

Simulation of cortical waves using large scale networks of spiking neurons interconnected by plastic synapses

The WaveScalES experiment in the Human Brain Project

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Novel experimental techniques

permit a quantitative exploration of the Brain Architecture at micro-, mesoand macro scale

Understanding the brain, at different levels of abstraction. Since ever, one of the greatest intellectual ambitions. A quantitative approach is emerging. Europe, brain disorders and trauma cost: 798 billion € /year

- Increasing, due to the progressive population aging
- Possible therapies from better understanding

Computational Neuroscience: an Emerging Quantitative Discipline



Novel Brain **Experimental** Techniques, multi-modal High Spatial and Temporal Definition

Simulations on Massive Parallel Computers, Robots, Neuromorphic platforms

Computational Neuroscience

Theoretical Models: Long-Range and Short Range Connectome (architecture of connections), Dynamic laws for Neuron evolution (computation) and Synaptic Plasticity (learning), Consciousness Theories The Human Brain. A simplistic view. Grey Matter, White Matter, Areas, Columns, Layers

- About 100 Giga NEURONS (cells) in a human brain
- about 10000 SYNAPSES (connections) per NEURON
- Synapses placed on the AXONAL arborization of each neuron
- Each neuron receives inputs from synapses touching its
 SOMA and DENDRITIC arborization
- GRAY MATTER: neurons and short range connections
- WHITE MATTER: long range connections



Image: John A Beal CC-BY license. 2005 Louisiana State Univ.

Top-down cortical architecture hierarchy: There are (about a hundred of) AREAs

- Each area: a bidimensional grid of CORTICAL COLUMNS (typical grid step: about hundred micron)
- about 6 LAYERS in a typical cortical column





Investigating the brain architecture. A long journey







Ramon y Cajal (1899) Comparative study of Human Sensory Areas Ramon y Cajal (1905) Chick Cerebellum



Year 1909 – Definition of Brodmann Cortical Areas









Example of recent experimental development: White Matter Long Range Connectome



Year 2015 – White matter mapping, DTI - fiber tractography

Spiking activity of individual neurons observed in a Zebra Fish Larva





Misha B Ahrens, Philipp J Keller, «Whole-brain functional imaging at cellular resolution using light-sheet microscopy», Nature Methods, 18 March 2013, DOI:10.1038/NMETH.2434 Howard Hughes Medical Institute, 3D recording of temporal spiking activity of ~100 000 neurons. Note: the effective time resolution is still only ~1 s.

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Minimal scale example of simulation produced by the simulator DPSNN of INFN APE lab (it can simulate tens of G synapses)



- 200 inhibitory neurons
- 800 excitatory neurons
- Each dot in the rastergram represents an individual neuron spike
- The evolution of the membrane potential of individual neurons is simulated
- About 1M synapses in this simulation
- The evolution of individual synaptic strength is computed (not shown in the picture)
- individual synaptic delays are taken into account
- Individual connections and neural types can be programmed

Collective Spiking Rastergram and activity of individual neurons



The Human Brain Project - Intro



Planned European fund. 500M Euro, Oct 2013 – 2023

- □ Original Consortium: 112 research institutes
- Ramp up phase: Oct 2013 March 2016

□ Second half 2015

- Competitive call for new scientific proposals/partners (evaluation by external reviewers)
 - INFN leads the WaveScalES proposal, 4 proposals selected among 57 submitted

□ HBP Commitment: before 2018 define transformation into legal entity

- □ National Stakeholders board will be proportional to national investments
- □ National /Regional Partnering Projects
- □ Scientific Board (presently, 13 + 10 members)
- □ Periodic (bi-annual) plan revision, new competitive calls, additional partners
- □ First HBP operational phase, April 2016-March 2018
 - WaveScalES started April 2016
 - □ 1 MEuro/year, if good results, until 2023

Slow Waves and Perturbations



During deep-sleep and anaesthesia the cortex moves in a lowcomplexity mode:

Collective oscillations, $\sim @ 0.1 - 4 \text{ Hz}$, between two states:

Down state: neurons nearly silent (firing @ few Hz)

- □Up state: neurons active (firing @ tens of Hz) for a few hundreds ms, then inhibition switch the system to the down-state
- Local oscillation phase -> slow-waves moving on the cortical surface (planar, spirals, ...)
- □ Perturbative approach:

