The impact of Gaussian and exponential lateral connectivity on distributed spiking neural network simulation

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On their behalf

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Specific motivation for this study (1/2)

Recent experimentally defined model of probability of intra–areal connection among excitatory neurons:

slow exponential decay with distance

\[ P_{\text{conn}} = A \exp(-r/\lambda_{s,t}) \]

\( r := \text{distance between neuron} \)

\( 150 \, \mu\text{m} < \lambda_{s,t} < 350 \, \mu\text{m} \) (depends on the source and target layers and neuron kind)

inside a cortical area (\( r < 1 \, \text{cm} \)), at least 75% synaptic connections have a long-range origin (i.e. from outside the local neural column).

...not counting inter-areal connectivity arriving through white-matter fibers (\( r > 1 \, \text{cm} \))

... total number of synapses per neuron approaching 10 K
Specific motivation for this study (2/2)

- Previous studies estimated at about 75% local interconnectivity (and simulations accordingly performed)
  
  previous faster, shorter range Gaussian decay of connection probability

  \[ P_{\text{conn}} = B \exp(-r^2/2\sigma^2), \]

  \( r \):=distance between neuron

  typical \( \sigma \sim 100 \mu \text{m} \)

  ... and a lower total number of synapses per neuron

  -> longer range (and higher number of) connections to be supported in simulations -> **impact on distributed simulations**
Cortical Slow Wave Activity (SWA)

The transition from and toward expression of SWA, a phenomenon of great theoretical and applied interest. When Slow Waves appear, consciousness fades out, but they are an essential, fundamental mode of activity:

- SWA during dreamless deep sleep (every night the first phase of a good sleep), deep anaesthesia (unconscious kinds of), default mode of activity of isolated cortical modules
- SWA ubiquitous across animal species
- SWA more frequent, and essential, in juveniles
- Probable effects of physiologic SWA include improvement of coding of memories acquired during wakefulness and restoration of optimal cortical working point
Example of simulation requiring realistic intra-areal connections: cortical slow wave activity, single area simulated at high resolution (1/2)

Cortical area, described using a two-dimensional grid of cortical column.

Thousands of spiking neurons per column (excitatory and inhibitory).

Thousands of synapses per neuron

Simulation of a large field of cortical columns (pixels of the bottom snapshots),

Top-right panel: firing rate of the central column (green) of the cortical field and the net synaptic input it receives from neighboring columns (blue): local vs global contribution.

Parameters of the theoretical model defined by ISS (M. Mattia, P. Del Giudice, C. Capone)

Capone, Rebollo et al. (2017) Cerebral Cortex. Slow Waves...
Targeting the simulation of 1 cm$^2$ of cortex at biological resolution ...

Species and brain area dependent requirements.
For the rat neocortex (V1)

Neural density 54 K neurons / mm$^2$, 5 K synapses / neuron
->
1 cm$^2$, 5.4 M neurons, 27 G synapses
... and measuring the impact of shorter and longer range interconnects

In this study, three problem sizes are mapped from 1 to 1024 hardware cores / MPI processes to evaluate the impact of connectivity on strong and weak scaling and memory occupation.

<table>
<thead>
<tr>
<th>GRID</th>
<th>COLUMNS</th>
<th>NEURONS</th>
<th>Number of SYNAPSES</th>
<th>MPI Processes / hardware cores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Gaussian shorter range interconnect</td>
<td>Exponential longer range interconnect</td>
</tr>
<tr>
<td>24x24</td>
<td>576</td>
<td>0.7 M</td>
<td>1.2 G</td>
<td>1.8 G</td>
</tr>
<tr>
<td>48x48</td>
<td>2304</td>
<td>2.9 M</td>
<td>3.5 G</td>
<td>5.9 G</td>
</tr>
<tr>
<td>96x96</td>
<td>9216</td>
<td>11.4 M</td>
<td>14.2 G</td>
<td>23.4 G</td>
</tr>
</tbody>
</table>

... when executed on our own DPSNN (Distributed Plastic Spiking Neural Network) simulation engine, which is grounded on a data distribution strategy oriented to memory locality.
Mean number of synapses (in thousands) projected according to Gaussian and exponential laws

