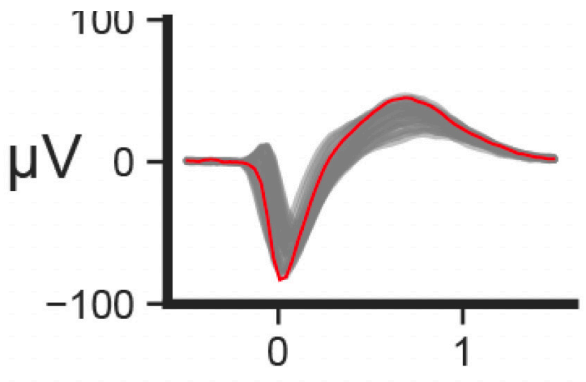
Neuropixel Ultra



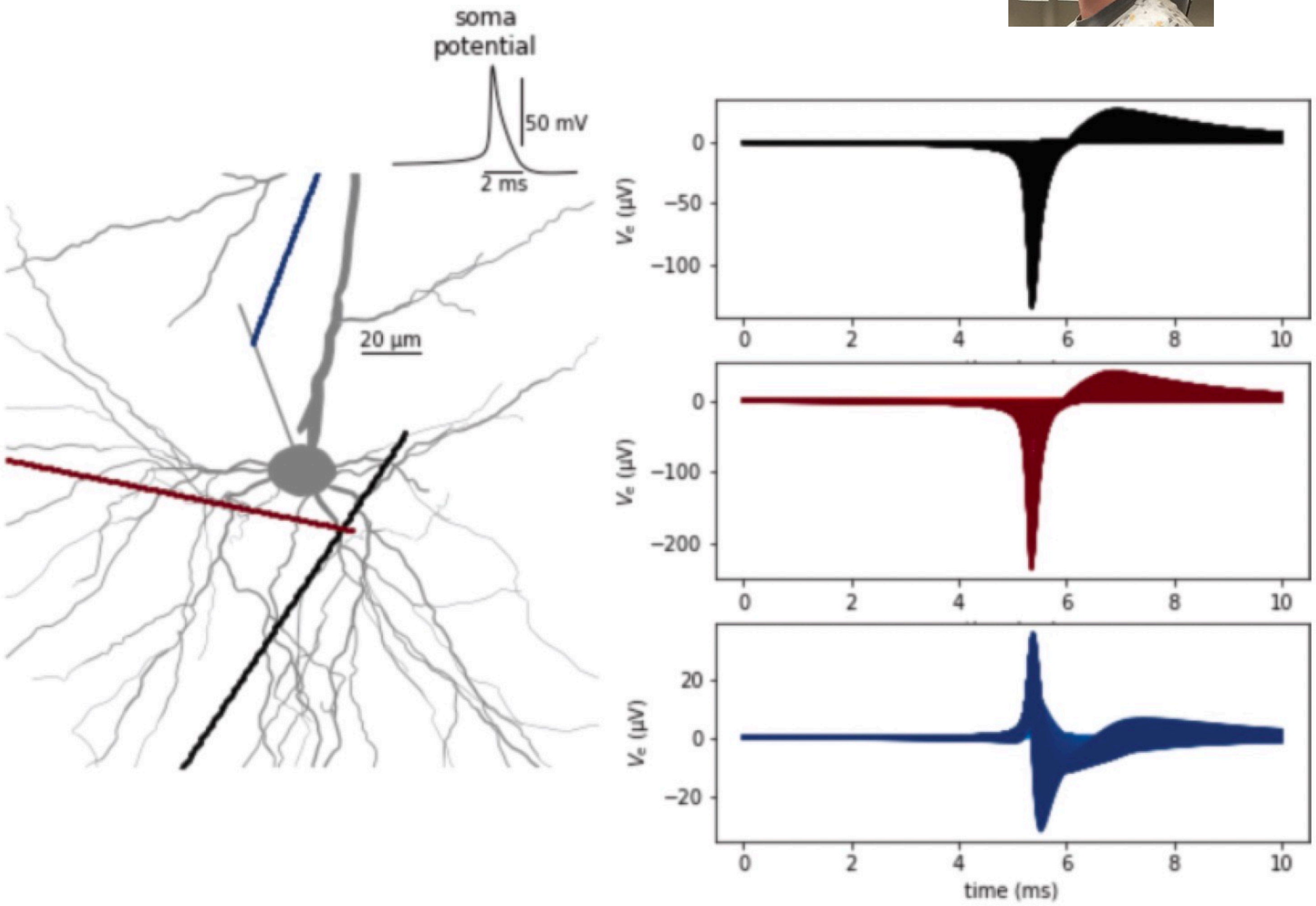
Ye,…,Siegle, Koch, Olsen, Harris, Steinmetz, in preparation

Neuropixel Ultra – computational modeling

Torbjørn Ness



Regular-spiking cell



Ye,…,Siegle, Koch, Olsen, Harris, Steinmetz, in preparation

Imaging through wearable, transparent Wind*ans*ee

Anna
Devor

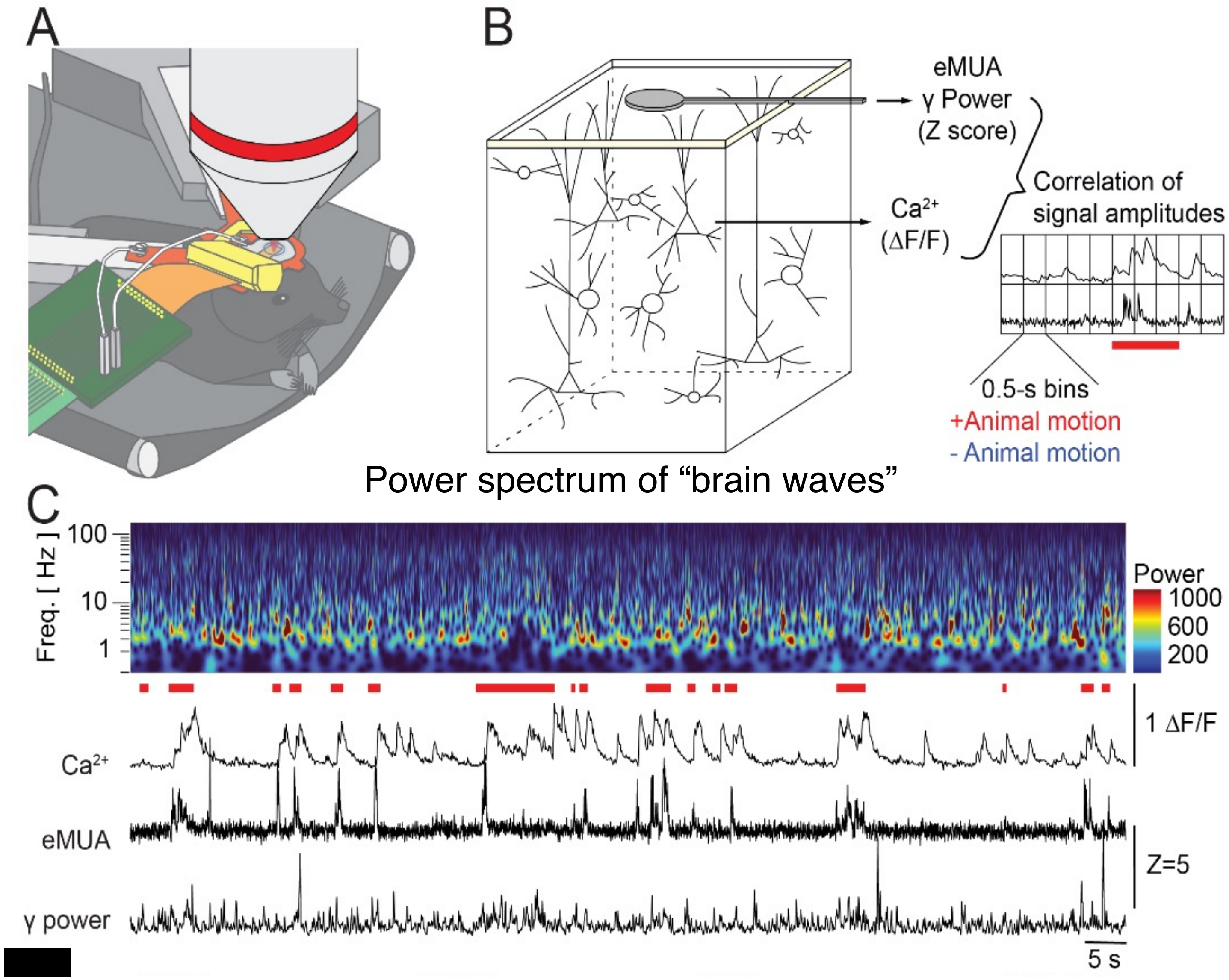
Shadi
Dayeh

Martin
Thunemann

Lorraine
Hossain

Nick
Rogers

Kıvılcım
KILIÇ

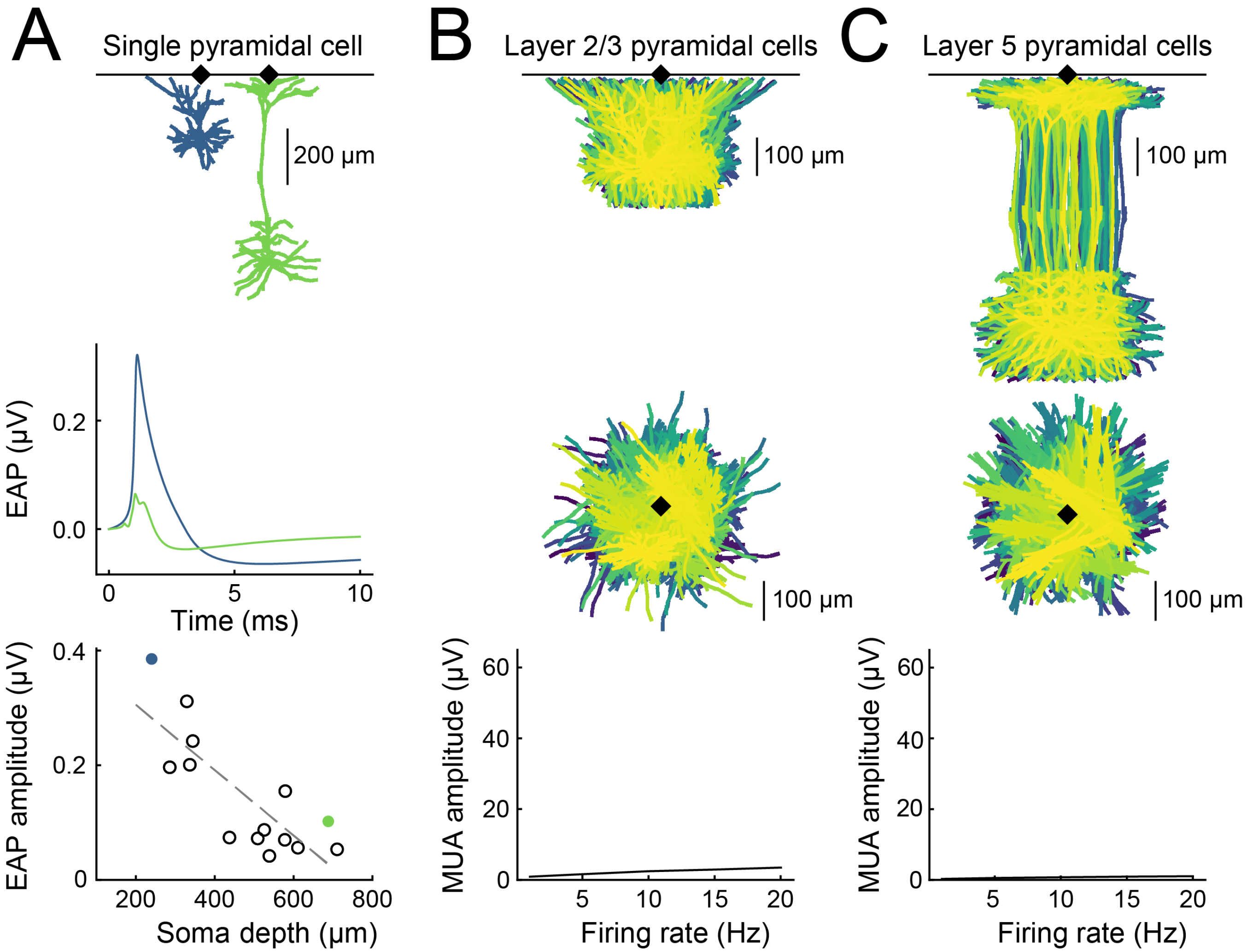


[redacted]

Thunemann, Hossain et al. bioRxiv doi: https://doi.org/10.1101/2022.09.01.506113

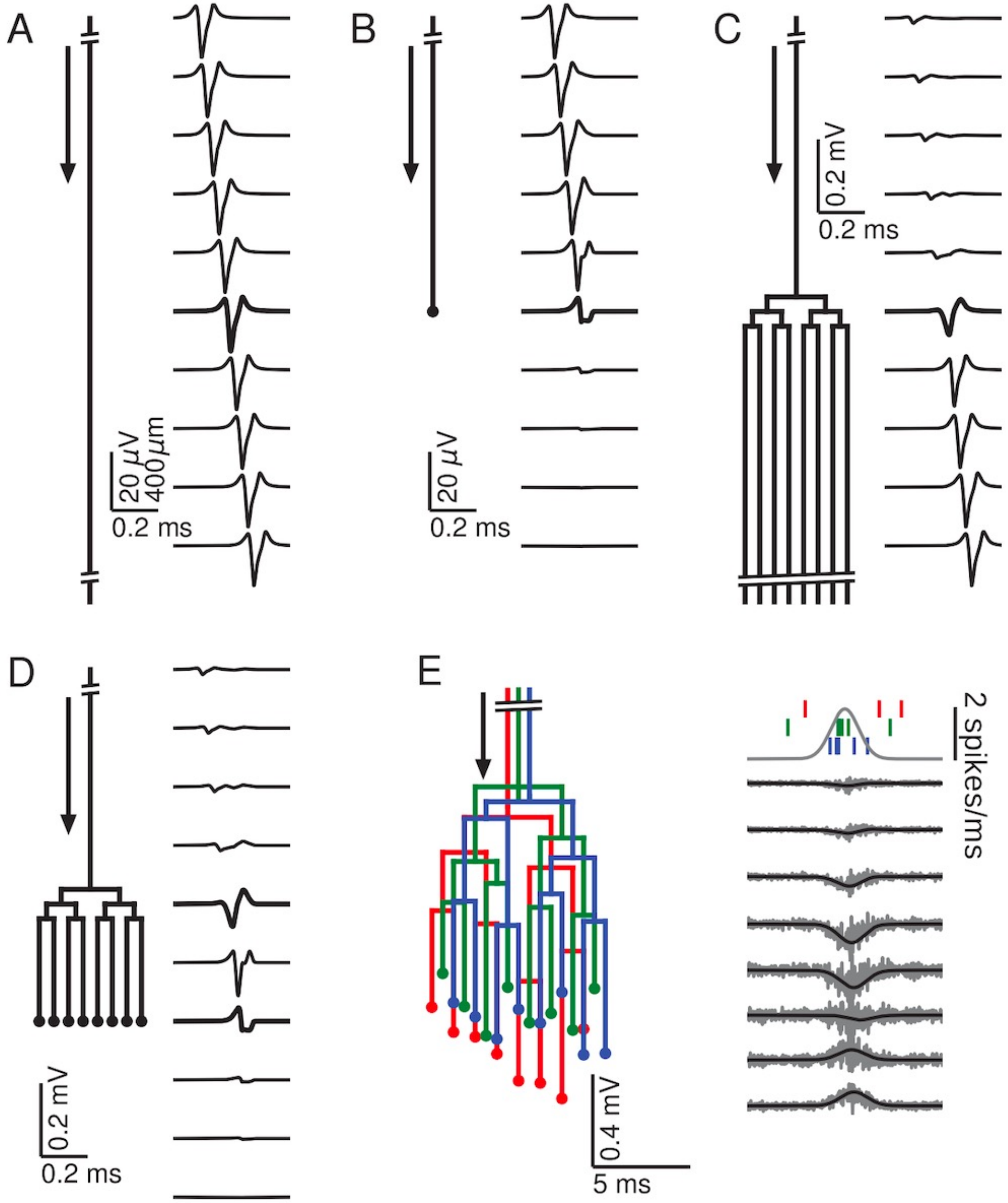
What is the source of surface MUA?