Localized spatio-temporal impulse

Measure the impulse response

Quantification of consciousness potential and damages in disease/trauma, forecast of emergence from coma

WaveScalES in HBP - Summary



- Experimental WaveScalES partners (will) measure brain Slow Waves during deep-sleep and anaesthesia, and during the transition to consciousness, including:
 - Inon invasive techniques on human: high-def. electro-encephalographic response to transcranial magnetic stimulations
 - lectro-physiological response to in-vitro/in-vivo
 opto-pharmacologic stimulation of murine models
- □ INFN in WaveScalES mainly in collab. with ISS Roma

□large scale parallel/distributed simulation of Slow Waves and perturbation responses

WaveScalES partners / topics / key persons

- INFN, Istituto Nazionale di Fisica Nucleare, APE Parallel/Distributed Computing Lab, Roma, Italy
- Consorci Institut d'Investigacions Biomèdiques August Pi i Sunyer, Barcelona, Spain – Murine electro-physiology
- Università degli Studi di Milano, Italy Measures in humans
- Fundació Institut de Bioenginyeria de Catalunya, Spain – Optopharmacological Perturbations
- Istituto Superiore di Sanità, Italy Theoretical Models

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Human Brain Project

WaveScalES Experiment, in the

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Maria Victoria Sanchez-Vives







Marcello Massimini Mario Rosanova

Mario anova



Pau Gorostiza

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Miquel Bosch



Maurizio Mattia



Paolo Del Giudice





WaveScalES measures: from the human bedside down to the murine slice.



TMS/EEG to assess pathological changes in cortical communication and complexity induced by sleep-like bistability;

Intracortical single-pulse electrical stimulations (SPES) and stereo-EEG recordings in combination with scalp hd-EEG to link slow-wave dynamics to overall network connectivity and complexity.

Electrical / optical stimulations / recordings in brain (slices) to study the effects of (opto)pharmacological manipulations on bistability, connectivity and complexity.





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- 3. Slow-wave activity in murine transgenic models of neurological disease (IDIBAPS)
- Modulation of slow-wave 4. activity with optopharmacology (IBEC)
- 5. Slow wave simulation platforms (INFN)

simulations (up to hundreds of billions synapses) distributed over (up to tens of) thousands of MPI processes, including columnar, areal and inter-areal connectivity models.

Computational objectives: match, explain and predict experimental observations. Improve simulators / HPC interconnects

Five Tasks:

1.

2.

Example of simulation produced using the INFN simulator DPSNN in cooperation with ISS (Paolo Del Giudice, Maurizio Mattia)





Simulation of a large field of cortical columns (pixels of the bottom snapshots), each composed of 2500 excitatory and inhibitory leaky IF neurons. Top, firing rate of the central column (green) of the cortical field and the net synaptic input it receives from neighbouring columns (blue): local vs global contribution. Simulations performed within CORTICONIC project (ISS/INFN) with a total of 10^6 cells and 10⁹ synapses.

Network of point-like spiking neurons with plastic synapses



- □ The Brain is a hierarchical complex system with a multiscale spatial and temporal architecture
- It can be analyzed, modeled and simulated at several different level of abstraction
- The modeling and simulations presented in this talk are at an intermediate level of abstraction: network of point-like spiking neurons with plastic synapses.
- Spiking networks: an attempt to capture both a few key aspects of the biological architecture and to reproduce the computational properties of large scale networks of neurons, still maintaining some biological plausibility

1 hour talk: I had to introduce brutal approximations allover this presentation

Synapses matter most, not neurons ...



- N:=neurons, M:=mean number of synapses/neuron, f:=mean firing rate (spikes per second per neuron), s:=seconds to be simulated, b:=bytes per synapses
- □ For every neuron, thousands of synapses (M>1000)
- Every time a neuron spikes, events are triggered on all the synapses on its axonal arborization
 - A key software and hardware issue for parallelization is the efficient delivery of the spiking messages to synapses
 - The computational cost of a simulation grows with the total number of synaptic events N*M*f*s.
- Execution times can be normalized dividing them by N*M*f*s to get an execution time per synaptic event
- Memory consumption is dominated by the storage of the synaptic database: N*M*b

DPSNN: Simulation platform parallelized for INFN efficiency on thousand processing cores

Human Brain Project Scaling to 1024 software processes and hardware cores of the distributed simulation of a spiking neural network including up to 20G synapses arXiv:1511.09325 (2015) E. Pastorelli, P.S. Paolucci et al. (the APE lab) (in collaboration with ISS, Del Giudice, Mattia)

> Impact of exponential long range and Gaussian short range lateral connectivity on the distributed simulation of neural networks including up to 30 billion synapses

arXiv:1512.05264 (2015) E.