Example:
24 x 24 neural columns,
Grid step, 100μm

Green: Gaussian
Shorter range decay of connection probability, σ=100μm

Orange: exponential longer range decay, λ=290μm

Locally projected: 992 K synapses in both cases

|   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  | 24  |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1 | 1.2 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 2 | 1.2 | 5.0 | 8.7 | 5.0 | 1.2 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 3 | 5.0 | 22.3| 37.2| 22.3| 5.0 |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| 4 | 1.2 | 8.7 | 37.2| 992 | 37.2| 8.7 | 1.2 | 0.7 | 0.8 | 0.9 | 1.0 | 1.1 | 1.2 | 1.2 | 1.1 | 1.0 | 0.9 | 0.8 | 0.7 |     |     |     |     |     |     |
| 5 | 5.0 | 22.3| 37.2| 22.3| 5.0 |     | 0.7 | 0.9 | 1.1 | 1.2 | 1.4 | 1.5 | 1.6 | 1.7 | 1.6 | 1.5 | 1.4 | 1.2 | 1.1 | 0.9 | 0.7 |     |     |     |     |     |
| 6 | 1.2 | 5.0 | 8.7 | 5.0 | 1.2 | 0.8 | 1.0 | 1.2 | 1.4 | 1.7 | 2.0 | 2.2 | 2.3 | 2.4 | 2.3 | 2.2 | 2.0 | 1.7 | 1.4 | 1.2 | 1.0 | 0.8 |     |     |     |
| 7 | 1.2 | 0.7 | 1.0 | 1.2 | 1.5 | 1.9 | 2.3 | 2.7 | 3.0 | 3.2 | 3.3 | 3.2 | 3.0 | 2.7 | 2.3 | 1.9 | 1.5 | 1.2 | 1.0 | 0.7 |     |     |     |     |     |
| 8 | 0.7 | 0.9 | 1.2 | 1.5 | 2.0 | 2.5 | 3.1 | 3.7 | 4.2 | 4.6 | 4.7 | 4.6 | 4.2 | 3.7 | 3.1 | 2.5 | 2.0 | 1.5 | 1.2 | 0.9 | 0.7 |     |     |     |     |
| 9 | 0.8 | 1.1 | 1.4 | 1.9 | 2.5 | 3.2 | 4.1 | 5.0 | 5.8 | 6.4 | 6.6 | 6.4 | 5.8 | 5.0 | 4.1 | 3.2 | 2.5 | 1.9 | 1.4 | 1.1 | 0.8 |     |     |     |     |
| 10| 0.9 | 1.2 | 1.7 | 2.3 | 3.1 | 4.1 | 5.3 | 6.6 | 8.0 | 9.0 | 9.4 | 9.0 | 8.0 | 6.6 | 5.3 | 4.1 | 3.1 | 2.3 | 1.7 | 1.2 | 0.9 | 0.7 |     |     |     |
| 11| 1.0 | 1.4 | 2.0 | 2.7 | 3.7 | 5.0 | 6.6 | 8.6 | 10.7|12.5|13.2|12.5|12.5|10.7|8.6|6.6|5.0|3.7|2.7|2.0|1.4|1.0|     |     |     |     |
| 12| 1.1 | 1.5 | 2.2 | 3.0 | 4.2 | 5.8 | 8.0 | 10.7|14.0|17.2|18.7|17.2|14.0|14.0|10.7|8.0|5.8|4.2|3.0|2.2|1.5|1.1|     |     |     |     |
| 13| 1.2 | 1.6 | 2.3 | 3.2 | 4.6 | 6.4 | 9.0 | 12.5|17.2|22.8|26.4|22.8|17.2|12.5|9.0 |6.4 |4.6 |3.2 |2.3 |1.6 |1.2 |     |     |     |     |
| 14| 1.2 | 1.7 | 2.4 | 3.3 | 4.7 | 6.6 | 9.4 | 13.2|18.7|26.4|992 |26.4|18.7|13.2|9.4 |6.6 |4.7 |3.3 |2.4 |1.7 |1.2 |     |     |     |     |
| 15| 1.2 | 1.6 | 2.3 | 3.2 | 4.6 | 6.4 | 9.0 | 12.5|17.2|22.8|26.4|22.8|17.2|12.5|9.0 |6.4 |4.6 |3.2 |2.3 |1.6 |1.2 |     |     |     |     |
| 16| 1.1 | 1.5 | 2.2 | 3.0 | 4.2 | 5.8 | 8.0 | 10.7|14.0|17.2|18.7|17.2|14.0|14.0|10.7|8.0|5.8|4.2|3.0|2.2|1.5|1.1|     |     |     |
| 17| 1.0 | 1.4 | 2.0 | 2.7 | 3.7 | 5.0 | 6.6 | 8.6 |10.7|12.5|13.2|12.5|10.7|8.6|6.6|5.0|3.7|2.7|2.0|1.4|1.0|     |     |     |     |
| 18| 0.9 | 1.2 | 1.7 | 2.3 | 3.1 | 4.1 | 5.3 | 6.6 | 8.0 | 9.0 | 9.4 | 9.0 | 8.0 | 6.6 | 5.3 | 4.1 | 3.1 | 2.3 | 1.7 | 1.2 | 0.9 | 0.7 |     |     |     |
| 19| 0.8 | 1.1 | 1.4 | 1.9 | 2.5 | 3.2 | 4.1 | 5.0 | 5.8 | 6.4 | 6.6 | 6.4 | 5.8 | 5.0 | 4.1 | 3.2 | 2.5 | 1.9 | 1.4 | 1.1 | 0.8 |     |     |     |
| 20| 0.7 | 0.9 | 1.2 | 1.5 | 2.0 | 2.5 | 3.1 | 3.7 | 4.2 | 4.6 | 4.7 | 4.6 | 4.2 | 3.7 | 3.1 | 2.5 | 2.0 | 1.5 | 1.2 | 0.9 | 0.7 |     |     |     |
| 21| 0.7 | 1.0 | 1.2 | 1.5 | 1.9 | 2.3 | 2.7 | 3.0 | 3.2 | 3.3 | 3.2 | 3.0 | 2.7 | 2.3 | 1.9 | 1.5 | 1.2 | 1.0 | 0.7 |     |     |     |     |     |
| 22| 0.8 | 1.0 | 1.2 | 1.4 | 1.7 | 2.0 | 2.2 | 2.3 | 2.4 | 2.3 | 2.2 | 2.0 | 1.7 | 1.4 | 1.2 | 1.0 | 0.8 |     |     |     |     |     |     |     |
| 23| 0.7 | 0.9 | 1.1 | 1.2 | 1.4 | 1.5 | 1.6 | 1.7 | 1.6 | 1.5 | 1.4 | 1.2 | 1.1 | 0.9 | 0.7 |     |     |     |     |     |     |     |     |
| 24| 0.7 | 0.8 | 0.9 | 1.0 | 1.1 | 1.2 | 1.2 | 1.1 | 1.0 | 0.9 | 0.8 | 0.7 |     |     |     |     |     |     |     |     |     |     |     |     |     |