Torbjørn Ness



Thunemann, Hossain et al. bioRxiv doi: https://doi.org/10.1101/2022.09.01.506113

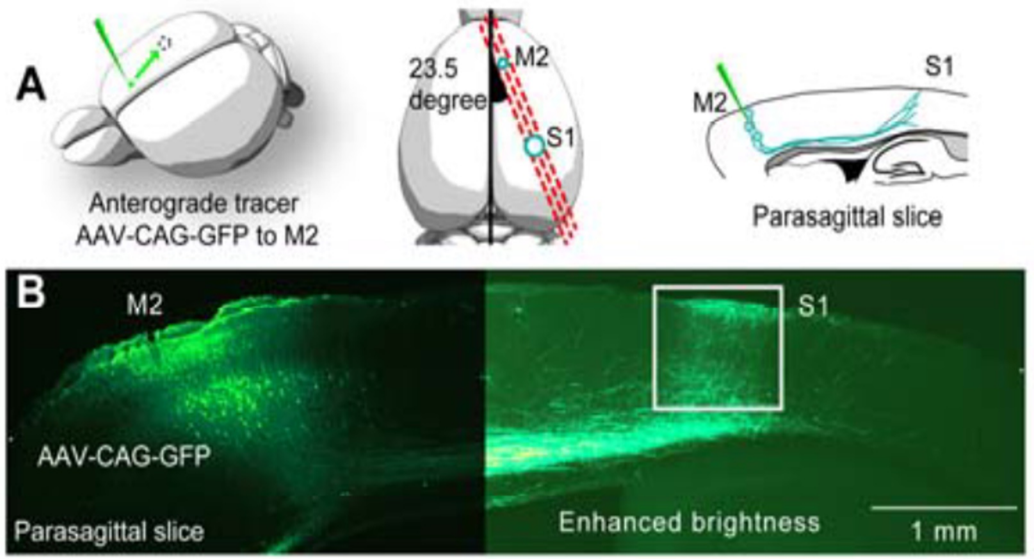
Bifurcating axons may give large EP signals



McColgan et al, eLife (2017)

EP signals from ascending axons in S1

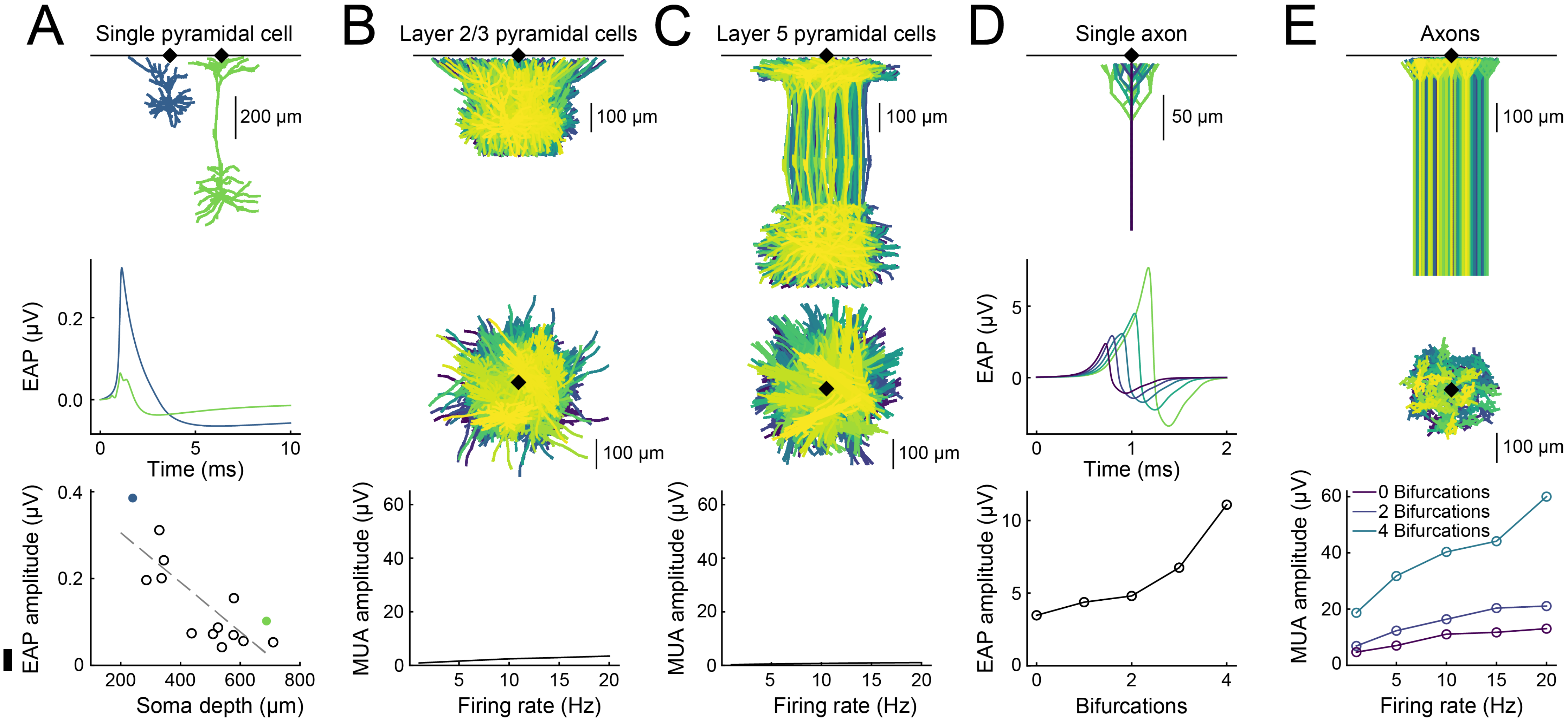
- Murayama (personal communication):
  - “Hindpaw stimulation to mice evokes two temporally distinct components, fast and late activity in S1. The late activity comes from M2 via top-down projection. Their axons reach to the bottom layer in S1 and then to L1, shown in Suppl.fig. S2B.”



Manita et al, Neuron (2015)

What is the source of surface MUA?

Torbjørn Ness

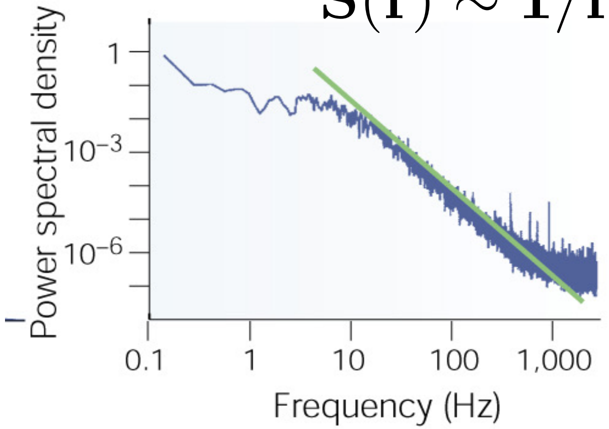


Thunemann, Hossain et al. bioRxiv doi: https://doi.org/10.1101/2022.09.01.506113

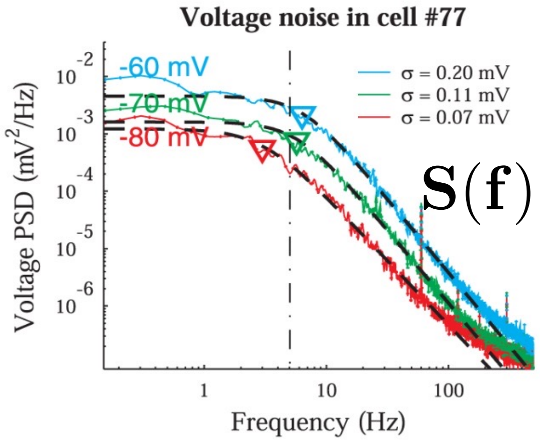
Power laws in electrical brain recordings

Soma membrane potential

$$\mathbf{S(f) \sim 1/f^{2.6}}$$



Destexhe et al., 2003

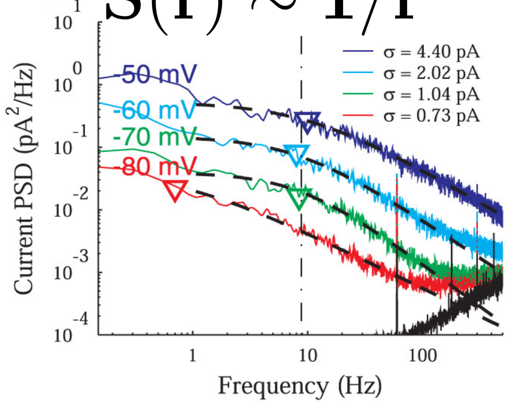


$$\mathbf{S(f) \sim 1/f^{2.4}}$$

Diba et al. 2004

Soma membrane current

$$\mathbf{S(f) \sim 1/f^{1.1}}$$

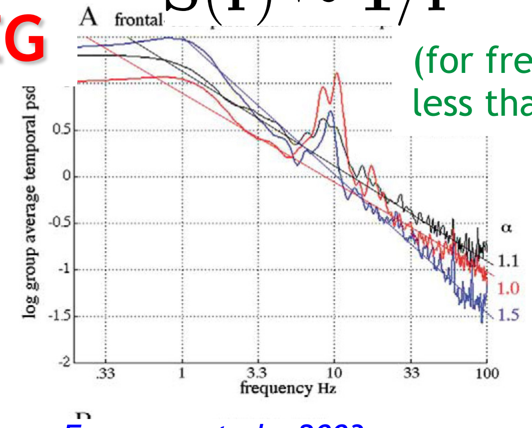


Diba et al. 2004

EEG

$$\mathbf{S(f) \sim 1/f^{1-2}}$$

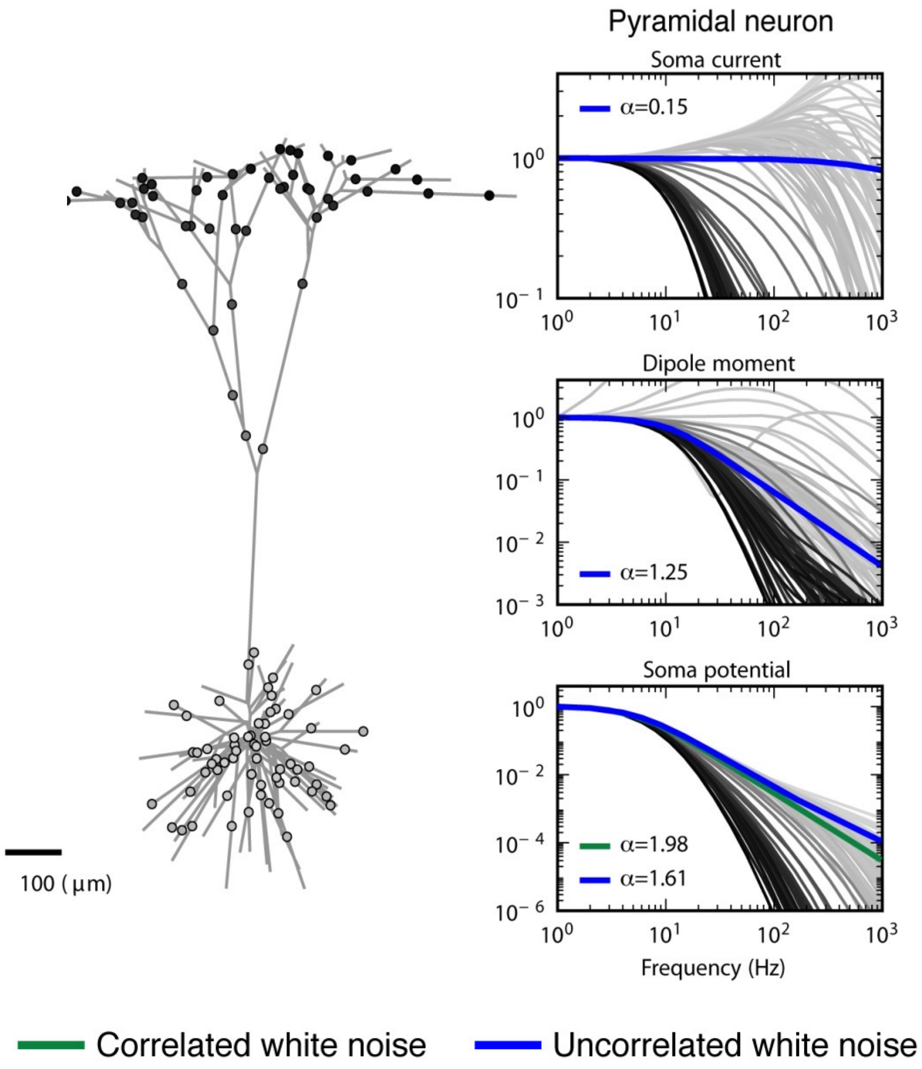
(for frequencies less than 100 Hz)



Freeman et al., 2003

Power laws from cable equation with **many evenly distributed** membrane current inputs

- «White-noise» current injected at different positions on dendrites



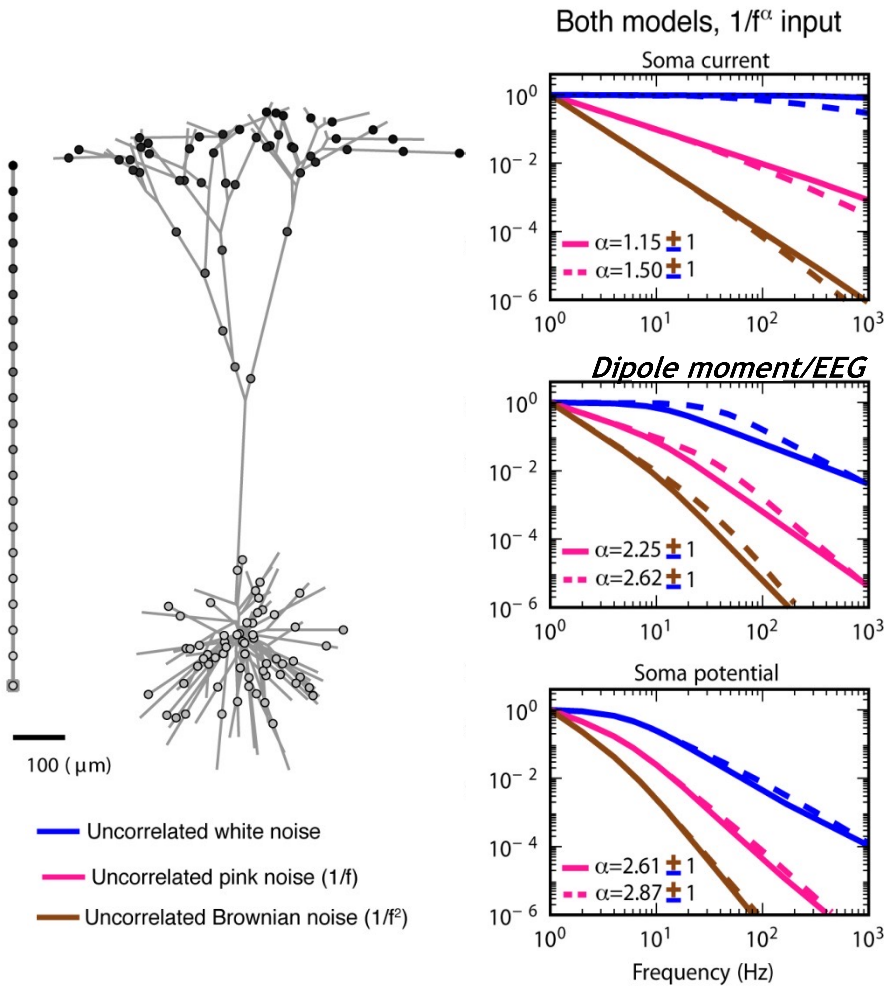
$$\mathbf{S(f) \sim 1/f^{\alpha}}$$

(α is here estimated at 1000 Hz)

- Note: Power-law coefficients α vary between <u>different measurements</u> even with a common underlying noise source

Pettersen et al, PLoS Comp Biol, 2014

Model power-law coefficients vs experiments

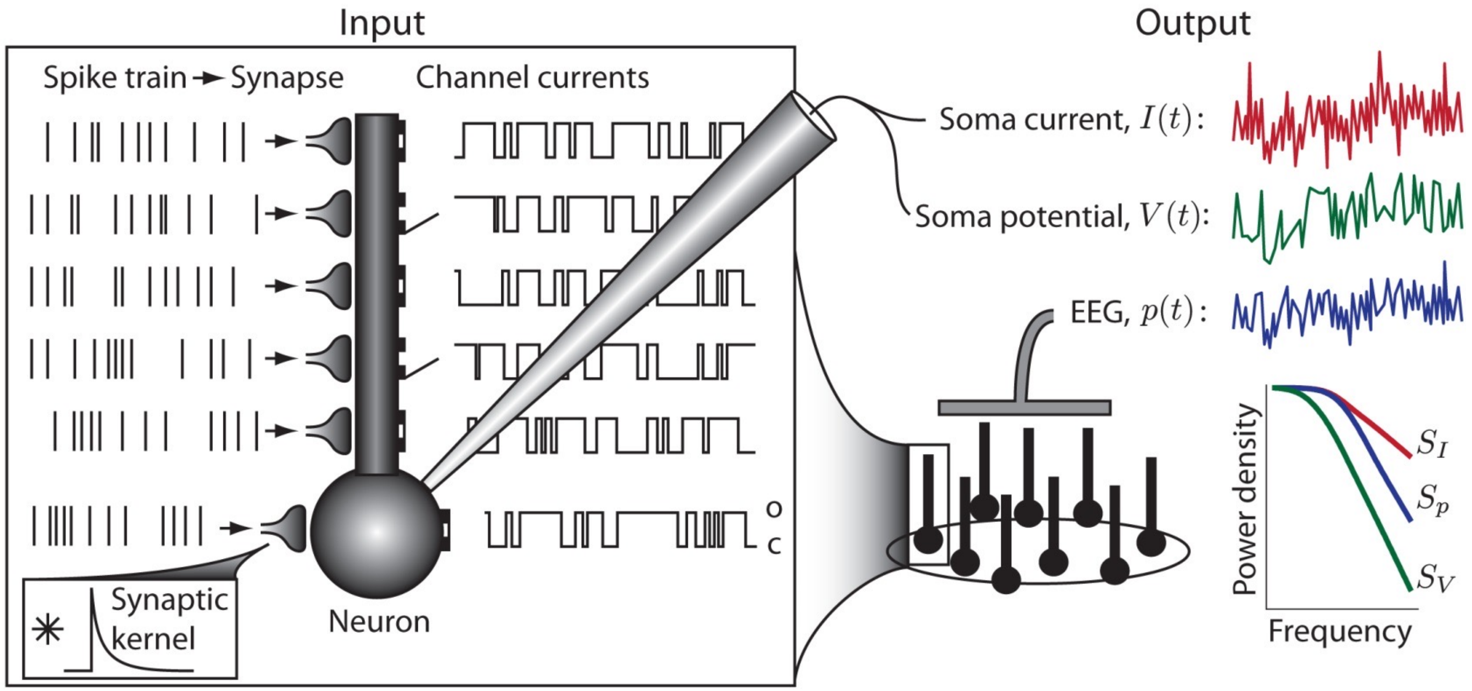


Model *(uncorr., pink noise input)*	***Experiments***
$\alpha \approx$ **1.15**	$\alpha \approx \mathbf{1.2}$
$\alpha \approx$ **2.25**	$\alpha \approx \mathbf{1-2}$ (for frequencies less than 100 Hz)
$\alpha \approx$ **2.61**	$\alpha \approx \mathbf{2.4-2.7}$

- Overall, model with (i) **uncorrelated**, (ii) **evenly distributed** input currents each with (iii) a **pink-noise (*1/f*)** characteristic seem to be compatible with experiments