Pastorelli, P.S. Paolucci et al. (the APE lab) (in collaboration with ISS, Del Giudice, Mattia)

For an introduction to DPSNN see also:

P.S. Paolucci, et al., (2015) Journal of Systems Architecture, "... EURETILE ..."

P.S. Paolucci, et al., (2013) arXiv:1310.8478

Strong Scaling of DPSNN on Galileo, July 2015 elapsed sec / (simulated sec * total syn * firing rate)









Pier Stanislao Paolucci – parallel computing CV



- Since 1984, member of APE massive parallel comp. lab, INFN Roma
- Inventor/developer of parallelization algorithms, parallel hardware architectures, system software tools, applied to:
 - QCD, multidim. FFT, meteorology (cubed-sphere), synthetic aperture radar, oil exploration, acoustic arrays, digital signal processing, multiprocessor systems-on-chip, ..., large scale neural networks
- **2016-...** Coordinator, WaveScalES experiment in the Human Brain Project
- □ 2010-2015 Coordinator, European FP7 Project EURETILE, 5M€
- □ 2006-2009 Coordinator, European FP6 Project SHAPES, 9M€
- 2000-2010 Chief Technical Officer, Atmel Roma design center (NASDAQ: ATML), 4 year tech. tranf. detachment, then part-time researcher until 2010, then back to INFN (full-time researcher)
 - US patent 6,766,439, US patent 7,437,540
 - □ 2000-2006 Coordinator, Eureka Project DIAM,
- □ 1997-2000 Principal Investigator, ESPRIT European proj. mAgic-FPU

INFN APE lab



- Created in 1984 by Nicola Cabibbo & Giorgio Parisi
- Since then research & development of parallelization algorithms, system software and hardware architectures for numerical simulations /digital signal processing / HPC
- Developed several generations of parallel computing systems (APE, APE100, APEmille, APEnext) based on custom VLSI processor and custom interconnects
- Several technological / industrial spin-off
- Team (14 people) in Roma:
 - 4 research staff persons
 - 10 temporary research positions on external funds

Researchers to be recruited in INFN for WaveScalES (call deadline 24 June 2016, colloquium on 18 July, start October 1st) on large-simulation techniques and models for neuro-science

Development of Distributed Plastic Spiking Neural Net Simulator in INFN



- INFN Roma APE Lab coordinated **EURETILE(2010 2015)** FP7 project
 - □ Investigation of future generations of distributed/parallel computers
 - □ Focus on software/hardware scalability on many core systems
 - □ Start of DPSNN code development as a source of requirements and architectural inspiration for extreme parallel computing
- □ INFN third party of ISS Roma in **CORTICONIC (2013 2016)** FP7 project
 - □ Identify computational principles of the cerebral cortex
 - □ First comparison with in-vivo/in-vitro experimental results
 - DPSNN improved for CORTICONIC simulations (support of more realistic biological models) importing models from ISS Perseo scalar simulator (Paolo Del Giudice, Maurizio Mattia)
- DPSNN simulator key benchmark in EXANEST (2016-2018) FET Project (INFN, Piero Vicini)
- DPSNN will be further improved in the **HBP WaveScalES experiment**

Main + and - points of

our DPSNN simulation engine compared to

standard platforms



- Limited flexibility / configurability of models of neurons, synapses, connectivity
- Difficult maintenance
- DPSNN not a platform for the general neuroscientist. Requires the support of the developer
- Standard platforms exist and are constantly improving: e.g. NEST, NEURON
- □ Fast distributed network initialization
- Mixed time-driven (axonal messages between software processes) and event-driven (synaptic dynamic) scheme -> high temporal resolution on individual synaptic event AND good scalability on high number of MPI processes
- Highly application specific dirty down to the essential no bells and whistles -> speed / scalability potential
- Easy, essential benchmark kernel for hardware architectures

The paradigmatic biological neuron. In spikingnet simulations neurons are much simpler





Simplified model of computational state...