March 2018 - Pier Stanislao Paolucci

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Comparing the speed of simulations (1/2)

Simple and effective measure to compare the speed of neural simulations on different problem sizes and activity regimes of spiking neurons with instantaneous synaptic current injection:

- $N := \text{total \# neurons}$,
- $M := \text{mean \# synapses / neuron}$,
- $\nu := \text{mean firing rate of neurons (and synapses)}$,
- $T_S := \text{simulated time}, \quad T_E := \text{elapsed execution time}$

Total number of synaptic events to be simulated: $N \times M \times \nu \times T_S$

Execution time per simulated event = $\frac{T_E}{(N \times M \times \nu \times T_S)}$

Or the reciprocal, a simulation speed:

$\frac{\text{# simulated synaptic events}}{\text{second}}$
Comparing the speed of simulations (2/2)

MOTIVATION: There are N neurons, but NM synapses

- Simulation of individual spiking neuron: integration of a low dimensional differential equation. For example, LIF-SFA, Leaky Integrate and Fire neuron with rate dependent Spike Frequency Adaptation. Two dynamic variables, first order differential equations, plus forcing by synaptic current injection. If a threshold is exceeded, a spike is emitted. After spike, reset to post-spike values

- For each spike of an individual neuron, all its projected synapses are activated and have to inject a current in the target neuron

- NOTE AGAIN. For each neuron, there are thousands of synapses

- Current injection, an event driven approach can be adopted. Instantaneous synapses are not active when not spiking, and a time driven approach would be highly inefficient.
Measures on DPSNN engine

DPSNN (Distributed Plastic Spiking Neural Network simulation engine)

Developed by INFN APE Parallel/Distributed Computing Lab. Objectives: maximum speed on selected problems. Benchmarking tool for application specific computing/interconnect architectures

Natively distributed, exploits memory and temporal locality.

Synapses mapped in the same process of target neurons

Clusters of neurons and incoming synapses in a process

Really fast and scalable... INFN APE Lab. Since 1984 developed several generations of application specific parallel/distributed platforms.
Strong scaling for Gaussian Connectivity, DPSNN simulation engine

Execution Platform: GALILEO @ CINECA

Up to 64 IBM Nodes, 1024 cores.

Two Intel Xeon Haswell 8-core E5-2630 V3 processor per node @ 2.4 GHz.