Pettersen et al, PLoS Comp Biol, 2014

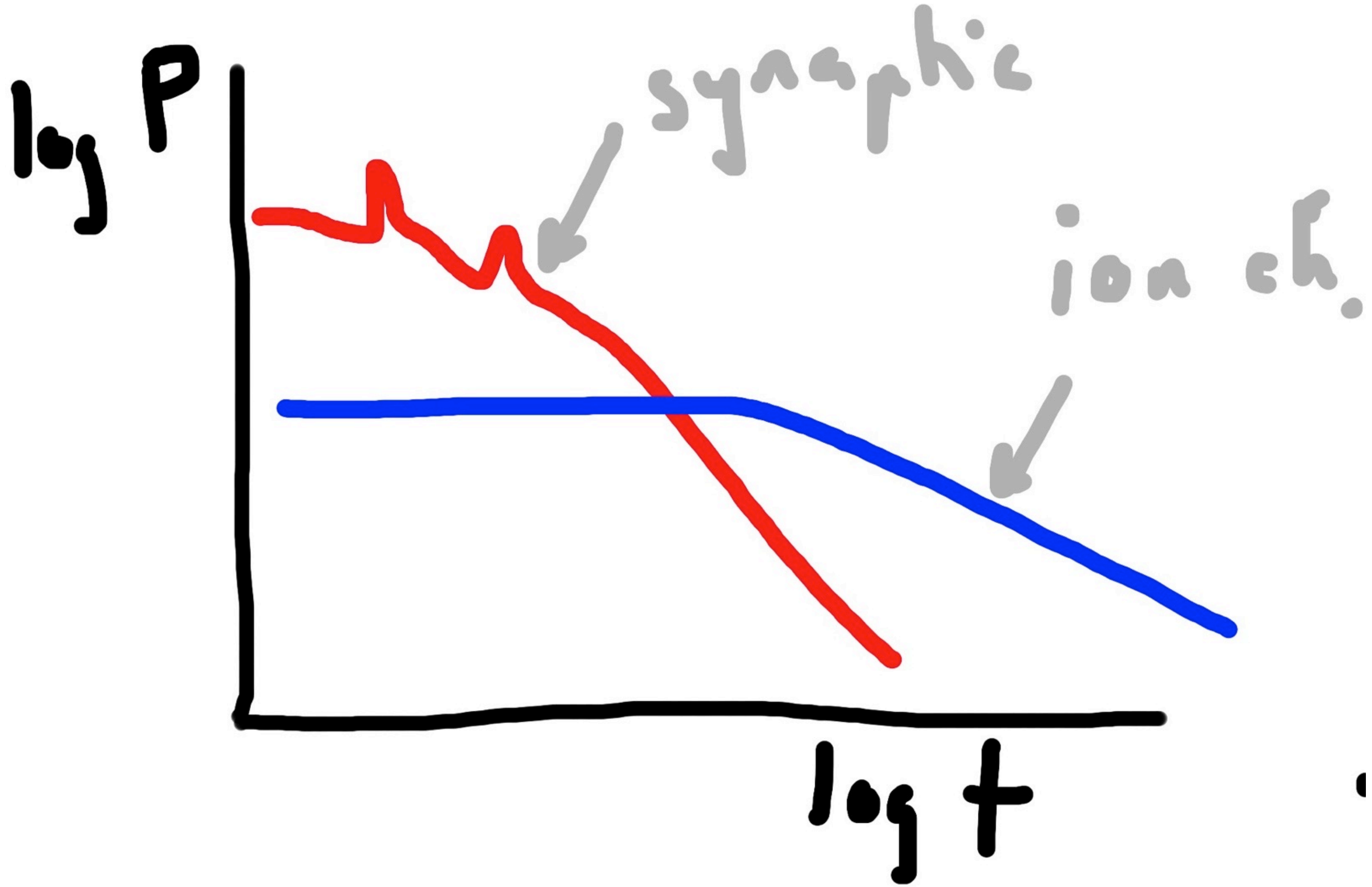
Biophysical origin of current noise underlying power laws



- Experiments support model with (i) **uncorrelated**, (ii) **evenly distributed** input currents with (iii) a **pink-noise (*1/f*)** spectra

- Conjecture: Intrinsic potassium ion channels dominate power-law part of spectra as
  1. potassium channels with *1/f* spectra have been seen, and
  2. synaptic noise would give larger power-law coefficients

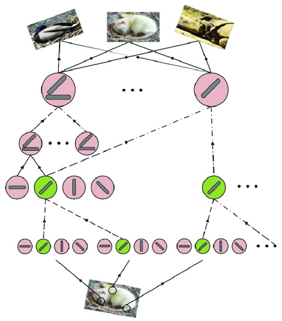
Pettersen et al, PLoS Comp Biol, 2014


log P
synaptic
ion ch.
log t

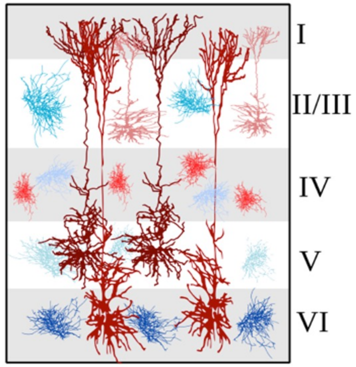
Models for image recognition in mouse

COMPUTATIONAL

ALGORITHMIC



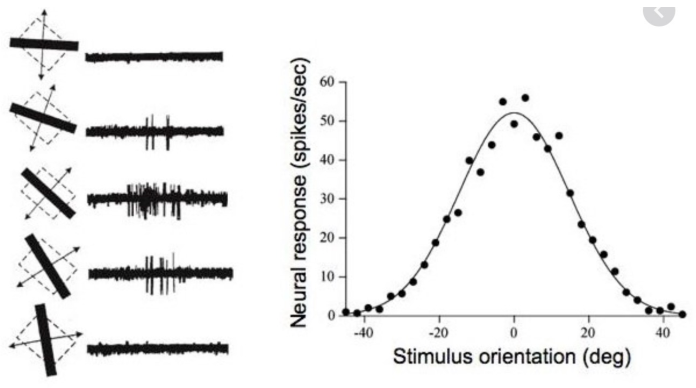
PHYSICAL



Analysis of in vivo experiments

- Until now: Focus mainly on **neural representations**

- **Receptive fields in primary visual cortex**
  - simple/complex cells
  - orientation-selective cells
  - direction-selective cells
  - end-stopping cells
  - ….



Hubel & Wiesel (1960s)

Mini-Symposium

Journal of Neuroscience, 2005

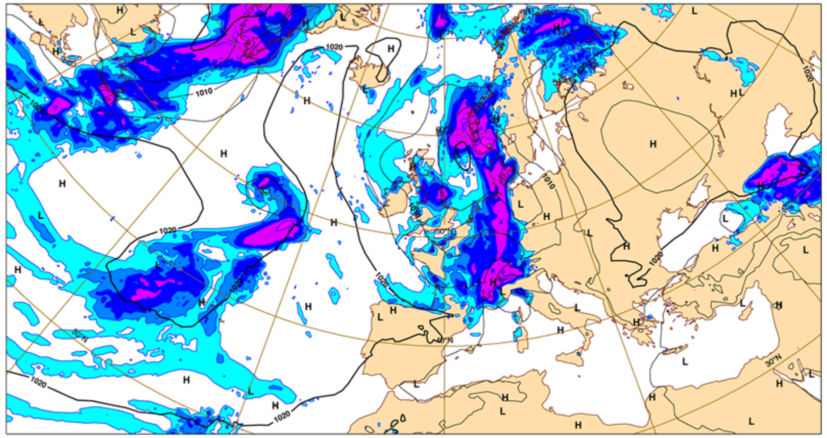
Do We Know What the Early Visual System Does?

Matteo Carandini,[1] Jonathan B. Demb,[2] Valerio Mante,[1] David J. Tolhurst,[3] Yang Dan,[4] Bruno A. Olshausen,[6] Jack L. Gallant,[5,6] and Nicole C. Rust[7]

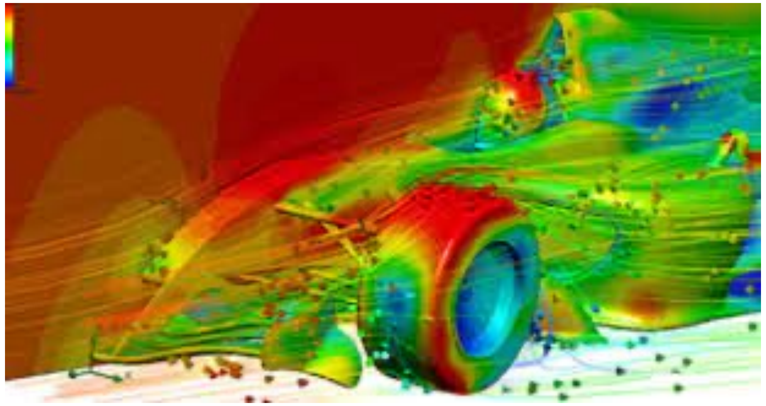
First line of abstract: *We can claim that we know what the visual system does once we can predict neural responses to arbitrary stimuli, including those seen in nature.*

Multipurpose model

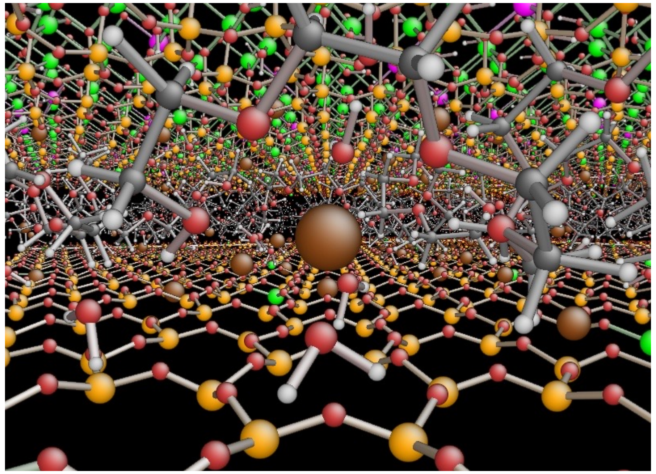
Multipurpose modeling in natural sciences



Weather forecasting



Fluid dynamics

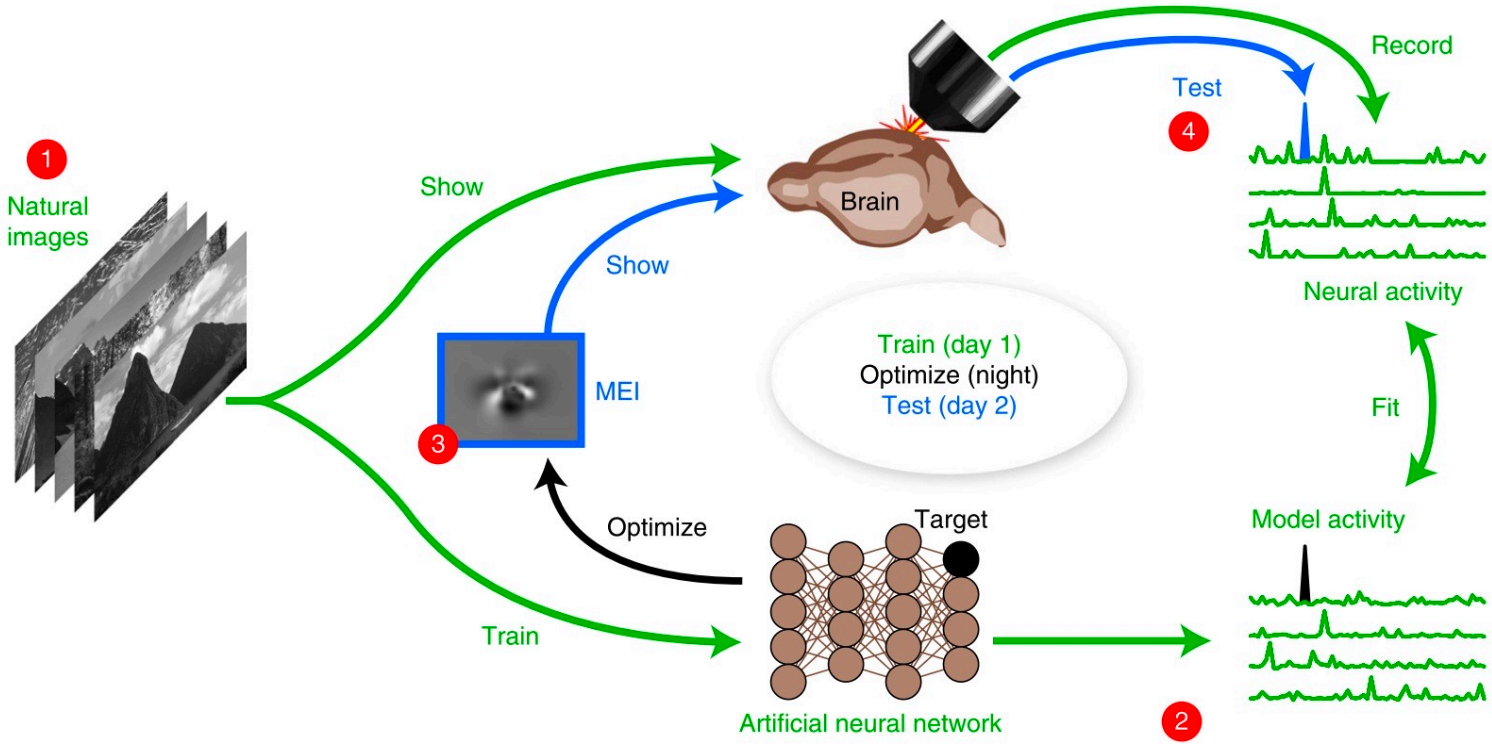


Material science

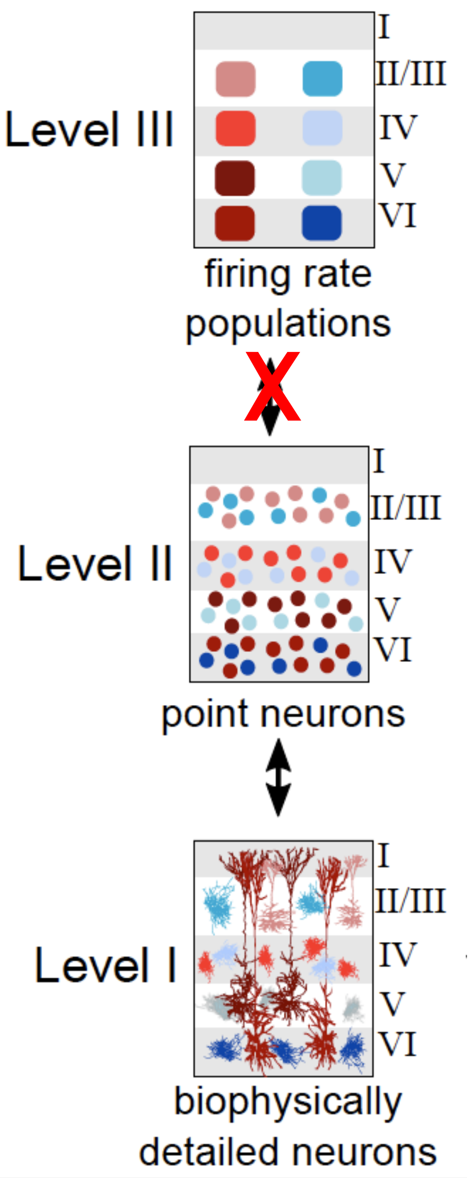
Towards multipurpose descriptive models

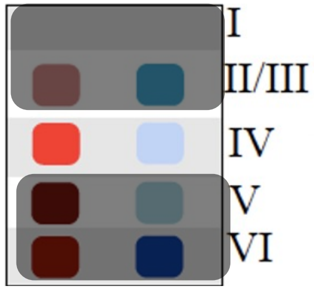
Inception loops discover what excites neurons most using deep predictive models

Edgar Y. Walker[1,2,8*], Fabian H. Sinz[1,2,3,4,8*], Erick Cobos[1,2], Taliah Muhammad[1,2], Emmanouil Froudarakis[1,2], Paul G. Fahey[1,2], Alexander S. Ecker[1,3,5,6], Jacob Reimer[1,2], Xaq Pitkow[1,2,7] and Andreas S. Tolias[1,2,7*]

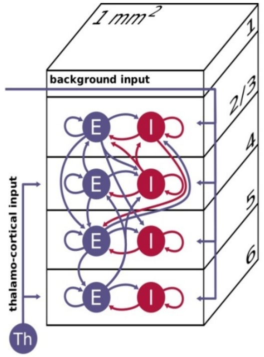


Mechanistic modeling of primary visual cortex

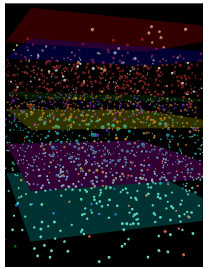


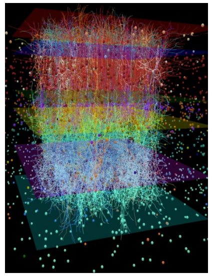


- Typically 1 or 2 populations (dynamical variables)
- Typically ‘**single purpose**’, and predicts:
    - Orientation selectivity
    - Direction selectivity
    - Contrast invariance
    - …

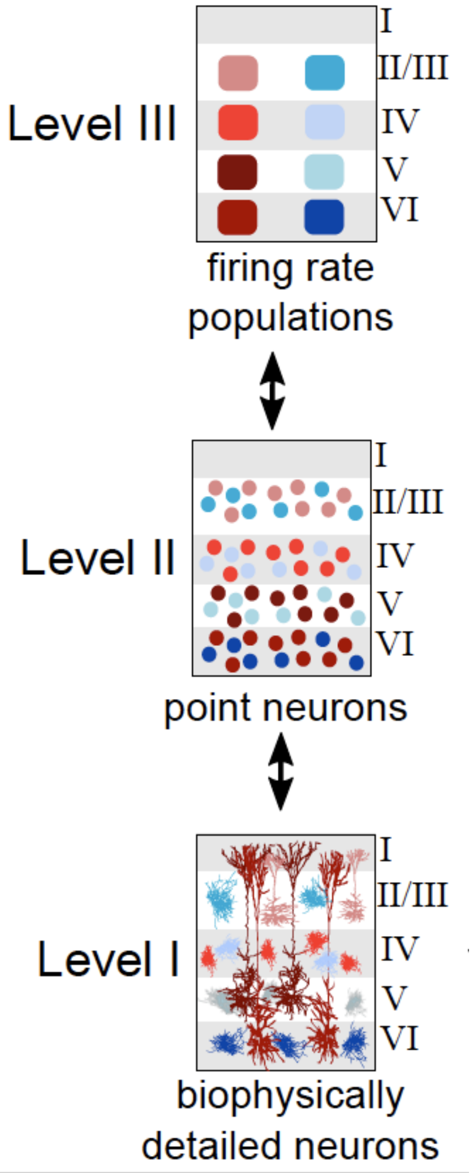


Cat V1 “column” model,
80.000 neurons
(Potjans & Diesmann, Cerebral Cortex, 2014)