- The membrane of a neuron: a double-lipidic insulator crossed by ionic channels and ionic-pumps, (simplified model, a capacitor in parallel to several voltage generators with variable conductances)
- Membrane potential and computational state. The computational state of each neuron is expressed mainly by the electric potential across its membrane.
 - Polarized state. Most of the time, the membrane potential fluctuates at about -65 mV. When polarized, no signals are transmitted to other neurons
 - □ SPIKE. Mainly as a consequence of synaptic signals, the neuron membrane can emit a SPIKE: in about 1ms the neuron first depolarizes to about +30mV and then returns to its polarized state, typically with an hyperpolarization and a spiking refractory period of a few ms

For each SPIKE, an electric signal is transmitted to all synapses through the axonal arborization (an active signal regeneration system)

... and Memory model



- □ Long-term memories can be stored in the highly sparse graph of its connections (synapses), by the weights of the synapses (i.e. the quantity of current injected in target neurons when synapses are activated by a spike) and by the delay introduced by each axosynaptic connection.
- Short-term memories (and recalled memories) can also by represented by the reverberant computational activity of groups of neurons on a moving time window
- Memory of Darwinian evolution mainly sculpted in the architecture probabilistic description

A computational representation of the neuro-synaptic system



□ State of the systems and of the current computation:

- a few state variables Vi(t), Ui(t), ... for each of the neuron 1=1...N (constant parameters Ai, Bi, ... specify the neural kinds)
- Each neuron projects (a mean of) M synapses towards other neurons and the

Long term memories represented by:

- □ *Wij(t)*, a sparse synaptic connection matrix (N>>M).
- **Dij**, propagation delay of the spike along the axonal arborization tree
- □ ... other info about the characteristics of the synapses

□ Micro-, Meso- and Macro-scale description of the architecture:

- Probabilistically modulated description of the composition of layers and columns (neural populations) and of the intra-columnar connections (intra-columnar connection probabilities, probability of weights, of propagation delays)
- Distance dependent laws for inter-columnar connections, delays

□ Matrices of Inter-areal connection probabilies

□ Random number generation everywhere (probabilistic modulation network generation, simulation of external events and noise)

Example of simplified neural dynamics. NOT the one used in WaveScalES as first choice. Two variables:



Membrane potential v and recovery current u

$$\begin{cases} if \ v(t) < v_{peak} & then \\ if \ v(t) \geq v_{peak} & then \end{cases} \begin{cases} \dot{v} = \mathbf{0} \cdot \mathbf{04} \ v^2 + 5v + \mathbf{140} - u + I \\ \dot{u} = a(bv - c) \\ v(t + \Delta t) = c \\ u(t + \Delta t) = u(t) + d \end{cases}$$

Where:

- **v** (t) is the neural membrane potential. This is the key observable;
 - we say that when v reaches v_{peak} a "neural spike" happened;
- I(t) is the potential change generated by the sum of all synapses incoming to the neuron.
 - Incoming currents are present if spikes arrived form presynaptic neurons;
- **u(t)** is an auxiliary variable (the recovery current bringing back v to equilibrium);
- **a, b, c, d** are four parameters, constant for each neuron,
 - by varying them the same equations model captures the behaviour of all type of known neural types.

Izhikevich, Eugene M. Simple Model of Spiking Neurons.

IEEE Transactions on Neural Networks, Vol. 14, No. 6, November 2003.Pier Stanislao PAOLUCCIJune 2016 – Scuola INFN - Alghero



Summary of the neurocomputational properties of biological spiking neurons. Each horizontal bar corresponds to 20 ms. Upper curve: membrane potential. Lower curve: injected current. Picture reproduced with original author's permission (see www.Izhikevich.com)

