BrainScaleS via EBRAINS
“easily accessible analog”

Johannes Schemmel
Electronic Vision(s) Group
Kirchhoff Institute for Physics
Heidelberg University, Germany
BrainScaleS via EBRAINS
“easily accessible analog”

- Background
- Human Brain Project and EBRAINS
- Dimensions of neuromorphic computing
- BrainScaleS features
- BrainScaleS services in EBRAINS
- Recent example: parameter fitting
- Summary
Electronic Vision(s)

Kirchhoff Institute of Physics, Heidelberg University

Founded 1995 by Prof. Karlheinz Meier (†2018)

1995 HDR vision sensors
1996 analog image processing
2000 Perceptron based analog neural networks: EVOOPT and HAGEN
2003 First concepts for spike based analog neural networks
2004 First accelerated analog neural network chip with short- and long-term plasticity: Spikey

since 2010 BrainScaleS neuromorphic systems

HAGEN (2000):
Perceptron-based Neuromorphic chip introduced:
• accelerated operation
• mixed-signal Kernels

SPIKEY (2004):
spike-based Neuromorphic chip introduced:
• fully-parallel Spike-Time-Dependent-Plasticity
• analog parameter storage for calibratable physical model
Why focus on the brain? Three Reasons

- **Understanding the brain (Unifying Science Goal)**
  - Underpins what we are,
  - Data & knowledge are fragmented,
  - Integration is needed,
  - Large scale collaborative approach is essential.

- **Understanding brain diseases (Society)**
  - Costs Europe over €800 Billion/year,
  - Affects 1/3 people,
  - Number one cause of loss of economic productivity,
  - No fundamental treatments exist or are in sight
  - Pharma companies pulling out of the challenge.

- **Developing Future Computing (Technology)**
  - Computing underpins modern economies,
  - Traditional computing faces growing hardware, software, & energy barriers,
  - Brain can be the source of energy efficient, robust, self-adapting & compact computing technologies,
  - Knowledge driven process to derive these technologies is missing.

Neuromorphic Computing
Part of the EBRAINS initiative of the HBP
Neuromorphic computing with physical models

- Neuromorphic Machines
- Algorithms and Architectures for Neuromorphic Computing
  - Theory
  - Applications
EBRAINS’ mission:
Enabling brain research advances and innovation

EBRAINS offers the neuroscience community state-of-the-art services:

- Brain data and atlases
- Simulation and modelling tools
- Access to supercomputing resources

EBRAINS builds on the work of the Human Brain Project and makes it sustainable.
What EBBRAINS brings to the scientific community

Data and Knowledge
- Online solutions to facilitate sharing of and access to research data, computational models and software

Atlases
- Navigate, characterise and analyse information on the basis of anatomical location

Simulation
- Solutions for brain researchers to conduct sustainable simulation studies and share their results

Brain-Inspired Technologies
- Understand and leverage the computational capabilities of spiking neural networks

Medical Data Analytics
- The Medical Data Analytics service provides two unique EBBRAINS platforms, covering key areas in clinical neuroscience research

Co-developed by and with researchers
brain inspired technologies aka brain inspired computing

compute more like the brain:
- artificial neural networks
- neuromorphic computing

use novel technologies:
- digital and analog neuromorphic hardware
- high-performance neuro-simulations

![Diagram of neural network](image)

input pattern -- inner layers -- output pattern

synaptic connections: weights $\omega$
Machine Learning

- vector-matrix multiplication

\[ f\left(\sum_i w_i x_i + b\right) \]

- simple non-linear activation function \( f \) (ReLU):

- trained with backpropagation

Brain-Inspired Computing

- time-continuous dynamical system
- vector-matrix multiplication
- complex non-linearities
- binary neuron output
- allows to model biological learning mechanisms

Perceptron model (biology of 1950)

Spike-based model (current biology)

HAGEN (2001)

Spikey (2004)
# Neuromorphic Dimensions

## Conceptual Dimensions:
- Rate based ↔ Event based
- Continuous time, c. valued ↔ Discrete time, d. valued
- Exact computations ↔ Approximate, noisy, stochastic comp.
- Point neurons ↔ Structured neurons
- Linear dendrites ↔ Non-linear dendrites
- Static ↔ Plastic

## Technological Dimensions:
- Analog ↔ Digital
- Electrical ↔ Optical
- Standard CMOS ↔ Novel devices
- Fully programmable ↔ Fixed structure
- In-memory computing ↔ Von Neumann computing
- Constant speed ↔ Variable speed
  (real time or accelerated) ↔ (best effort)