Allen mouse V1 model
230.000 neurons
(Billeh et al, Neuron, 2020)



Multipurpose mechanistic modeling of primary visual cortex

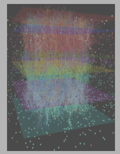
- Models that simultaneously can predict experimental data
  - for different **visual stimuli**
  - for different **measurement types**
  - for different **brain states**

- Multipurpose models
  - must likely be **high-dimensional** (like real brains)
  - should be reducable to several single-purpose **low-dimensional** models

Scheme for finding level I/II model for mouse V1

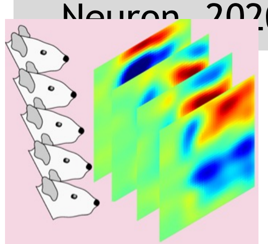
"Prior" data (Allen)
- Physiology (patch clamp)
- Anatomy (morphology, connectivity)

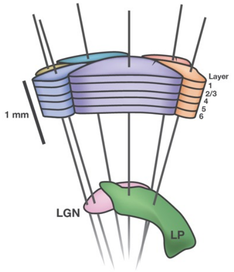
V1model({parameters})



New "prior" data (Allen):
- Synaptic physiology
scopy

Billeh,…, Arkhipov, Neuron, 2020





Choose stimulus/input data
- Feedforward, feedback,…
- Recorded, modeled, …

V1model({parameters}, {input})

Data (brain signals) for model testing (Allen):
- Electrophysiology (spikes,LFP,…)
- …

Compute brain signals (spikes, LFP,…)

Adapt {parameters}

Compute deviation for set metric

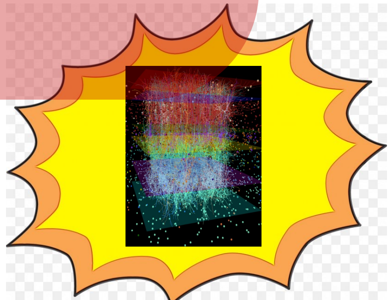
Brain signal targets for model

deviation< criterion?

No

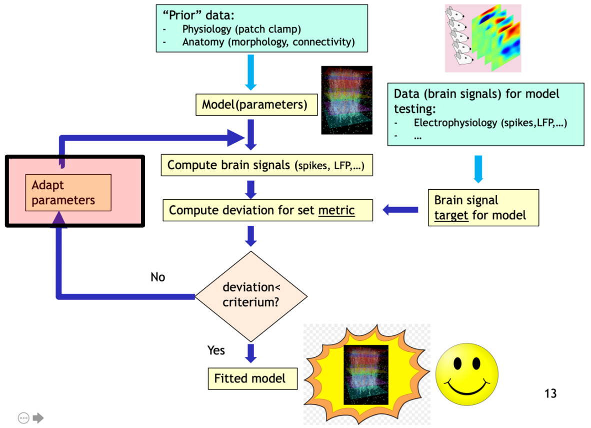
Yes

Fitted V1model

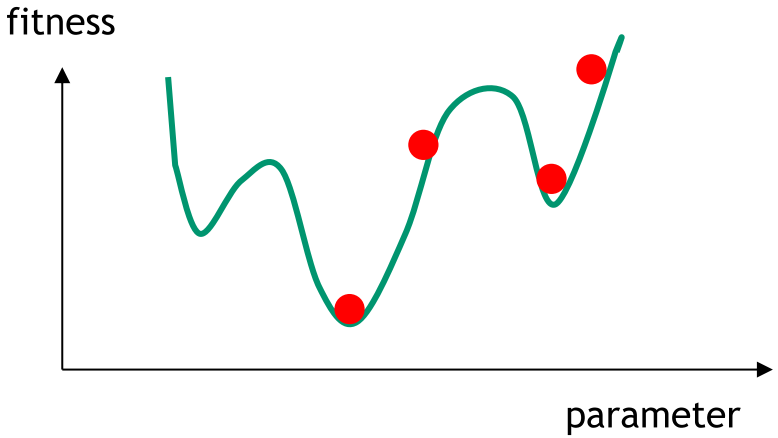


«Best» V1model(s) given present data

Model fitting
(«adapt parameters»)

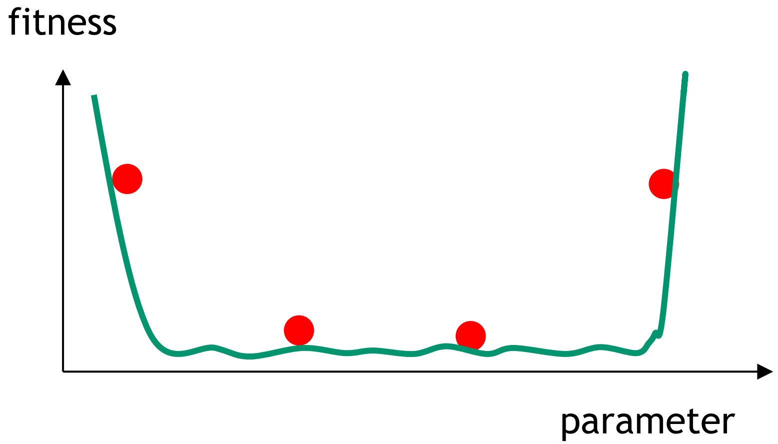


- Models with <u>few</u> parameters



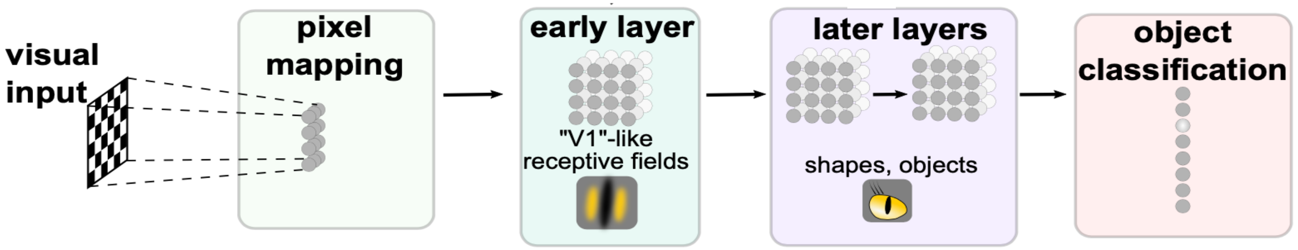
- Unique optimal model
- Gets easily stuck in local minima during fitting

- Models with <u>many</u> parameters (like V1 circuit)

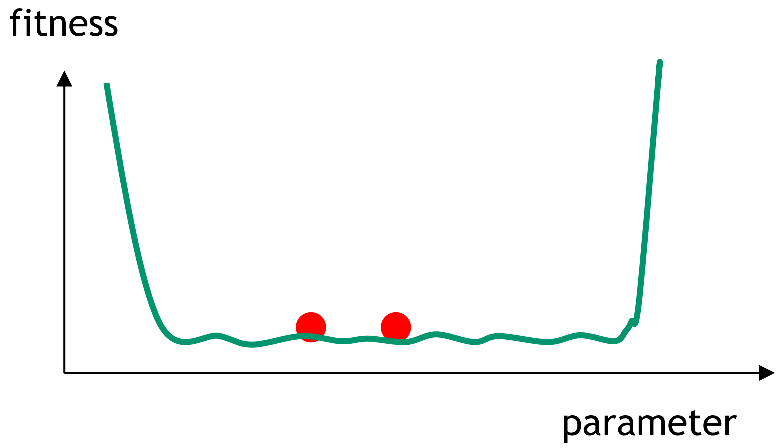


- Many «optimal» models
- Not easily stuck in local minima during fitting

Why are «deep networks» working so well?



- Two identical CNNs (Convolutional Neural Networks) trained on the same images:
    - **<u>similar</u>** performance, but
    - trained parameters (weights) are **<u>different</u>**



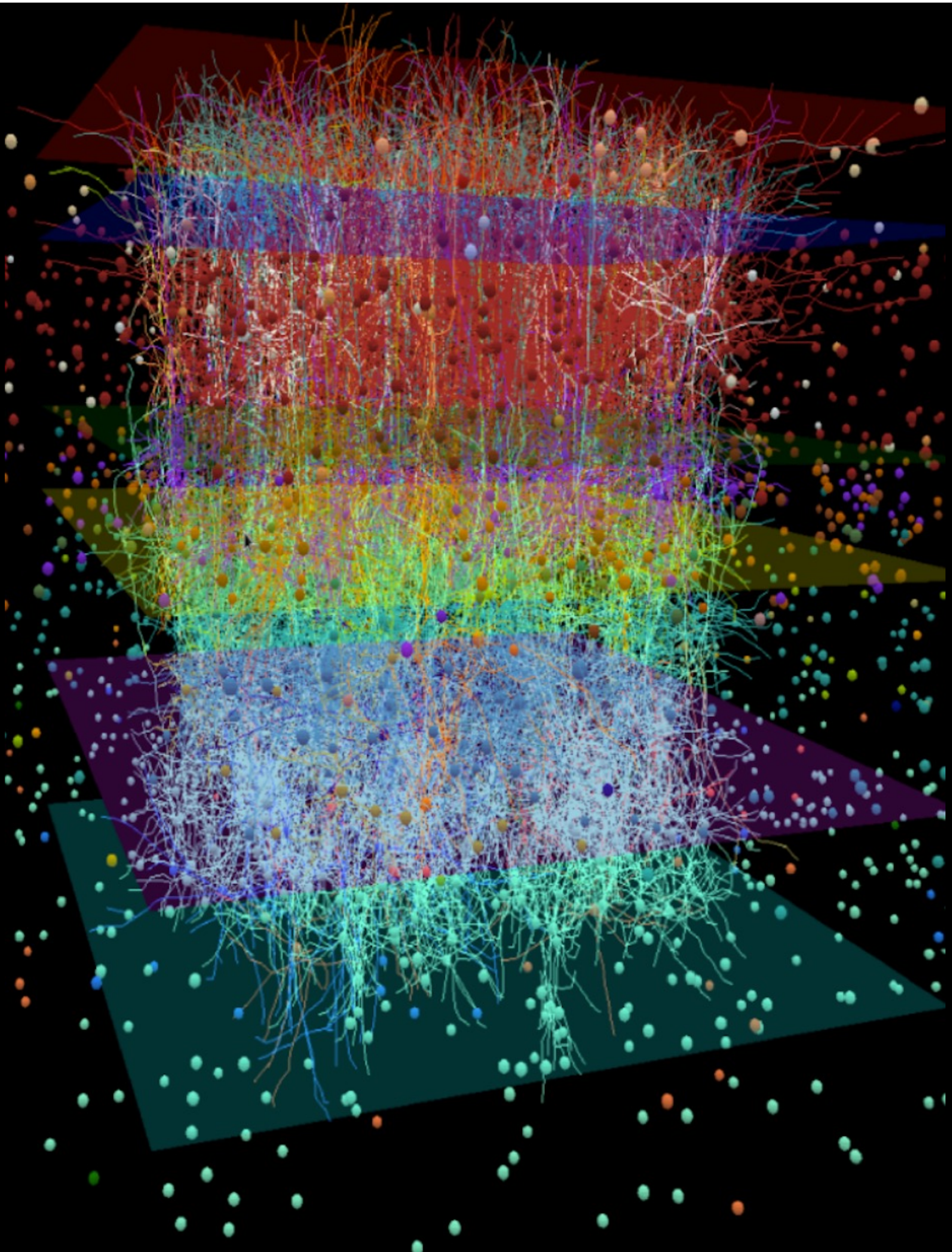
T. Sejnowski: *The Unreasonable Effectiveness of Deep Learning in Artificial Intelligence*, PNAS (2020)

Episode #2 in podcast «Sense and Science»: On AI and the underlying algorithms – with Terrence Sejnowski

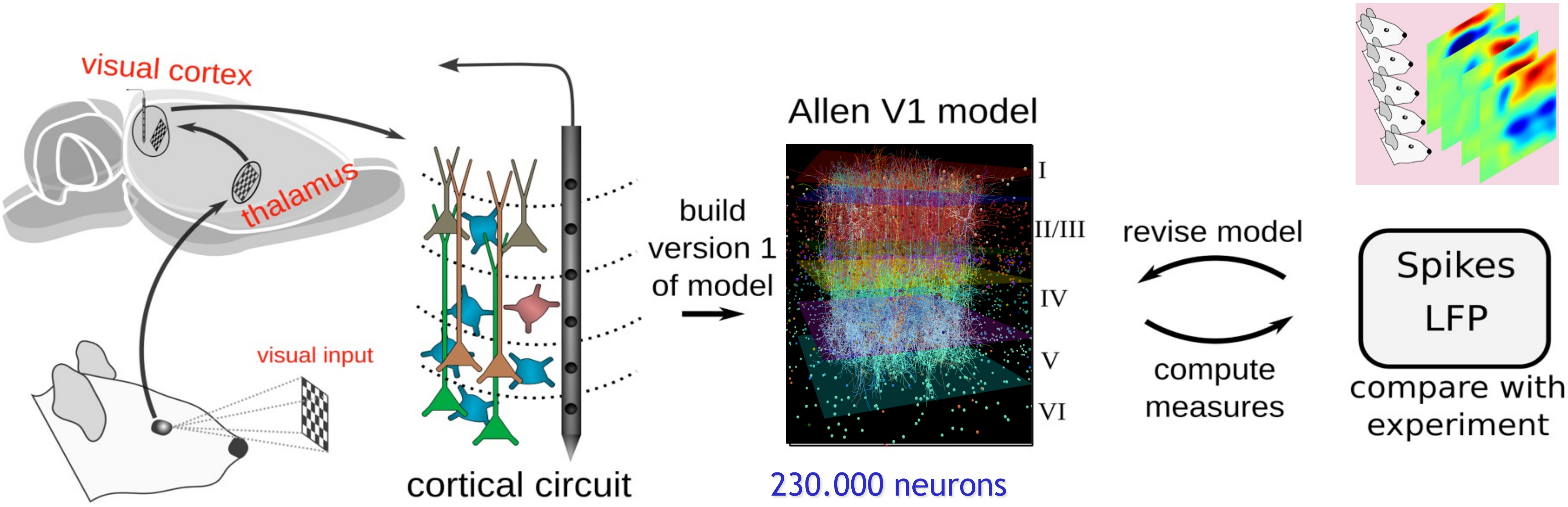
Allen model of mouse primary visual cortex

- 250000 neurons (52000 biophysically detailed)
- 21 neuron types

Billeh et al, Neuron (2020)



Collaborative research project



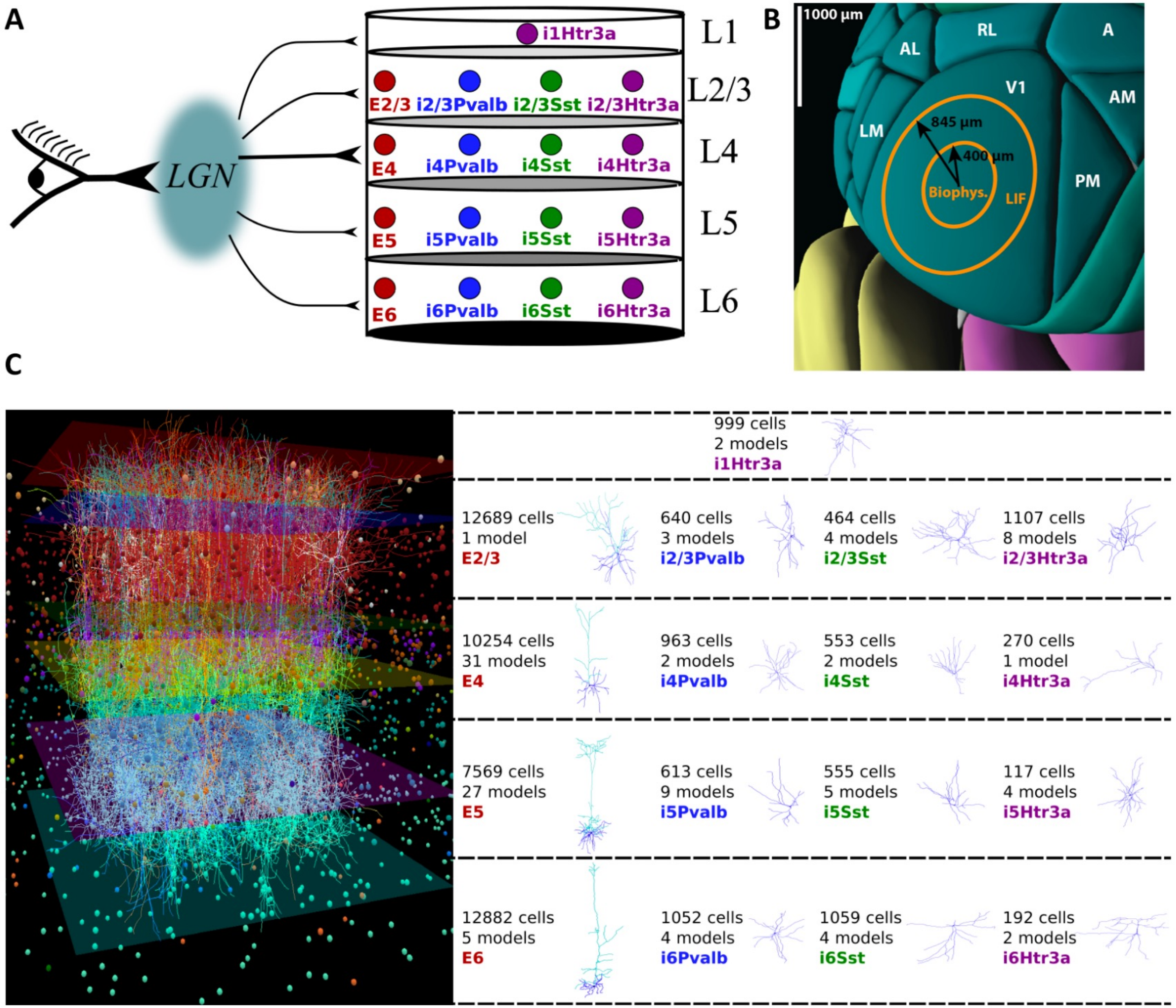
230.000 neurons
[Billeh et al, 2020]