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biological plausibility (# of features) (good) (poor)	inte qu re	egrat nteg adra inte son	e-ar irate ate- iikev	te-and te-and te-and ich (e I-fire rate- nd-fi fire	with and re-o	r-bu	apta rst	tion		•Fit.	zHuç	gh-N ņars	lagu I	mo Mori ose Ho	ris-Lo ₩ ••••	ecar filsoi	n uxle	•				
(efficient) implementation								n co	cost (# of FLOPS) (prohibitive)							e)							
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integrate-and-fire	-	+	-	-	-	-	-	+	-	-	-	-	+	-	-	-	-	-	-	-	-	-	5
integrate-and-fire with adapt.	-	+	-	-	-	-	+	+	-	-	-	-	+	-	-	-	-	+	-	-	-	-	10
integrate-and-fire-or-burst	-	+	+		+	-	+	+	-	-	-	-	+	+	+	-	+	+	-	-	-		13
resonate-and-fire	-	+	+	-	-	-	-	+	+	-	+	+	+	+	-	-	+	+	+	-	-	+	10
quadratic integrate-and-fire	-	+	-	-	-	-	-	+	-	+	-	-	+	-	-	+	+	-	-	-	-	1-1	7
Izhikevich (2003)	-	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	13
FitzHugh-Nagumo	-	+	+	-		-	-	+	-	+	+	+	-	+	-	+	+	-	+	+	-	-	72
Hindmarsh-Rose	-	+	+	+			+	+	+	+	+	+	+	+	+	+	+	+	+	+		+	120
Morris-Lecar	+	+	+	-		-	-	+	+	+	+	+	+	+		+	+	-	+	+	-	-	600
Wilson	-	+	+	+			+	+	+	+	+	+	+	+	+	+		+	+				180
Hodgkin-Huxley	+	+	+	+			+	+	+	+	+	+	+	+	+	+	+	+	+	+		+	1200

WaveScalES Experiment, in the

Floating-point operations per simulated integration step of a list of simplified neural models using timedriven integration schemes

Izhikevich, Eugene M. Which Model to use for cortical spiking neurons? *IEEE Transaction on Neural Networks, 15, no. 5 1063-1070 (2004).*

Example of Synaptic Learning Dynamic: STDP: Spike Timing Dependent Plasticity Song et Al. (2000) formulation.



Capturing causal and anti-causal relation between two connected neurons:

- the synapse is maximally potentiated if the delay introduced by the axon causes a delivery of the axonal signal to the target neuron just before the post-synaptic spike.
- The synapse is maximally depressed if the signal arrives just late.

$$t = t_{post} - t_{pre} - d_{axon} \begin{cases} if \ t \ge 0 \quad \Delta W_{pre,post} = A_{+}e^{-\frac{t}{\tau+}} \\ if \ t < 0 \quad \Delta W_{pre,post} = A_{-}e^{\frac{t}{\tau-}} \end{cases}$$

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Axonal delays could even create the representation for memories of precise temporal sequences of spikes.

lf:

- neuron A spikes at a certain time t₀,
- neuron B spikes two ms after,
- and C sends at t₀+14 ms,

3 spikes would reach simultaneously neuron D. This could trigger a spike on D at t_0 +21 ms.



The network would be recognizing this temporal activation sequence of A, B, C and D.

A different temporal spiking sequence of the same set of neurons

- A spiking at t_{0.}
- C at $t_0 + 3$ ms and
- B at t₀ +6 ms)

could trigger a spike on neuron E at time $t_0 + 17$ ms

Distribution of the same problem (a grid of 64 neural columns) on 4, 64 or 256 software processes



A sample grid of 64=8x8 neural columns.

Excitatory neurons projects 76% of their synapses toward neurons located in the same column, 3% to first neighboring columns, 2% to second neighbours and 1% to third neighbours.

Strong scaling measures: a,b,c) are examples of distribution of a grid composed of 64 neural columns over a varying number of software processes and computational cores.

One computational core can host one or more software processes

The number of software processes assigned to each computational core has been changed during the strong scaling measure.



a) 64 neural columns on 64 sw processes -The number of software processes is equal to the number of neural columns.

_	_		1%			_
		2%	3%	2%		
	1%	3%	76%	3%	1%	
		2%	3%	2%		
			1%			

c) 64 neural columns on 4 sw processes - In this case, 16 neural columns are managed by each software process.



b) 64 neural columns on 256 sw processes -Each neural column is distributed among four software processes.

> The simulation of the same grid of neural columns produces identical results on all distributions.