Infiniband network, 4x QDR switches. Hyper-threading off.
Impact of longer-range exponential connectivity, manageable on DPSNN engine

![Graph showing execution time per synapse event against number of processes/cores]

- 24x24 Gauss - 0.9 G syn, 0.7 M neu
- 48x48 Gauss - 3.5 G syn, 2.9 M neu
- 24x24 Expo - 1.5 G syn, 0.7 M neu
- 48x48 Expo - 5.9 G syn, 2.9 M neu

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Memory cost: normalized measure

Ideally, the memory cost should be proportionally to the number of represented synapses. A normalized measure to compare for different problem sizes and mappings

Normalized memory cost := divide the peak memory occupation by the number of total represented synapses

On DPSNN, when plasticity is switched-off (static synapse), a synapse is represented during execution by 12 Bytes on the process storing the target neuron:

4 B source neuron id, 4 B target neuron id, 2 B weight, 2 B syn kind

During initialization, synapses are represented on both source and target neuron -> minimum expected peak occupation:

24 B / represented synapse
Memory cost on DPSNN for shorter and longer range interconnects

the overhead is mainly due to: 1) MPI buffers 2) Internal DPSNN structures to demultiplex from axonal spike event messages to synaptic events
DPSNN simulation engine: objectives of INFN APE parallel/distributed computing lab

1) Quantitative assessment of requirements / benchmarking during development of embedded and HPC systems specialized for neural simulations, focusing on either:

- Specialized interconnects, for ARM and Intel based platforms
- Power efficiency, e.g. on ARM processors
- Acceleration of kernels (e.g. on FPGAs)
- Invention and test of improved distributed coding techniques on standard message passing software infrastructures to be ported on general purpose neural simulation platforms

2) Acceleration of specific scientific simulations: e.g. INFN coordinator of the WaveScalES experiment in the Human Brain Project (specific objectives in WaveScalES: simulation of cortical Slow Wave Activity (SWA) and matching with experimental results, understand interaction between sleep (SWA) and memories, transition from unconscious/anaesthesia states (characterized by SWA) to conscious states (asynchronous activity, gamma rhythms...)

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Main + and - points of our DPSNN simulation engine

- Fast distributed network initialization
- Mixed time-driven (axonial 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 architecture
- Limited flexibility / configurability of models of neurons, synapses, connectivity
- In house maintenance and reconfiguration for different problems needed
- Not a platform for the general neuroscientist. Requires the support of the developer
DPSNN engine: internals (1/3)

- Mixed time and event driven simulation engine
  - Event driven: synaptic events and integration of neural dynamics
  - Time driven: exchange of spiking messages among processes
- Data distribution strategy:
  - Synapses are localized in memory near the target neurons
  - Neurons and synapses contiguous in space are stored in the same process
- DPSNN processes are agnostic of the specific message passing library agnostic:
  - in this study DPSNN uses MPI,
  - in other studies DPSNN processes have been e.g. nodes of a Kahn network
- Natively parallel initialization:
  - each DPSNN process creates in total autonomy its own set of neurons and manages the creation of the connections of its own set of projected synapses and incoming synapses
Axonal arborization of spiking messages to a set of target synapses deferred to the processes that host target neurons

Suppression of superfluous interprocess communications using a pruning strategy performed in several steps: (two steps during initialization, two steps at each iteration of the simulation)

supported e.g. by a sequence of MPI_alltoallv() calls addressing subsets of targets of decreasing size, ....
Mainly event driven

**DPSNN engine:**

- **Internals (3/3)**
- **Mixed event and time driven execution flow**

**Main steps:**

1. **INTRA-PROCESS GATHER + COMPUTATION:** Identification of neurons that spiked + LTP = 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.

2. **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.

3. **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.

4. **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.

5. **COMPUTATION: Insertion of synaptic events + LTD:** = 1- synaptic events are stored in lists 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.

6. **COMPUTATION: Sorting of synaptic events:** = for each neuron, at each message passing time step, sorting of synaptic events previously stored in neural queues (both recurrent synapses and external (e.g. poissonian modeled)).

7. **COMPUTATION: Ordinary neural dynamic:** = for each synaptic event, computation of an evolution time step of the neuron dynamic.

8. **Rastergram & statistical functions:** = dump of statistical files.

9. **COMPUTATION: Long term synaptic plasticity:** = LTP and LTD contributions are used to evolve the long term plasticity of all synapses at each second of simulation.

**Execution flow:**

- Every millisecond
- Every second
Conclusions / Acknowledgements

- Long-range intra-areal synaptic connections projected according to distance dependent decay laws of probability compatible with experimental evidence have a measurable but manageable impact on scalability of spiking neural network simulations distributed on up to 1K cores and performed at biological resolution using simulators that exploit memory and time locality, like our DPSNN engine.

Acknowledgements:

- The Human Brain Project, EU grant No. 720270 (HBP SGA1)
- The ExaNeSt Project, EU grant No. 671553
- INFN-CINECA Computational Theoretical Physics Collaboration