ALLEN INSTITUTE *for* BRAIN SCIENCE

Collaboration with groups of Anton Arkhipov, Stefan Mihalas and Christof Koch at Allen Institute for Brain Science in Seattle

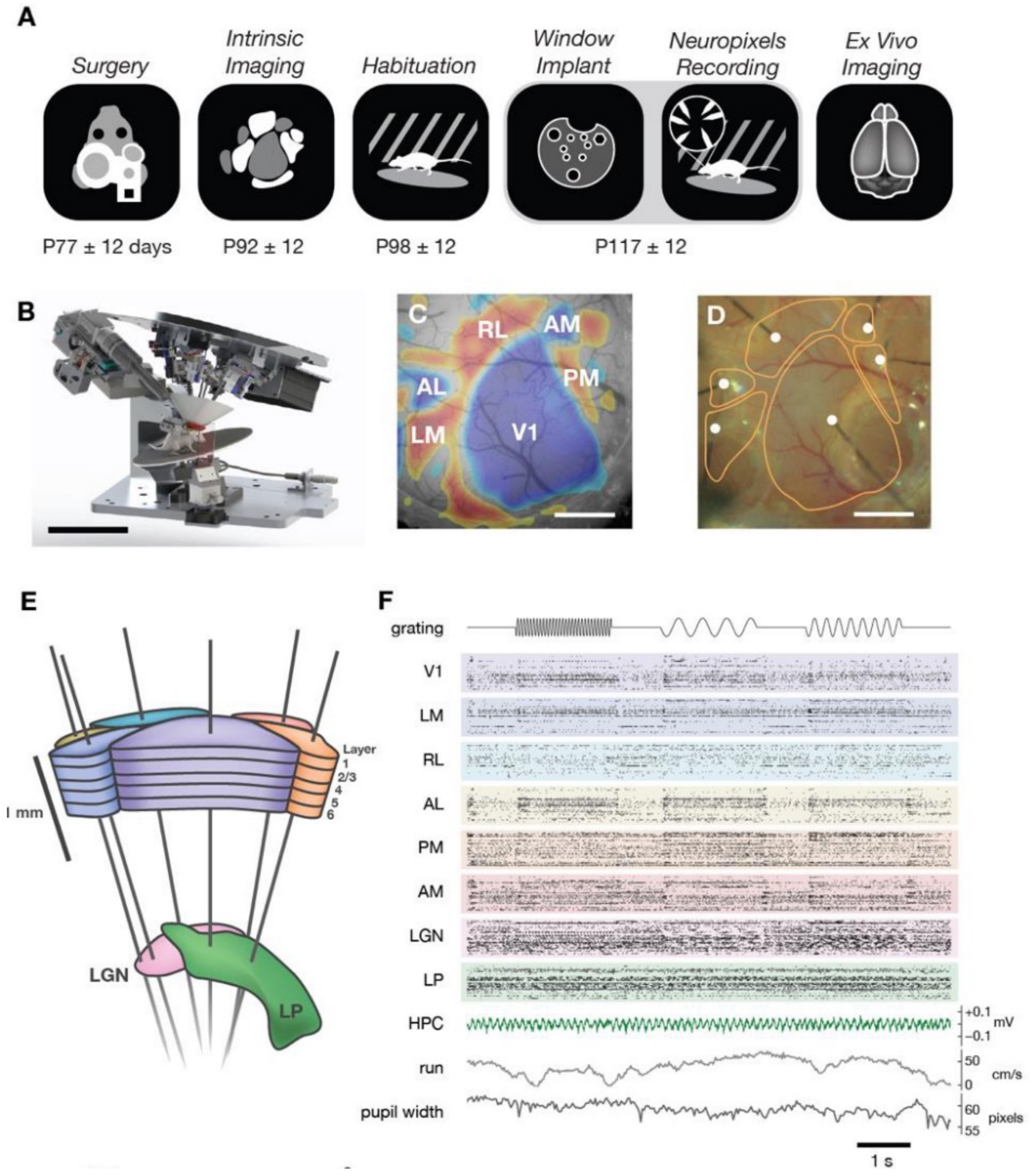
Rimehaug et al, eLife, 2023

Model



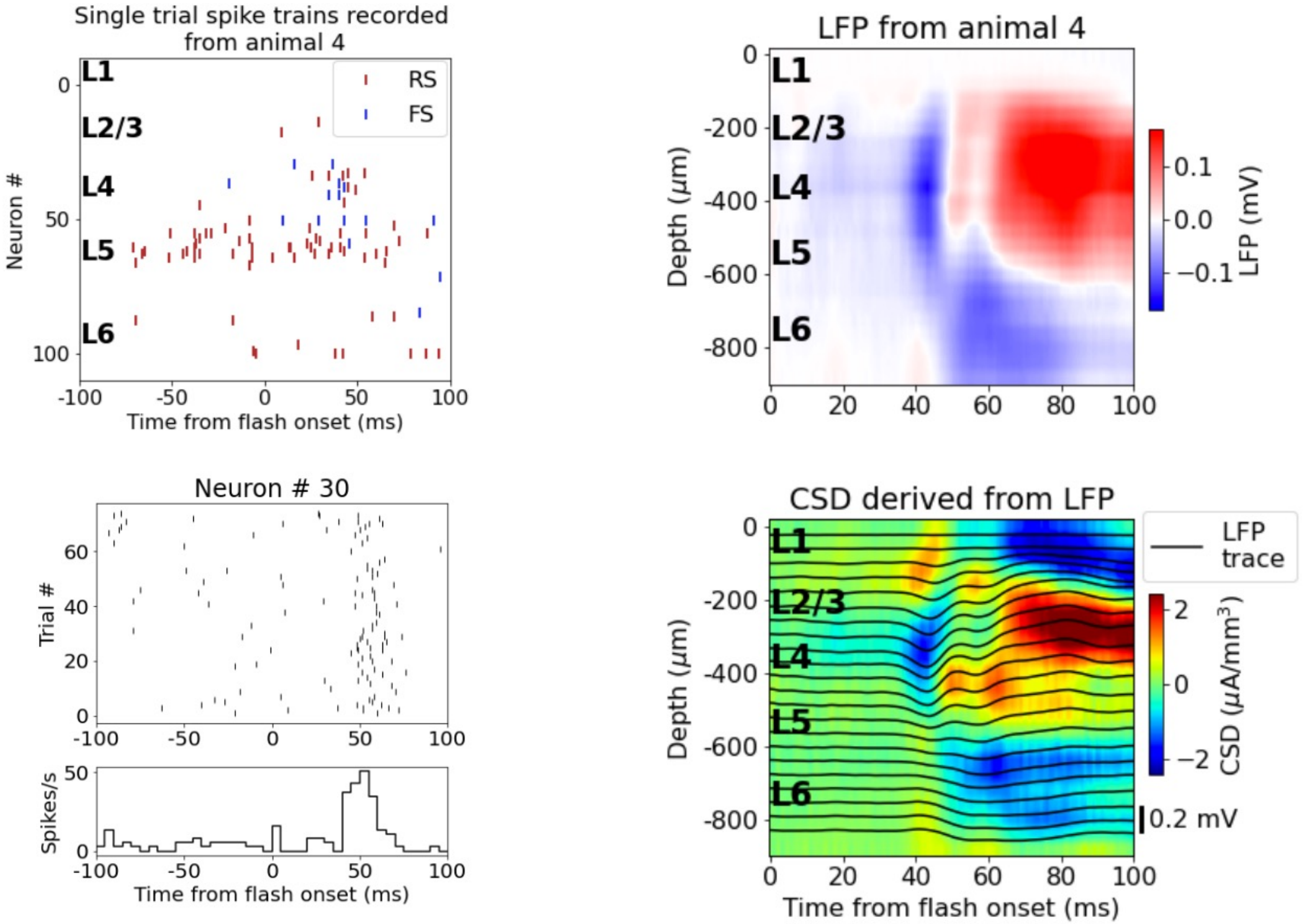
Billeh et al, Neuron, 2020

Neuropixel experiments

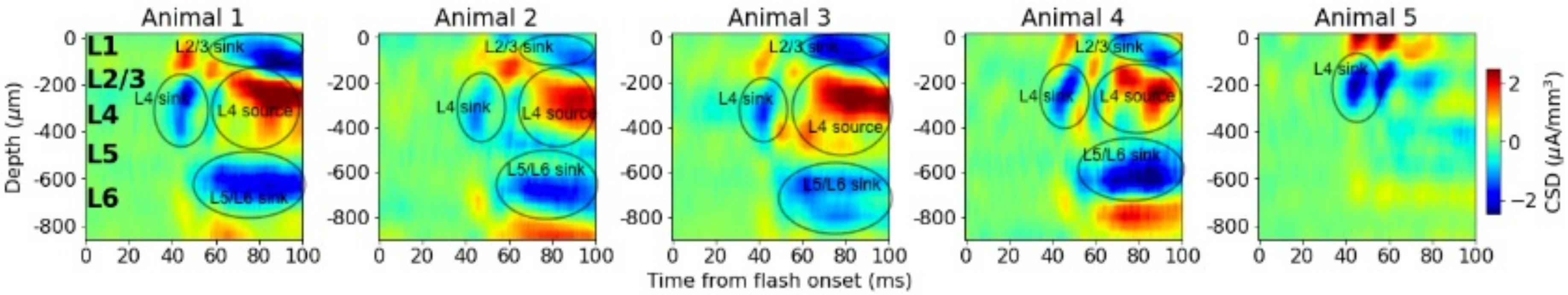


Siegle et al, Nature, 2021

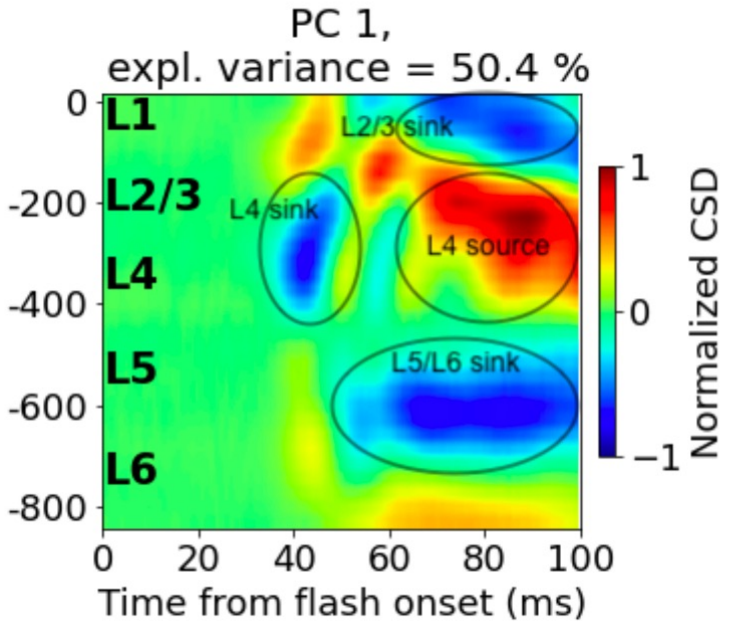
Neuropixel experiments



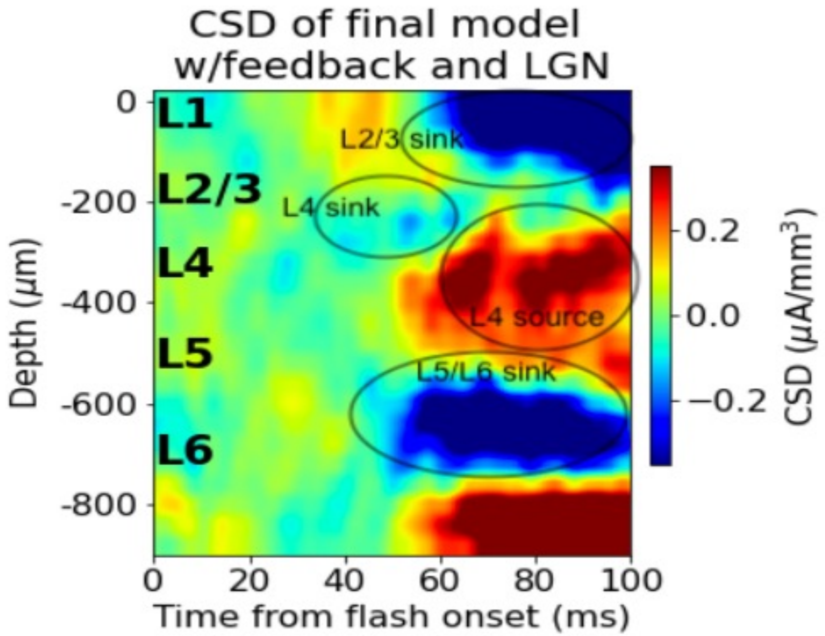
Rimehaug et al, eLife (2023)



Experiment (animal average)



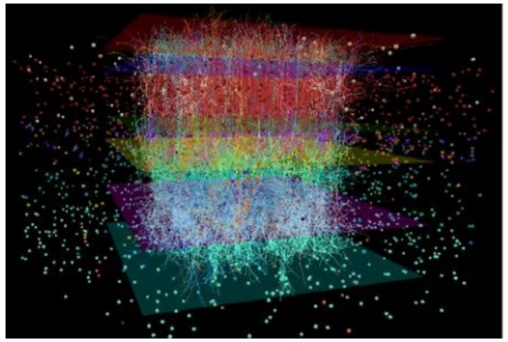
Model



Rimehaug et al, eLife (2023)

Virtual workshops:
«Towards multipurpose network models …»