	\checkmark	
Mainly event driven	INTRA-PROCESS GATHER + COMPUTATION: LTP + after spike dynamic:== 1- identification of the subset of neurons that spiked; 2- the time difference between the current neural spike timing and the last synaptic activation time is computed, only for the subsets of synapses incoming to those neurons that spiked; 3- only for those synapses, a contribution to the synaptic long term potentiation is computed ; 4- neural after spike dynamic (e.g. it includes the repolarization of the membrane), only for those neurons that spiked.	
	Barrier :== optional, the barrier can be inserted to simplify the measure of time spent in COMPUTATION vs. COMMUNICATION. If the barrier is not inserted, the time spent waiting for the processes that are still completing their computations will appear as a contribution to the time measured for the "Spikes dim" message passing phase.	
	*	
time driven	INTER-PROCESS MULTICAST: Spikes dim :== each process (cluster of neurons) informs its own subsets of potential target processes about the existence and the actual number of axonal spikes to be transmitted/received during the "spikes payload" phase.	
event driven	INTER-PROCESS MULTICAST: Spikes payload :== actual transmission of axonal spikes to the subset of processes where a target neuron exists for the subset of spiking neurons.	L
event driven	INTRA-PROCESS MULTICAST: Axonal to synaptic spikes :== 1- axonal spikes are inserted in a time delay queue. 2- axonal spikes are extracted from the time delay queue and each axonal spike is expanded to a list of synaptic spikes.	L
	—	
event driven	COMPUTATION: Add synaptic currents + LTD :== 1- the sum of currents injected by incoming active synapses are computed and stored in target neurons; 2- the time difference between the synaptic spiking time and the last post synaptic neural spiking time is used to compute a contribution to the long term depression of the subsets of incoming spiking synapses.	
	↓	
time driven	Thalamic input :== External thalamic current are injected onto a small subset of neurons.	L
	↓	
time driven	COMPUTATION: Ordinary neural dynamic :== computation of an evolution time step of the membrane potential and currents of each neuron.	1
	*	-
event driven	Rastergram & statistical functions :== dump of statistical files.	mil
	¥	1
time driven	COMPUTATION: Long term synaptic plasticity :== every sim second, the LTP and LTD contributions are used to evolve the long term plasticity of all synapses	T Eve
		sec



Orange Blocks: MPI communications

Green Blocks: Local Processing

> Red labels: Event Driven

Blue labels: Time Driven

Strong scaling (fixed problem sizes, increasing hardware cores) for Long-range (exp –x/L) and short-range (Gaussian –x^2/(2L^2)) connection probabilities

Strong Scaling for Gaussian and exponential connectivity elapsed sec / (simulated sec * total syn * firing rate)



WaveScalES Experiment, in the

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INFN

Memory consumption (no plasticity case)



Memory occupation in byte/synapse



References



About the proposal of measurable observables about consciousness and integration/differentiation and macro/scale connectivity

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About Consciousness: example of system of axiomes / postulates focusing on a balance of integration and differentiation

- G. Tononi (2015) "Integrated Information Theory" Scholarpedia
- G. Tononi and C. Koch (2015) "Consciousness: here, there and everywhere" Philos. Trans.

G Supporting mathematical framework

Oizumi M, Albantakis L, Tononi G (2014) From the Phenomenology to the Mechanisms of Consciousness: Integrated Information Theory 3.0. PLoS Comput Biol 10(5): e1003588. doi:10.1371/journal.pcbi.1003588

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- T.C. Potjans and M. Diesmann (2014) "The Cell-Type Specific Cortical Microcircuit: Relating Structure and Activity in a Full-Scale Spiking Network Model", Cerebral Cortex

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Conclusions



Brain research: emergence of a quantitative discipline, with scientific and translational impact

→ Computational Neuroscience: novel experimental methodologies and massive parallel simulations for multi-scale theoretical models

WaveScalES in the Human Brain Project coordinated by INFN Roma, APE Lab

Combines experiments, theory and simulations

□INFN effort for large scale simulations of spiking neural networks

Brain simulation as a key benchmark for future interconnects architectures (EXANEST FET Project, INFN Roma, APE Lab)

Researchers to be recruited in INFN for WaveScalES (call deadline 24 June 2016, colloquium on 18 July, start October 1st) on large-simulation techniques and models for neuro-science