## Application Dimensions:
- Research ↔ Commercial
- Brain emulation ↔ Machine learning, AI
- Energy, size, cost constrained ↔ Energy, size, cost agnostic
- Fixed function ↔ Needs to adapt
BrainScaleS overview: accelerated, analog NMC with hybrid plasticity

- modular neuron structure
- Adaptive Exponential I&F model
- full set of ion-channel circuits for each compartment
- 24 calibration parameters per compartment
- full on-chip plasticity supported by embedded SIMD CPUs

Complex neurons can be built by connecting individual compartments

\[
C \frac{dV}{dt} = -g_L(V - E_L) + g_L \Delta T \exp \left( \frac{V - V_T}{\Delta T} \right) + I - w, \\
\tau_w \frac{dw}{dt} = a(V - E_L) - w.
\]
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BrainScaleS service sub-categories within EBRAINS

• accelerated emulation of networks of structured neurons with non-linear dendrites
  (Emulating dendritic computing paradigms on analog neuromorphic hardware, Jakob Kaiser et.al., Neuroscience, 2021)

• large parameter sweeps for network operation tuning
  (Autocorrelations in homeostatic spiking neural networks as a result of emergent bistable activity, J Zierenberg et. al., Bulletin of the American Physical Society, 2022/3/14,
  Control of criticality and computation in spiking neuromorphic networks with plasticity, B Cramer et.al., Nature communications, 2020/6/5)

• biology inspired learning experiments with programmed local plasticity
  (Structural plasticity on an accelerated analog neuromorphic hardware system, S Billaudelle et. al., Neural Networks, 2021/1/1)

• learning-to-learn sweeps of meta-parameters
  (Neuromorphic Hardware Learns to Learn, T Bohnstingl et.al., Front Neurosci.,2019)

• inference experiments for solving tasks using optimized network parameters generated by hardware-in-the-loop gradient-based training
  (Surrogate gradients for analog neuromorphic computing, B Cramer et.al., pnas.2109194119, 2022;
  Fast and energy-efficient neuromorphic deep learning with first-spike times, J Göltz et.al, Nature machine intelligence, 2021/9)

• applications of spiking neural networks for approximate computing
  (Spiking neuromorphic chip learns entangled quantum states, S Czischek, et. al., SciPost Physics 12 (1), 039, 2022)

• parameter fitting to match experimental observations

• direct real-time coupling between in-vitro preparations in wet-labs and the BrainScaleS system
  → initially with HeiCINN in Heidelberg, but open for others

• repeated execution of a network and/or long operation to gather statistical information or for sampling from stochastic models

• interactive execution of small models with immediate visualization for educational purposes
  → girls’ day, advanced lab course

• experimental platform for analogue computing research
  (Towards Addressing Noise and Static Variations of Analog Computations Using Efficient Retraining, B Klein et.al., ECML PKDD, 2021/9/13)
  → first industry collaboration shows promising results in the area of optical communication
  (submitted to Signal Processing in Photonic Communications 22)
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A subset of these can be already accessed through the current HBP NMC online access and will be part of the hands-on demo!

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example:
fitting BrainScaleS neurons to experimental data

"Training deep neural density estimators to identify mechanistic models of neural dynamics", Pedro J Gonçalves et. al., eLife 2020;9:e56261 DOI: 10.7554/ELIFE.56261
early results from BSS-2 hardware

- chain of five dendritic compartments
- finding the correct parameter for leakage and inter-compartmental conductance

ongoing PhD thesis from Jakob Kaiser, in collaboration with Sebastian Schmitt, Tetzlaff lab, University Göttingen
fitting to a different chip

- reference is measured on a different chip
- no 100% fit of the data using only two parameters possible

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easily accessible analog computing:
EBRAINS neuromorphic service BrainScaleS

• make *conceptual neuromorphic dimensions* of BrainScaleS remote accessible

• encapsulate its *technological neuromorphic dimensions* into the EBRAINS remote user framework

• support all *application dimensions*

• by implementing all EBRAINS dimensions :
  • software
  • user interface
  • documentation
  • tutorials
  • support
  • hardware operation and maintenance
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2010 BrainScaleS-1 analog neuromorphic computing wafer scale system
2018 BrainScaleS-2 invents hybrid plasticity
2020 BrainScaleS-2 part of EBRAINS