Anton Arkhipov



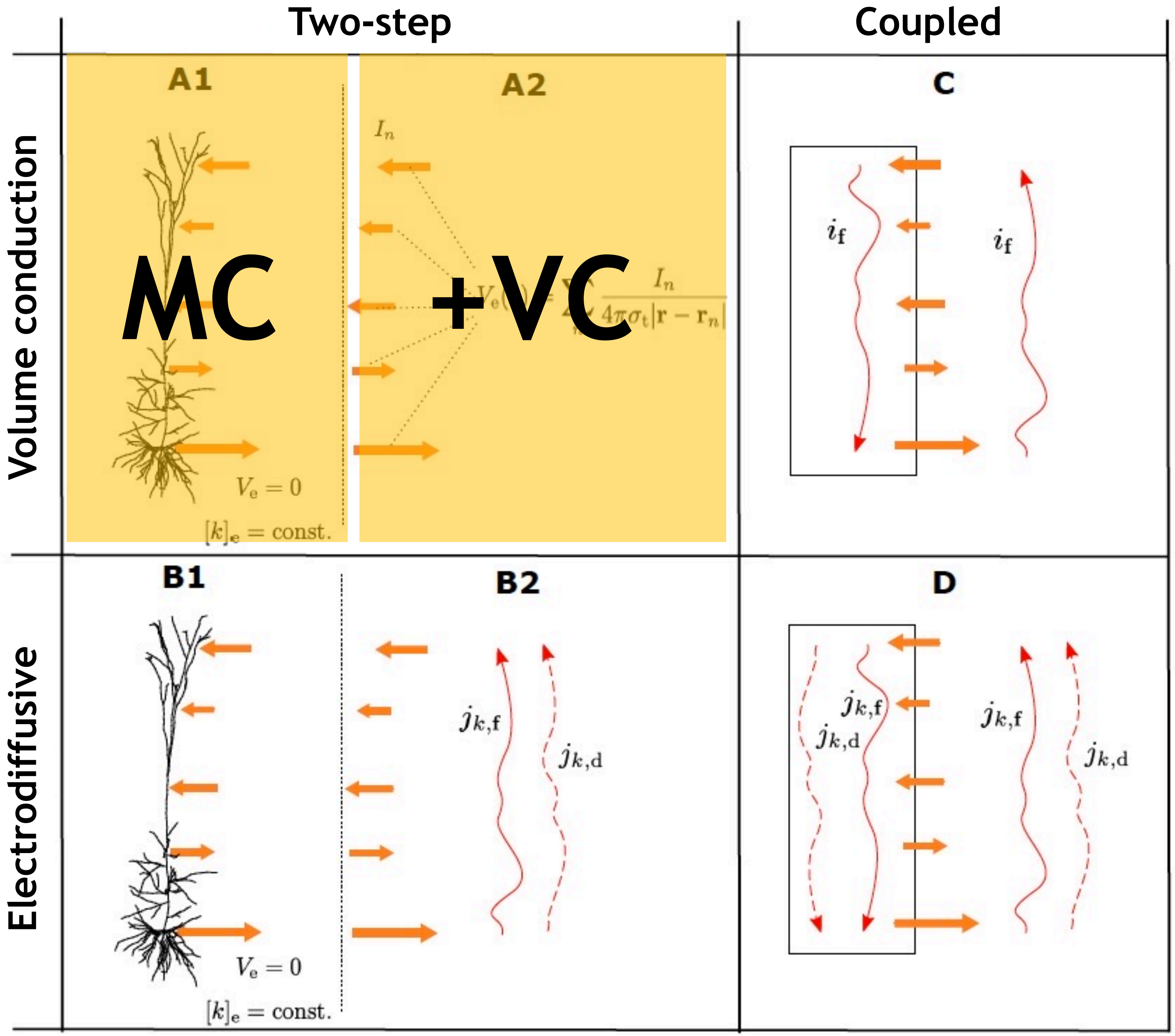
ALLEN INSTITUTE
MODELING
WORKSHOP

Towards multipurpose models of cortical circuits

08/12/2020
to
08/14/2020

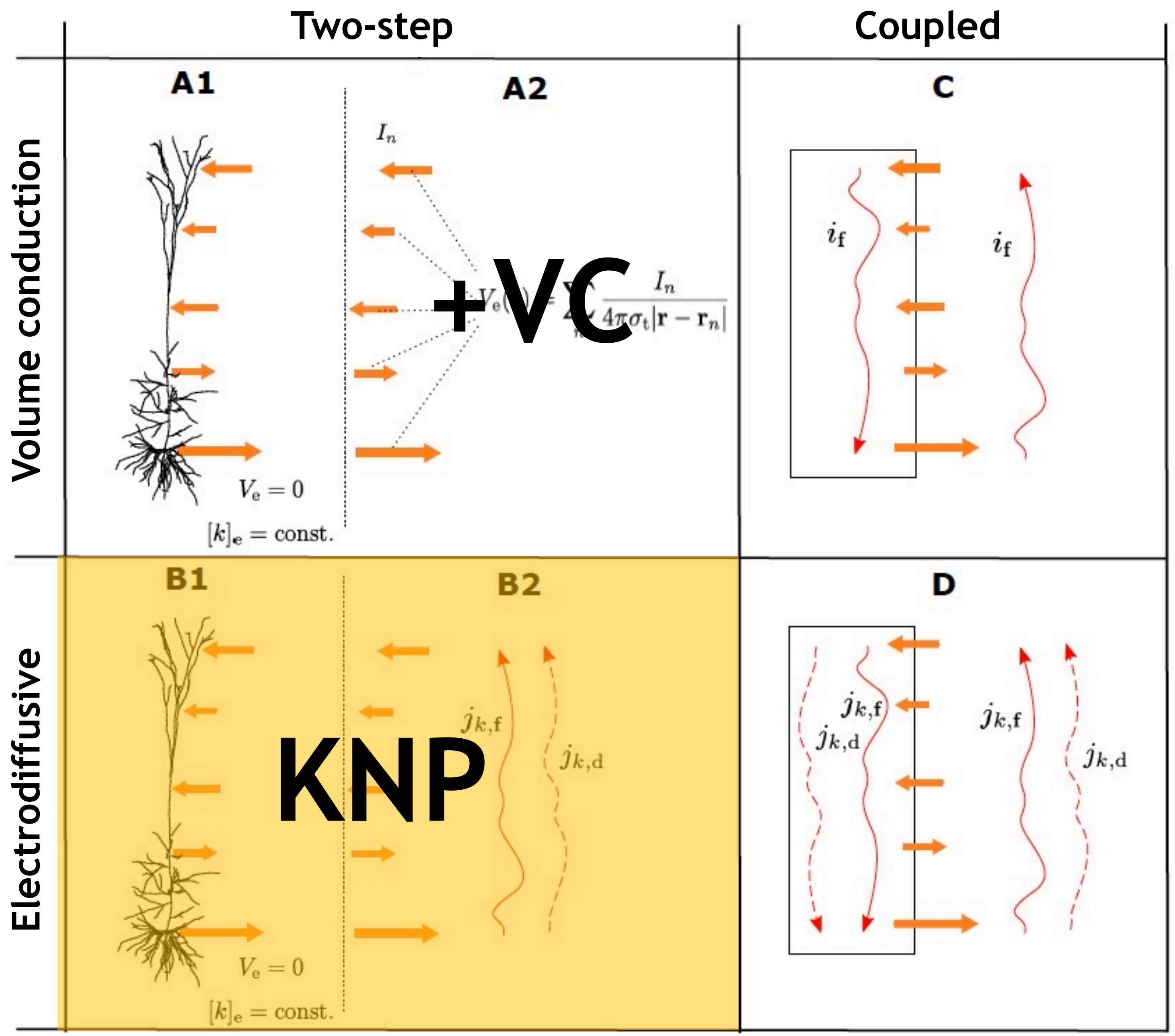
Starting with the work of Hodgkin, Huxley, Cole, Rall, Katz, Eccles and others in the 1950s and 1960s, we now have a reasonably good understanding of the principles by

Differents schemes for modelling of electric dynamics in brain tissue



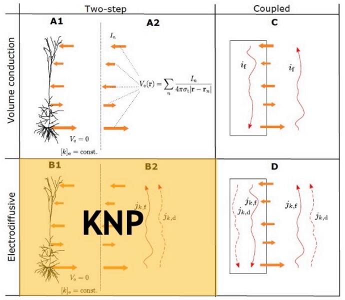
"Electric Brain Signals" (2024)

Differents schemes for modelling of electric dynamics in brain tissue



"Electric Brain Signals" (2024)

PLOS | COMPUTATIONAL BIOLOGY



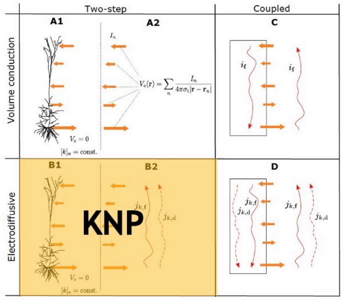
RESEARCH ARTICLE

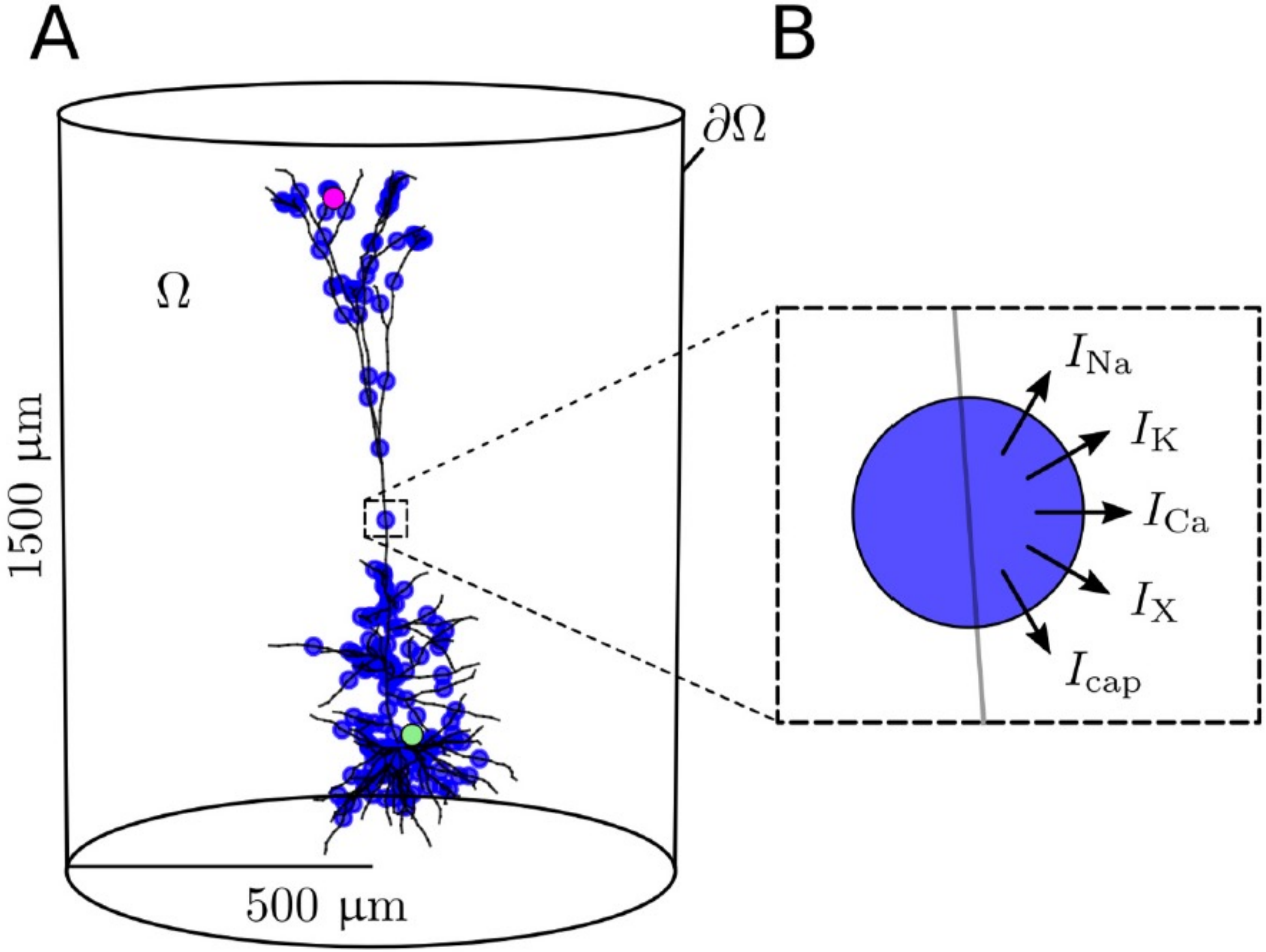
A Kirchhoff-Nernst-Planck framework for modeling large scale extracellular electrodiffusion surrounding morphologically detailed neurons

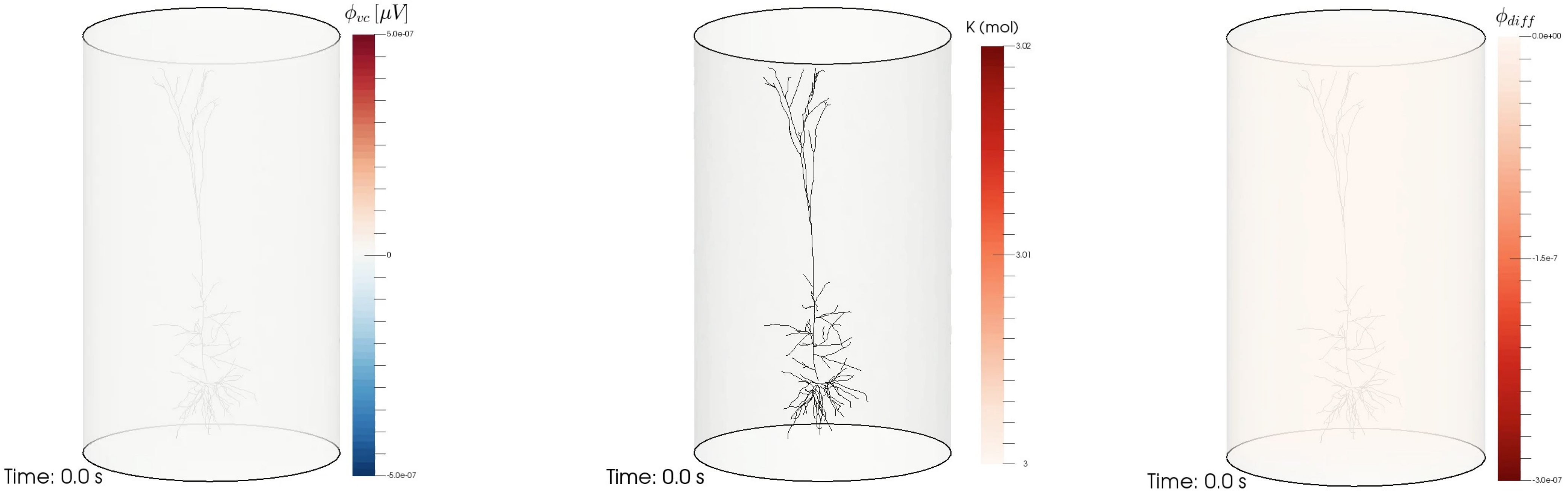
Andreas Solbrå[1,2], Aslak Wigdahl Bergersen[3], Jonas van den Brink[3], Anders Malthe-Sørenssen[1,2], Gaute T. Einevoll[1,2,4], Geir Halnes[4]*

1 Center for Integrative Neuroplasticity, University of Oslo, Oslo, Norway, **2** Department of Physics, University of Oslo, Oslo, Norway, **3** Simula Research Laboratory, Fornebu, Norway, **4** Department of Mathematical Sciences and Technology, Norwegian University of Life Sciences, Ås, Norway

* geir.halnes@nmbu.no

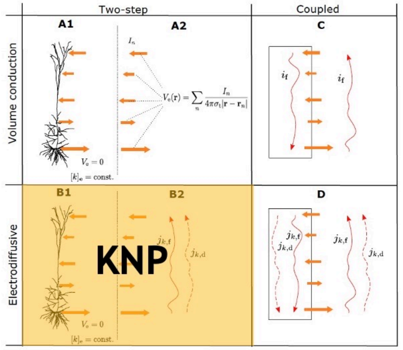

Two-step
Coupled
A1
A2
C
Volume conduction
B1
B2
D
Electrodiffusive
KNP

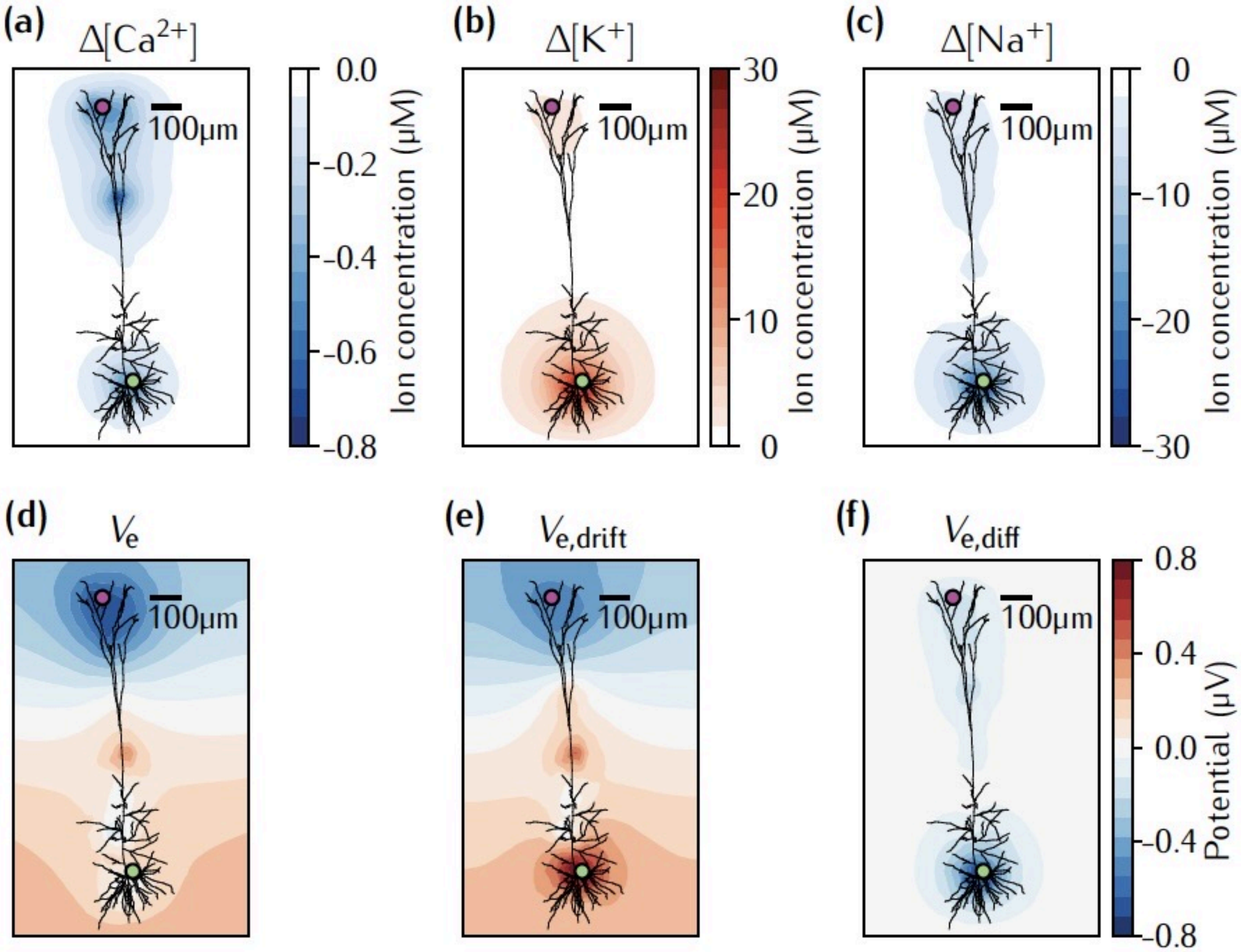

A
B
$\partial\Omega$
Ω
1500 µm
500 µm
I_{Na}
I_{K}
I_{Ca}
I_{X}
I_{cap}



The simulation was performed on standard desktop computer in 15 hours.

Solbrå et al, PloS Comp Biol, 2018





“Principles of Computational Modelling in Neuroscience, 2nd ed. (2023)

OPEN ACCESS Freely available online

PLOS COMPUTATIONAL BIOLOGY

Electrodiffusive Model for Astrocytic and Neuronal Ion Concentration Dynamics

Geir Halnes[1]*, Ivar Østby[1], Klas H. Pettersen[2], Stig W. Omholt[3], Gaute T. Einevoll[1]

1 Department of Mathematical Sciences and Technology, Norwegian University of Life Sciences, Ås, Norway, 2 Centre for Integrative Genetics, Department of Mathematical Sciences and Technology, Norwegian University of Life Sciences, Ås, Norway, 3 Centre for Integrative Genetics, Department of Animal and Aqucultural Sciences, Norwegian University of Life Sciences, Ås, Norway

Abstract

The cable equation is a proper framework for modeling electrical neural signalling that takes place at a timescale at which the ionic concentrations vary little. However, in neural tissue there are also key dynamic processes that occur at longer timescales. For example, endured periods of intense neural signaling may cause the local extracellular K^+-concentration to increase by several millimolars. The clearance of this excess K^+ depends partly on diffusion in the extracellular space, partly on local uptake by astrocytes, and partly on intracellular transport (spatial buffering) within astrocytes. These processes, that take place at the time scale of seconds, demand a mathematical description able to account for the spatiotemporal variations in ion concentrations as well as the subsequent effects of these variations on the membrane potential. Here, we present a general electrodiffusive formalism for modeling of ion concentration dynamics in a one-dimensional geometry, including both the intra- and extracellular domains. Based on the Nernst-Planck equations, this formalism ensures that the membrane potential and ion concentrations are in consistency, it ensures global particle/charge conservation and it accounts for diffusion and concentration dependent variations in resistivity. We apply the formalism to a model of astrocytes exchanging ions with the extracellular space. The simulations show that K^+-removal from high-concentration regions is driven by a local depolarization of the astrocyte membrane, which concertedly (i) increases the local astrocytic uptake of K^+, (ii) suppresses extracellular transport of K^+, (iii) increases axial transport of K^+ within astrocytes, and (iv) facilitates astrocytic relase of K^+ in regions where the extracellular concentration is low. Together, these mechanisms seem to provide a robust regulatory scheme for shielding the extracellular space from excess K^+.

Citation: Halnes G, Østby I, Pettersen KH, Omholt SW, Einevoll GT (2013) Electrodiffusive Model for Astrocytic and Neuronal Ion Concentration Dynamics. PLoS Comput Biol 9(12): e1003386. doi:10.1371/journal.pcbi.1003386

Editor: Olaf Sporns, Indiana University, United States of America

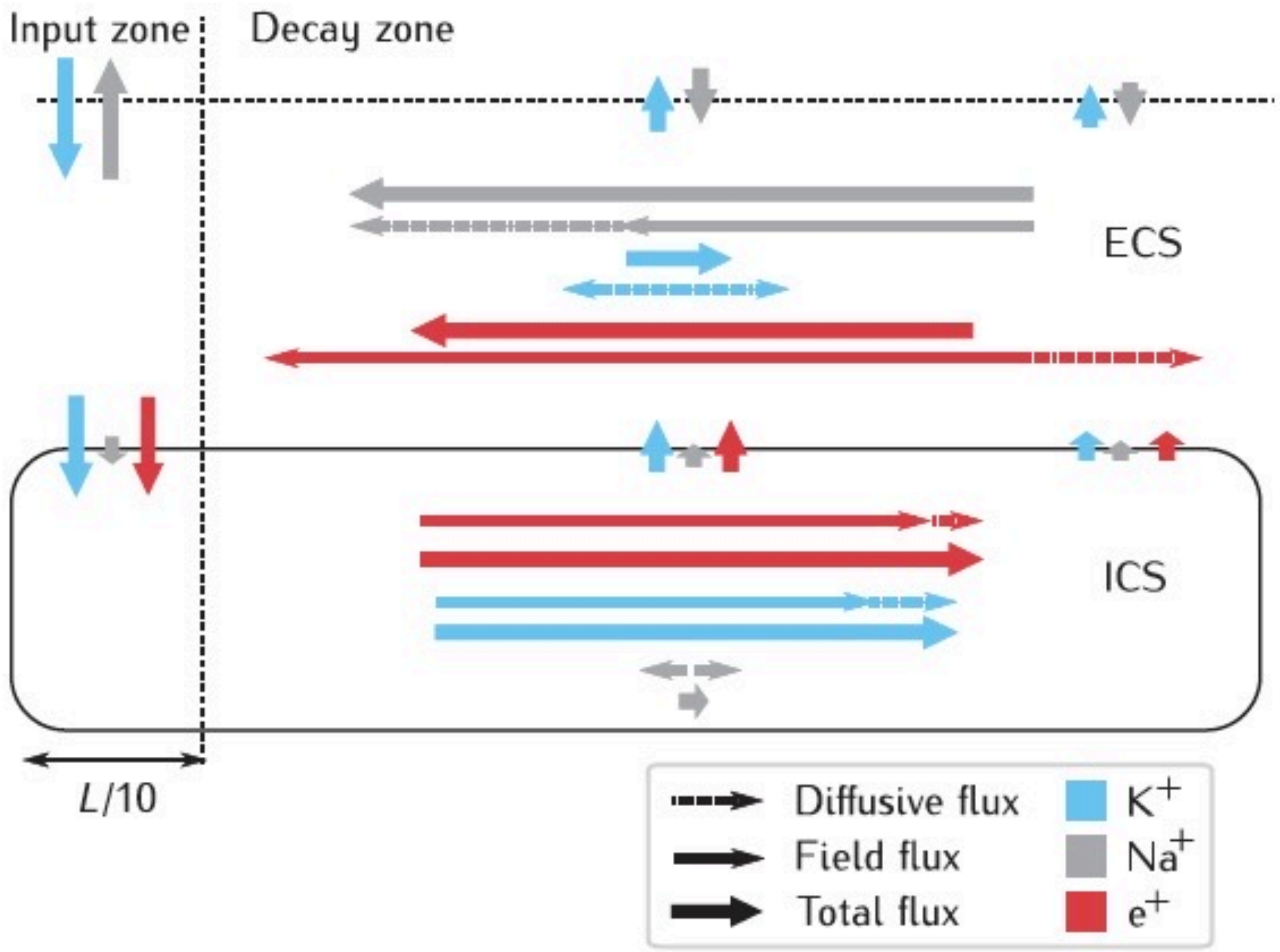
Received April 24, 2013; **Accepted** October 24, 2013; **Published** December 19, 2013

Funding: The project was supported by the Research Council of Norway (eVITA program; project numbers 178892 and 178901 and ISP-Fysikk; project number 216699), and EU Grant 269921 (BrainScaleS). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

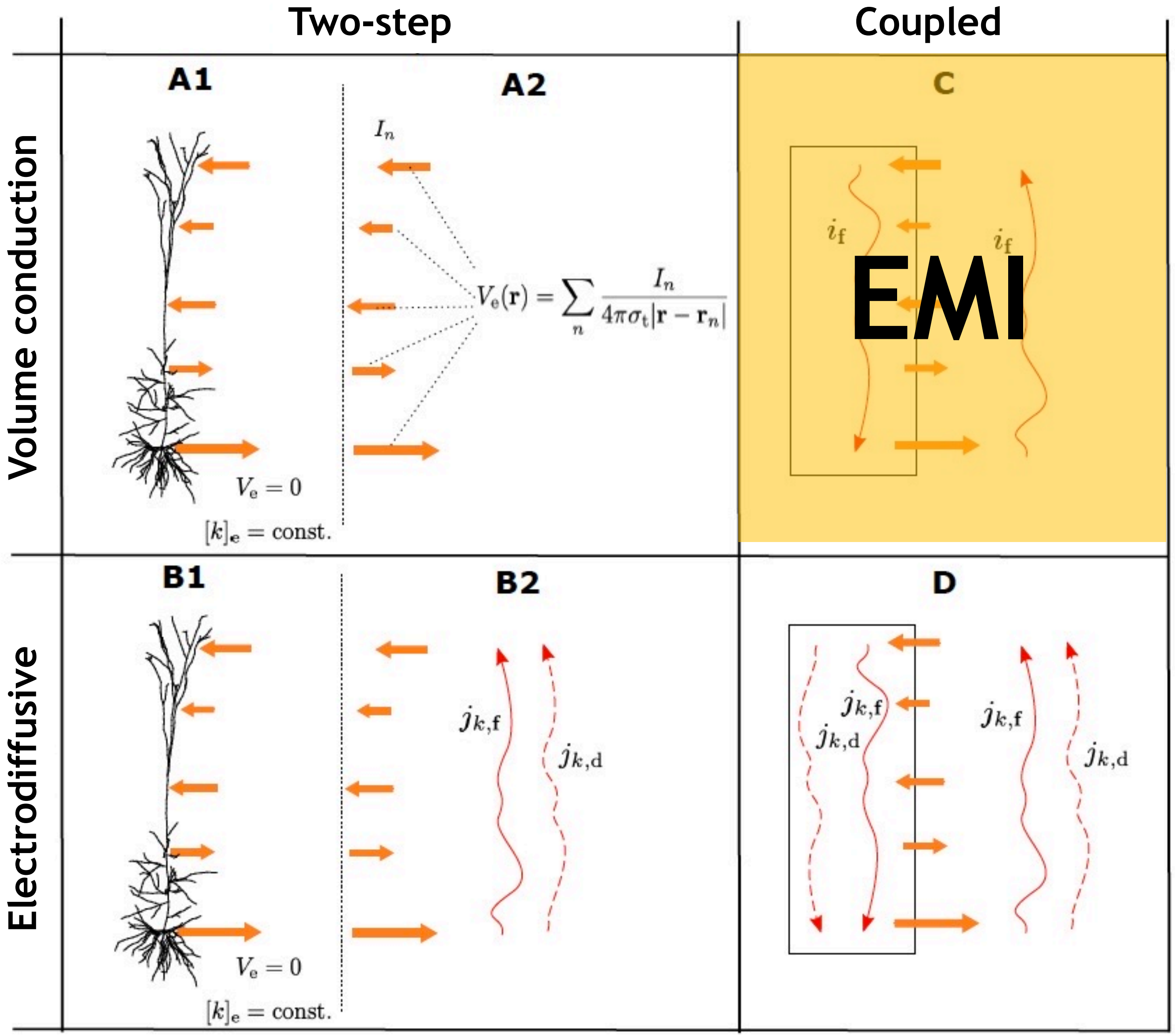
Competing Interests: The authors have declared that no competing interests exist.

* E-mail: geir.halnes@umb.no

Fig 10.15 Results from exploration of spatial buffering of potassium in the ECS using the KNP scheme (Halnes et al., 2013). Model geometry is depicted in Figure 10.14. An $L = 300\ \mu m$ section of a glial cable (ICS) is considered. The high-firing region where K^+ enters the ECS from neurons (downward pointing blue arrow in upper left corner) corresponds to the left one tenth of the cable. The model includes three ion types (K^+, Na^+, Cl^-) and a variety of ion channels, as well as a Na–K ion pump, embedded in the glial membrane. The flowchart summarises the main transport routes of K^+ and Na^+ at steady state, which is reached



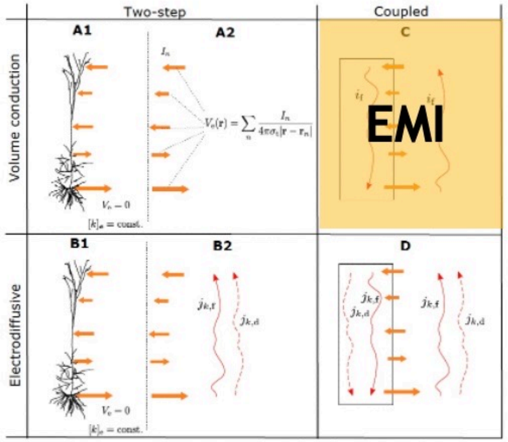
Differents schemes for modelling of electric dynamics in brain tissue



"Electric Brain Signals" (2024)

frontiers in Computational Neuroscience

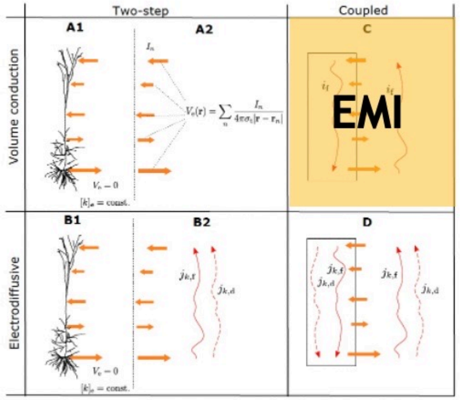
ORIGINAL RESEARCH
published: 24 April 2017
doi: 10.3389/fncom.2017.00027



Check for updates

An Evaluation of the Accuracy of Classical Models for Computing the Membrane Potential and Extracellular Potential for Neurons

Aslak Tveito[1,2]*, Karoline H. Jæger[1], Glenn T. Lines[1], Łukasz Paszkowski[3], Joakim Sundnes[1,2], Andrew G. Edwards[1,4], Tuomo Māki-Marttunen[5], Geir Halnes[6] and Gaute T. Einevoll[6,7]



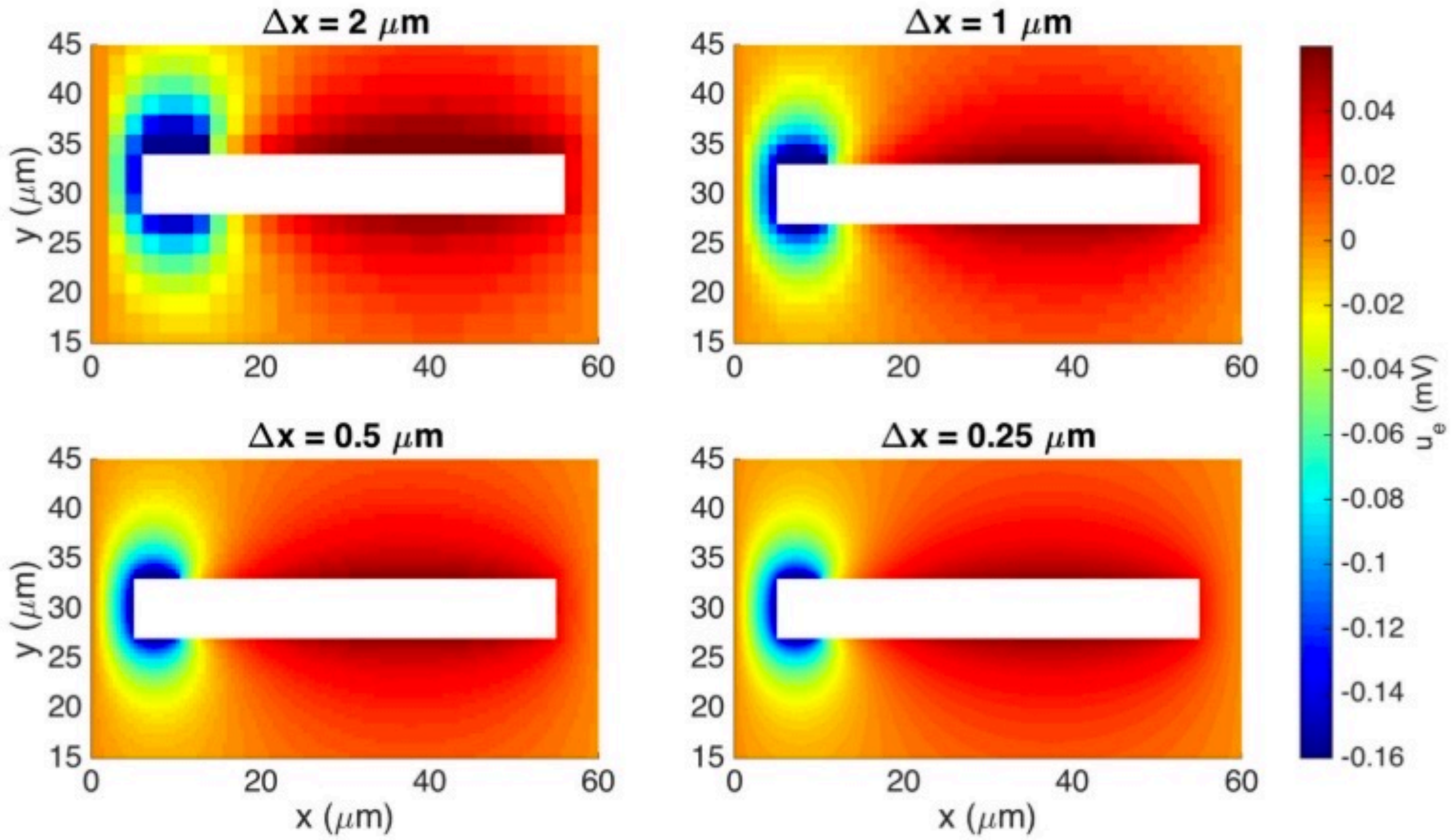
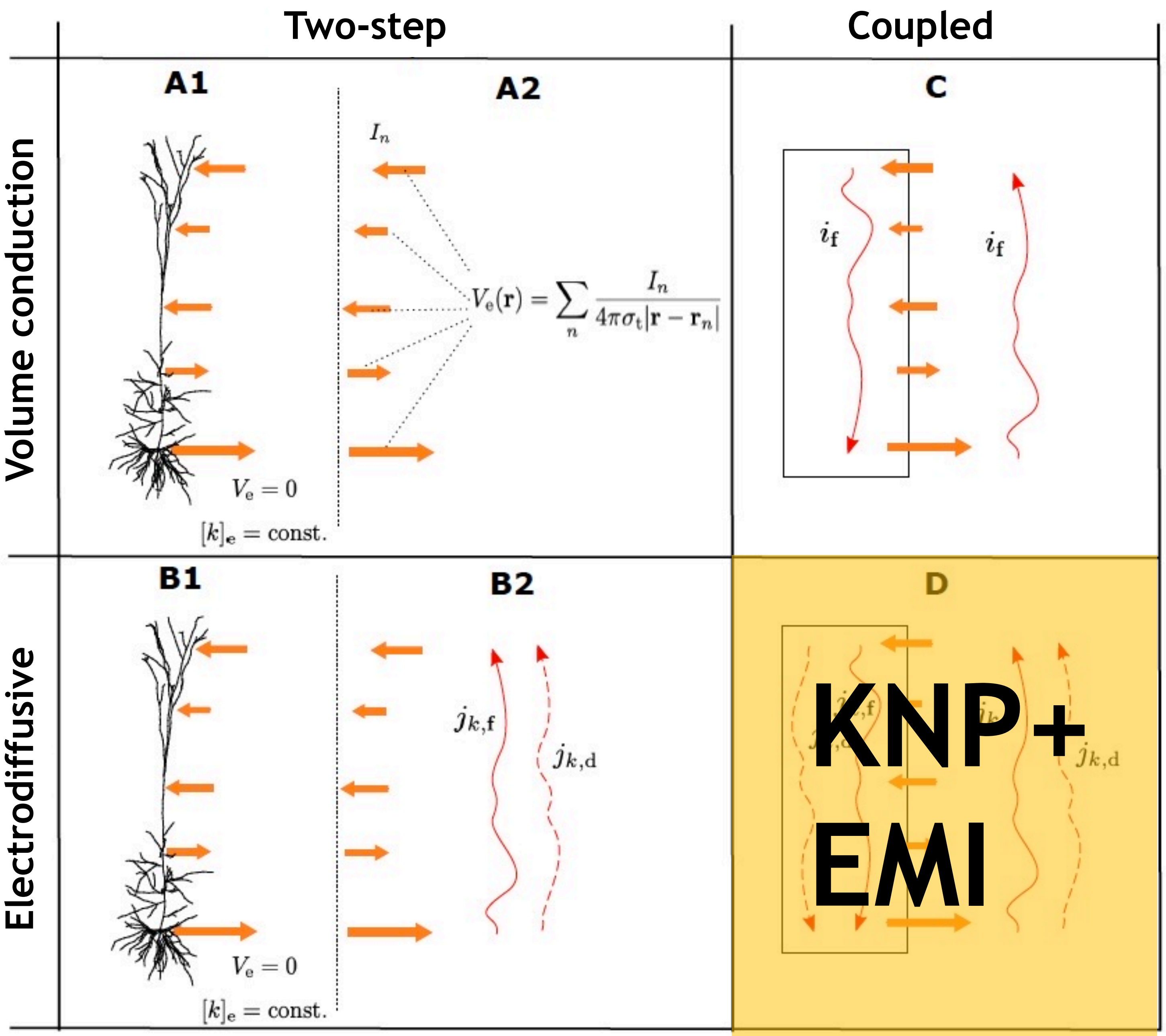


FIGURE 6 | Extracellular potential computed by the stationary EMI model for four different values of $\Delta x = \Delta y = \Delta z$. We show the solution in a rectangle of size 60×30 μm on the plane in the center of the domain in the z-direction. The white area represents the cell. We use the parameters given in **Table 2** except for an increased value of $g_L = 3 \cdot 10^{-5}$ μS/μm^2 and a domain of size $60 \times 60 \times 60$ μm.

Differents schemes for modelling of electric dynamics in brain tissue



“Electric Brain Signals” (2024)

PLOS COMPUTATIONAL BIOLOGY

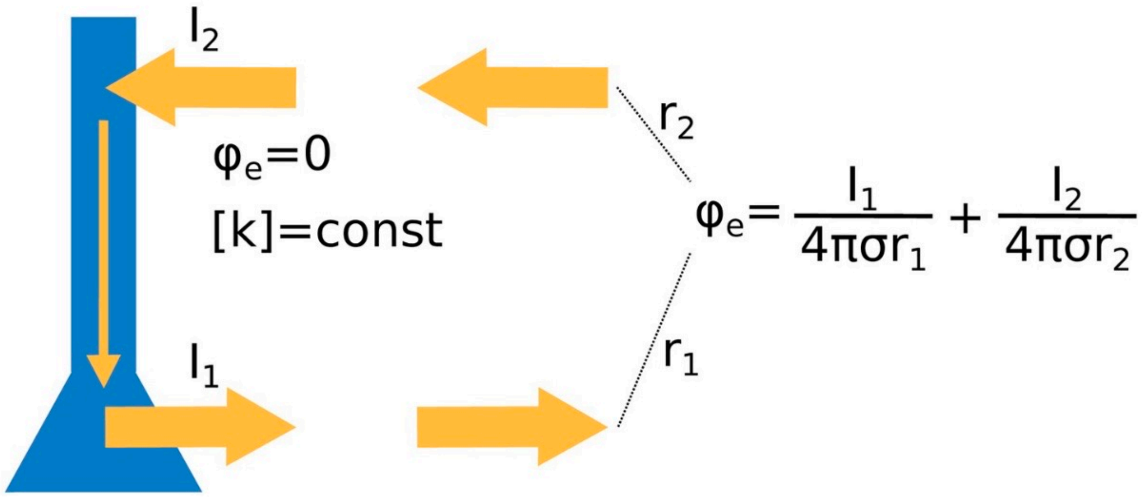
RESEARCH ARTICLE

An electrodiffusive, ion conserving Pinsky-Rinzel model with homeostatic mechanisms

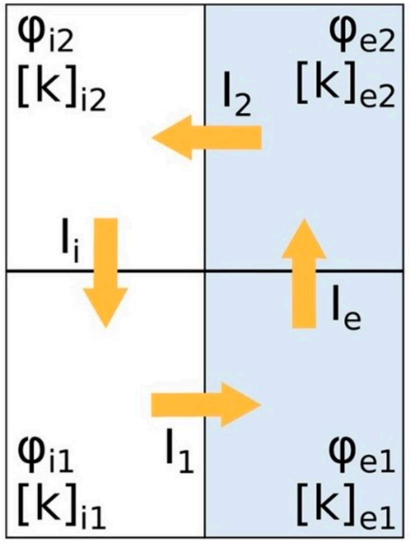
Marte J. Sætra[1,2], **Gaute T. Einevoll**[1,2,3], **Geir Halnes**[1,3]*

1 Centre for Integrative Neuroplasticity, University of Oslo, Oslo, Norway, **2** Department of Physics, University of Oslo, Oslo, Norway, **3** Faculty of Science and Technolgy, Norwegian University of Life Sciences, Ås, Norway

Two-step (MC+VC)



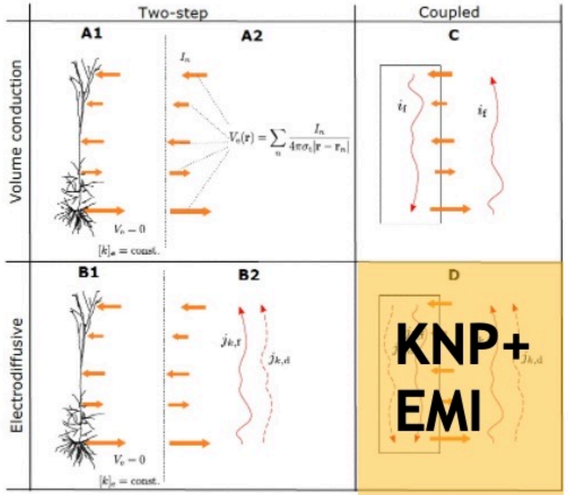
Coupled electrodiffusive (KNP+EMI)



Sætra et al, PLoS Comp Biol, 2020

frontiers
in Neuroinformatics

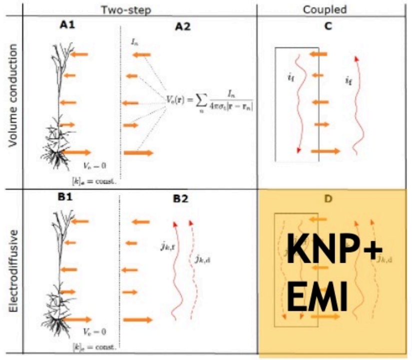
ORIGINAL RESEARCH
published: 25 March 2020
doi: 10.3389/fninf.2020.00011



Finite Element Simulation of Ionic Electrodiffusion in Cellular Geometries

Ada J. Ellingsrud[1†], Andreas Solbrå[2,3†], Gaute T. Einevoll[2,3,4], Geir Halnes[2,4†] and Marie E. Rognes[1†]*

[1] Department for Scientific Computing and Numerical Analysis, Simula Research Laboratory, Oslo, Norway, [2] Centre for Integrative Neuroplasticity, University of Oslo, Oslo, Norway, [3] Department of Physics, University of Oslo, Oslo, Norway, [4] Faculty of Science and Technology, Norwegian University of Life Sciences, Ås, Norway



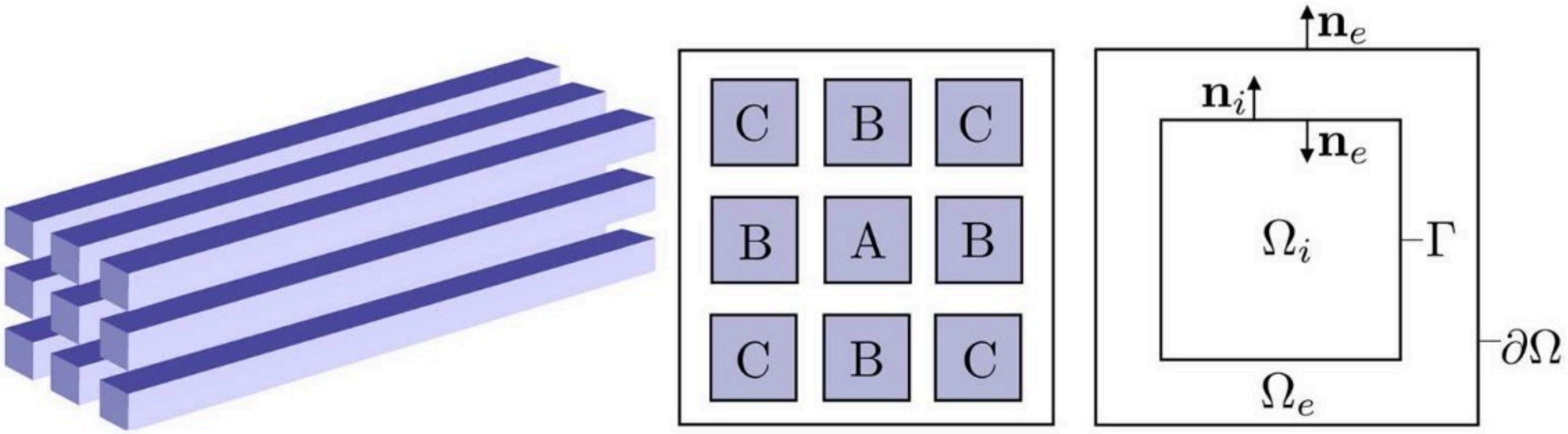
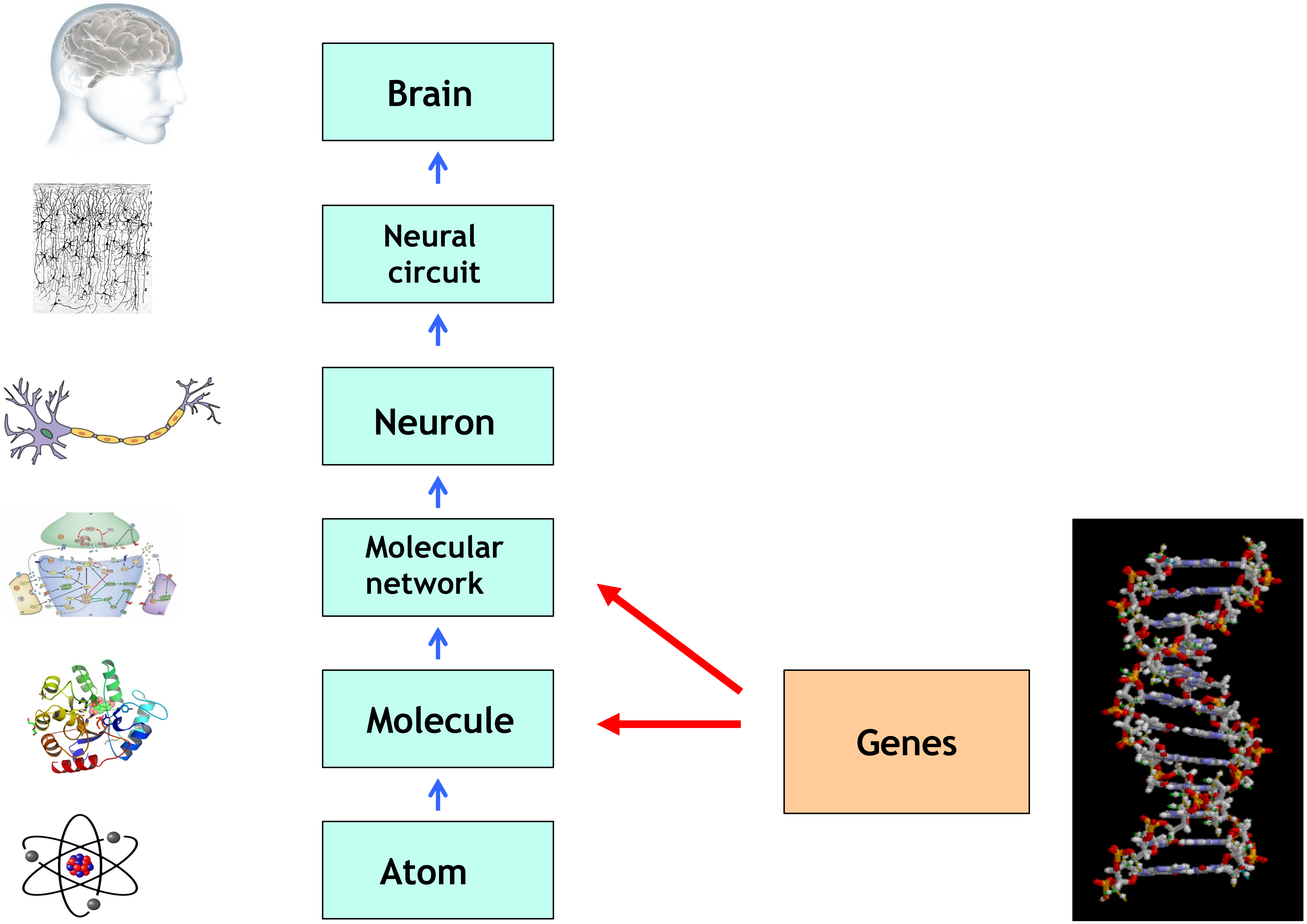


FIGURE 1 | Overview of the computational domains. **(Left)** Idealized axon bundle consisting of 9 cuboid-shaped axons. **(Middle)** Cross-section of the axon bundle, where the axons are labeled with repeated labels for symmetric positions. **(Right)** Idealized 2D computational domain with one intracellular region Ω_i and extracellular region Ω_e.



Brain
Neural circuit
Neuron
Molecular network
Molecule
Atom
Genes

Biological Psychiatry CNNI

Functional Effects of Schizophrenia-Linked Genetic Variants on Intrinsic Single-Neuron Excitability: A Modeling Study

Tuomo Mäki-Marttunen, Geir Halnes, Anna Devor, Aree Witoelar, Francesco Bettella, Srdjan Djurovic, Yunpeng Wang, Gaute T. Einevoll, Ole A. Andreassen, and Anders M. Dale

Tuomo Mäki-Marttunen

Mäki-Marttunen *et al. Translational Psychiatry* (2017)7:5
DOI 10.1038/s41398-017-0007-4
Translational Psychiatry

ARTICLE Open Access

Pleiotropic effects of schizophrenia-associated genetic variants in neuron firing and cardiac pacemaking revealed by computational modeling

Tuomo Mäki-Marttunen[1,2], Glenn T. Lines[2], Andrew G. Edwards[2], Aslak Tveito[2], Anders M. Dale[3,4,5]
Gaute T. Einevoll[6,7] and Ole A. Andreassen[1,8]

OXFORD

Cerebral Cortex, February 2019;29: 875–891

doi: 10.1093/cercor/bhy291
Advance Access Publication Date: 22 November 2018
Original Article

ORIGINAL ARTICLE

Alterations in Schizophrenia-Associated Genes Can Lead to Increased Power in Delta Oscillations

Tuomo Mäki-Marttunen[1,2], Florian Krull[2], Francesco Bettella[2], Espen Hagen[3,4], Solveig Næss[5], Torbjørn V. Ness[4], Torgeir Moberget[2], Torbjørn Elvsåshagen[2,6], Christoph Metzner[7], Anna Devor[8,9,10], Andrew G. Edwards[1], Marianne Fyhn[11], Srdjan Djurovic[12,13], Anders M. Dale[8,9], Ole A. Andreassen[2,14] and Gaute T. Einevoll[3,4]

frontiers in Psychiatry

REVIEW
published: 06 August 2019
doi: 10.3389/fpsyt.2019.00534

Check for updates

Biophysical Psychiatry—How Computational Neuroscience Can Help to Understand the Complex Mechanisms of Mental Disorders

Tuomo Mäki-Marttunen[1,2]*, Tobias Kaufmann[2], Torbjørn Elvsåshagen[2,3], Anna Devor[4,5,6], Srdjan Djurovic[7,8], Lars T. Westlye[2,9], Marja-Leena Linne[10], Marcella Rietschel[11], Dirk Schubert[12], Stefan Borgwardt[13], Magdalena Efrim-Budisteanu[14,15,16], Francesco Bettella[2], Geir Halnes[17], Espen Hagen[18], Solveig Næss[19], Torbjørn V. Ness[17], Torgeir Moberget[2], Christoph Metzner[20,21], Andrew G. Edwards[1], Marianne Fyhn[22], Anders M. Dale[4,5], Gaute T. Einevoll[17,18] and Ole A. Andreassen[2]

Edited by:
Cynthia H. Y. Fu,
University of East London,
United Kingdom

[1] Department of Computational Physiology, Simula Research Laboratory, Oslo, Norway, [2] NORMENT, Division of Mental

Collaborators on modeling of extracellular potentials

Norw. Univ. Life Sci.
- Torbjørn Bækø Ness
- Geir Halnes
- Espen Hagen
- Jan-Eirik W. Skaar
- Klas Pettersen (Oslo)
- Henrik Lindén
- Tom Tetzlaff (Jülich)
- Maria Stavrinou (Oslo)
- Eivind S. Norheim
- Kristin Tøndel
- Nicolay Haug
- Alexander Stasik

UC San Diego
- Anders Dale
- Eric Halgren

Boston University
- Anna Devor

University of Oslo
- Atle Rimehaug
- Solveig Næss
- Andreas Solbrå

SIMULA, Oslo
- Marte Julie Sætra
- Ada Ellingsrud
- Aslak Tveito
- Marie Rognes
- Eirill Hauge

FZ Jülich
- Markus Diesmann
- Sonja Grün
- David Dahmen
- Sacha van Albada

Nencki Inst, Warsaw
- Szymon Leski
- Daniel Wojcik
- Helena Glabska

Oxford University
- Chaitanya Chintaluri

Humboldt Univ Berlin
- Michiel Remme

UMC Hamburg
- Stefano Panzeri

SSSA (Italy)
- Alberto Mazzoni

Radboud, Nijmegen
- Dirk Schubert
- Stephanie Miceli

Allen Institute, Seattle
- Anton Arkhipov
- Christof Koch

ESI, FIAS & Goethe Univ, Frankfurt
- Hermann Cuntz

University of Washington
- Nick Steinmetz

Funding in Norway:

Research Council of Norway
EU (BrainScaleS, Human Brain Project)
DARPA (NESD)

END

END